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Barriers to the adoption of new technologies in rural areas: The case of unmanned aerial vehicles for precision agriculture in India

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ABSTRACT

Technological advances can significantly transform agrarian rural areas by increasing productivity and efficiency while reducing labour intensive processes. For instance, the usage of Unmanned Aerial Vehicles (UAVs) can offer flexibility collecting real-time information of the crops enabling farmers to take timely decisions. However, little is known about the barriers to the adoption of such technologies by rural farmers in emerging economies like India. Building on an extensive literature review, focussed group discussions, and field visits, the barriers impacting the adoption are identified and classified into technical, social, behavioural, operational, economic, and implementation categories. The relevance of each barrier and its importance is evaluated using a hybrid multi-criteria framework built on the theory of Fuzzy Delphi and Fuzzy Analytical Hierarchy Process to identify the most crucial barriers to the adoption of UAVs to implement precision agriculture in rural India. The paper suggests new avenues for accelerating technology adoption in rural areas of emerging economies.

1. Introduction

Developing and disseminating technological solutions is crucial for attaining Sustainable Development Goals (SDGs), as highlighted at the UN Rio+20 conference [1]. However, technology adoption in agrarian rural areas is impeded for multiple reasons slowing the attainment of SDGs [2]. Although conventional agricultural practices have their advantages, most of them are becoming ineffective because of climate change, population explosion, and increased food demand. Thus, these technologies require modification, upgradation, and replacement, and/or adoption in many countries. The adoption of modern technologies, such as UAVs, robotics, the Internet of Things (IoT) can help to increase productivity, sustainability, and efficiency in agriculture. Referred to as precision agriculture, it leverages modern technologies for acquiring data about the soil, weather, and crops, and using this information makes informed decisions about planting, irrigation, fertilization, and pest control.

Among these technologies, the use of UAVs, popularly known as drones, is gaining traction around the world. The capabilities of UAVs offer flexibility to the farmers in analysing the crops at a desired spatial and temporal resolutions enabling them to take timely decisions [3]. Most of the currently available agricultural drones are semi-automatic devices that are edging towards complete automation [4]. These unmanned devices have significant potential in collecting various spatial attributes to assist in agricultural planning. Recent developments in this technology offer safe, reliable, and affordable solutions for various activities involved in agriculture [5]. Fig. 1 presents the typical UAVs being used in the agricultural domain.

Fixed wing drones are configured with a fixed wing system and are similar to traditional manned aircrafts [6]. They have well known advantages such as longer flight duration, higher speed range, payload capacity and stability during flight. However, they require a considerable runway space for landing and take-off. Due to the design limitations, they cannot handle missions with agile and complex manoeuvres. In contrast, Monocopter drones enable vertical take-off and landing (VTOL) and do not require a runway or operational space [7]. They offer

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Fig. 1. Conventional type of drones used in agriculture (a) Fixed wing drone (b) Monocopter/helicopter (c) multi-rotor drones.

higher manoeuvre flexibility by controlling the propeller speed thereby enabling agile movements during missions. However, they do not offer sufficient stability and control during missions, particularly at higher and payloads.

In the recent times, multirotor drones are designed to overcome the challenges of fixed wing and monocopter drones [8]. They are equipped with multiple propellers at calculated geometrical locations on the drone body. Changing the speed and direction of rotation of these propellers enables the users to maintain the required stability as well as agility in manoeuvring them. They can be engineered to carry various payloads [8].

Deployment of a drone over agricultural farms helps farmers to experience aerial views of the harvest. The data thus obtained help to derive information on the efficiency of the water system, soil characteristics, and presence/absence of pests [4]. Drones with payloads such as multispectral cameras can also aid in determining crop health at a large scale, which is challenging to the naked eye. Data derived using these cameras can also assist farmers in monitoring the yield periodically and taking necessary actions [9,10]. Drones have also been successfully used for various agricultural applications [11–15]. Despite the notable success of UAV in Agro applications, its adoptability by farmers in emerging economies is limited due to various barriers. For instance, applications of UAVs in different phases of agricultural works are still in the nascent stages in India, and little is known about the barriers to their adoption. This paper addresses the following research questions to bridge this gap:

RQ1. What are the prime barriers to the adoption of UAVs by farmers in India?

RQ2. What initiatives can help in the adoption of UAVs among Indian farmers?

Based on the comprehensive literature review complemented by a survey with experts from Krishi Vigyan Kendra[1] (https://kvk.icar.gov.in) and the National Academy of Agricultural Science, a total of 33 barriers encompassing Technical, Social, Behavioural, Operational, Economic, and Implementation categories for the adoption of UAVs are identified. The identified barriers are analysed using Fuzzy DELPHI and Fuzzy Analytical Hierarchy Process (AHP) to evaluate the relevance and significance.

The study makes several contributions to the extant scholarship on identifying and evaluating the barriers to adopting UAVs by farmers for agricultural operations. Firstly, to the best of our knowledge, this is the first paper to identify, analyse, and prioritize the barriers that impact the adoption of UAVs by farmers in India. Secondly, it provides new insights into how the adoption of UAVs can be accelerated to attain SDGs globally.

The rest of the paper is organized as follows. The following section presents an overview of literature on UAVs and its applications in agriculture. Section 3 provides a summary of the barriers for adopting UAVs, as identified in the extant literature. The Fuzzy Delphi and Fuzzy AHP methods used to analyse the identified barriers are discussed in section 4. Section 5 presents the results of the empirical analysis. Section 6 offers a discussion and a roadmap to promote the adoption of UAVs for precision agriculture. Section 7 concludes the paper and presents the limitations and future research scope.

2. Role of UAVs in agriculture

The emerging literature on the role of UAVs in agriculture is presented broadly under various themes including crop health monitoring, water stress monitoring, spraying, and miscellaneous covering other potential applications of UAVs in agriculture.

Crop health monitoring: Multi-spectral data of a vineyard collected using an UAV helped understand crop heterogeneity based on Normalized Difference Vegetation Index (NDVI), as confirmed by evidence from field studies that was in line with the outcomes of image-based classification [16]. NDVI of a rice crop, evaluated with the help of radio-controlled helicopter, was used as a parameter to estimate the yield demonstrating the data collected using UAVs is a reliable alternative to satellite images [17]. Wide range of Vegetation Indices (VI), computed using the data obtained from UAVs, assisted in the quantitative and qualitative evaluations of vegetation cover and growth dynamics [18]. An UAV developed in-house, capable of capturing multispectral images, was used to determine various spectral indices such as the Optimized Soil Adjusted Vegetation Index (OSAVI), Soil Adjusted Vegetation Index (SAVI), and Enhanced Normalized Difference Vegetation Index which helped in the effective farm management [19]. A UAV weighing 400 g with a 250-band hyperspectral sensor, helped to estimate the chlorophyl content in rice paddies accurately in the presence of unstable illuminations. These maps help in precision farming aiding to delineate the regions requiring additional fertilisers [20]. Similar approach can be adopted to determine the nitrogen content in rice crops [21].

Water stress monitoring: Instantaneous and seasonal Crop Water Stress Index within a vineyard was estimated using high resolution thermal images collected using an UAV and it was noted that the estimates are comparable to the stem water potential and stomatal conductance measured from field studies indicating the effectiveness of the UAV survey [22]. UAV falling under small category mounted with multi-spectral camera effectively (91 $\pm$ 7% accuracy) classified citrus orchards farm on the basis of water stress levels [23]. Similar payload was mounted to Vulcan Hexacopter to determine the water stress and health of pomegranate crops aiding water management within the agricultural land [24].

Spraying: Drones have emerged as a compelling alternative to manual mechanical spraying, effectively addressing long-standing challenges associated with traditional spraying methods. Adopting agro drones for pesticide spraying, farmers can overcome issues like excessive chemical application, uneven distribution, airborne pesticide dispersion, and the significant reliance on manual labor, thus revolutionizing agricultural practices [4,25]. A Quadcopter mounted with sprayer helped minimize the resources required and to ensure controlled spraying over the chosen farm [26]. Subsequently, numerous advancements in the algorithms used to spray fertilizer using UAVs came into existence. A significant breakthrough in the field of unmanned aerial vehicles (UAVs) was achieved with the successful development of autonomous route-changing capabilities, empowering these aircraft to

[1] An integral part of the National Agricultural Research System (NARS).

adapt swiftly and seamlessly in dynamic working environments. This milestone is considered as a substantial advancement that greatly enhanced spraying efficiency, revolutionizing agricultural practices [27]. Synchronized operation of multiple UAVs to collaboratively work and expedite the fertilizer spraying process is achieved with the help of Genetic Algorithm powered drones. These GA drones significantly helped to reduce the overall time required to spray the fertiliser over the entire farm [28].

A comprehensive farm monitoring, encompassing water level detection, weed identification, and disease diagnosis was performed using a Hexacopter and remarkable outcomes in terms of potential savings of up to 20–90% fertiliser, human resources, and water consumption are observed [29]. These findings highlight the benefits of using UAVs to optimize and conserve resources in farming operations. In a recent advancement, UAVs with a variable spraying system controlled by Artificial Neural Network (ANN) was developed to achieve precise and controlled spraying, ensuring optimal droplet deposition in accordance with specific requirements and desired outcomes [30]. In addition to the drones that are capable of either spraying or monitoring crop health, a multi-functional quadcopter capable of monitoring and pesticide spraying, was also developed and successfully deployed. This drone assisted in implementing precision agriculture with ease [31]. Owing to the limitation of flight time due to high payloads, attempts are being made to develop an octocopter drone with lower weight spraying systems [32]. By reducing the overall weight of the payload, significant enhancements in the endurance time of these drones can be achieved, unlocking new possibilities for extended and efficient aerial operations.

In addition to the above, Thermal infrared (TIR) imagery obtained using a fixed wing UAV has promising potential for detecting drainage pipe locations, particularly under dry surface conditions, where visible and near infrared imagery were less effective [33]. In view of varying performance of TIR, VIS, and NIR payloads, detailed evaluation considering varying soil conditions and multiple test sites can help to understand the applicability in drainage pipe mapping. Combining LiDAR data obtained using multi-rotor drone with Global Navigation Satellite System (GNSS) and Inertial Measurement Unit (IMU) data, crop height can be determined with high precision. These estimates allow to correlate crop volume with nitrogen treatments [34].

Thus, the extant literature suggests that drones can be a reasonable alternative that can enable farmers to execute various tasks involved in pre-harvesting, harvesting, and post harvesting stages. Notable technical advancements have taken place over time and there is a significant likelihood that there will be accelerated technological innovations in drone technologies. Spraying systems that were semi-automatic have evolved over time and transformed into automatic systems with the intervention of Artificial Neural Networks and Genetic Algorithms. Furthermore, the capabilities of drones have evolved over time with their applications in multiple phases of farming. Fig. 2 presents the summary of the wide range of drone applications in agriculture.

The use of UAVs for agricultural activities is a relatively new concept which is also apparent from the bibliometric analysis conducted by Rejeb et al. (2022) [35]. The study analysed the annual scientific production from which suggests that the use of UAV in agriculture has gained significant traction in recent times [35]. The study depicted that most of the research works was conducted in the USA and China [35]. Although the use of UAVs for agricultural practices is fairly popular in developed countries such as the USA, Australia, EU, it is in nascent stages in India, as acknowledged by a study conducted by the National Academy of Agricultural Science in the year 2022 [36].

Few studies have examined the applicability of UAVs in Indian agriculture [37]. To promote the adoption of UAVs in the Indian context, a comprehensive understanding of barriers arising from various dimensions is crucial. Successful identification and analysis of such barriers can help to plan strategies that can aid in harnessing the benefits of UAVs in different phases of agriculture. However, studies examining such barriers that impede the adoption of drones Indian agricultural context are limited. For bridging this gap, the present study aims to identify and analyse various barriers that limit the adoption of UAV falling under the small and medium category as per the classification made by DGCA.

Fig. 2. Schematic illustration of agricultural tasks performed using UAV.

3. Identification of barriers for the adoption of UAVs

An extensive literature review was conducted to identify the barriers to the adoption of drones. To ensure completeness, a questionnaire-based survey was conducted to collect expert opinions on the relevance of the barriers identified through literature review in the Indian context. The outcomes of literature review and questionnaire survey complement each other. Section 3.1 and section 3.2 present the literature review and the questionnaire-based survey.

3.1. *Literature scoping to identify barriers*

Research works focusing on the barriers to adopt UAVs to perform tasks in agriculture are limited. Owing to this, selected studies identified from the Scopus repository with key words as UAV, drones, agriculture, emphasizing the applications of drones in various sectors are reviewed to identify the barriers relevant in the context of agricultural applications. Furthermore, reports highlighting the use of drones in the agricultural domain are reviewed to identify other types of barriers. As a result, as shown in Table 1, six barrier categories encompassing thirty-three barriers are identified.

3.2. *Focus group discussion*

The outcomes of this focus group discussion aim to ensure the completeness of the identified barriers presented in Table .1. Researchers (n = 7) working in the domain of the UAV, Members and Associates (n = 2) from the National Academy of Agricultural Science (NAAS), members (n = 6) from Krishi Vigyan Kendra (KVK) have participated in the survey conducted virtually. Participated members from KVK had prior experience in conducting hands-on workshops demonstrating the capabilities of UAVs for spraying fertilizers and interacting with farmers.

Considering the recommendations given by Greenbaum (2000) [55],

Table 1
List of factors restricting the adoption of UAVs.

Category	Impeding factor	Relevance	Reference
Technical	Internet connectivity	For the successful operation of UAV, access to internet connectivity is imperative to various operations, including (i) updating of firmware (ii) checking if the deployment site is within the flying zone as per the regulations (iii) on-site flight planning from the available base maps.	[38]
	Endurance time	Endurance time refers to the total time a chosen UAV with the payloads can fly on one charge. The conventional drones have a limitation in terms of flying time which would not enable the farmer to cover the entire agricultural farm.	[39]
	R&D	Considering the limited availability of multi-functional Agro-UAVs, fostering R&D activities to design drones that can assist in all phases of harvesting is essential. Such muti-functional drones can significantly minimize expenses associated with purchasing, operating, and maintaining separate equipment. Also, there a significant need for developing various tools that analyse the collected data and take automated timely actions.	[40]
	Payload weight	The adoptability of UAVs is primarily impeded due to the load-carrying capacity. This challenge is exceptional in the case of adopting UAVs, especially for spraying fertilisers.	[41]
Social	Infringe of privacy	Deploying UAVs over the buildings may not be acceptable to all the community residents as the UAV movement can make the community residents cautious since UAVs are known for monitoring and surveillance.	[42,43]
	Threat to property and animals	UAVs if crashed within the building promises could either harm residents, animals and can also damage the property.	[44]
	Educational background	Educational qualification indirectly influences the choice of adopting the use of UAV in agricultural activities.	[45]
	Noise Pollution	Community residents may experience noise pollution during the flight of the UAV due to propellers rotating at high speeds.	[46]
Behavioural	Attitude to adopt	It refers to the subjective probability of an individual explaining if they perform a specific task or demonstrate specific behaviour. Considering this help to analyse the intention of the farmer to adopt using UAV for various agricultural purposes.	[47]
	Awareness	Lack of subjective knowledge about UAVs impediments to understand its benefits. Considering this parameter help to	[42]
	Perceived ease of use	It signifies the degree to which an individual believes using the UAVs would involve no effort. Considering this parameter help to test the comfortable levels of farmers to adopt UAV for agricultural purposes.	[48]
	Fear of unemployment	Intervention of autonomous systems in any sector may substitute the need of manpower which consequently create the fear of unemployment as agriculture is the primary occupations in the rural areas.	[49]
	Perceived behavioural control	It demonstrates the behavioural ease of the person in adopting UAV for agricultural purposes.	[50]
Operational	Skilled workforce	Deploying a drone requires necessary skill set and the needs training to get comprehensive understanding of the drone regulation and guidelines which is lacking among the farmers.	[43]
	Meteorological parameters	The regional climatic conditions control the UAV deployment. For instance, the typical wind speed in agricultural farms will be high leading the drifting of UAVs. Also, the weather conditions impact the deployment.	[51]
	Flying/non-flying zones	Different countries have classified the regions into flying and non-flying zones based on their own country-specific rules and guidelines. If an agricultural farm is within the proximity of restricted places, it may fall within a non-flying zone making deployment of UAVs a challenge.	[52]
Economic challenges	High maintenance cost	Since the technology is in nascent stages, the involved maintenance cost is relatively high.	[48]
	Cost of components	Drone industry being at the evolution stage, the cost of components as of today are relatively high.	[48]
	Cost of skilled labour	Since the availability of skilled workforce is limited, the capital involved in hiring a professional is relatively high.	[48]
	High investment cost	The capital cost involved in procuring the drones is not affordable.	[38,53]
Implementation	Lack of Incentives	The capital cost involved in procuring UAV is substantial and is a substantial investment for a farmer. There exist no government schemes that provide subsidy for the procurement of UAVs.	[40]
	Policy and regulations	Existing drone rules beside ensuring the safety and security also impediments its wide adoption due to restrictions set as a part of the guidelines.	[48]
	Access to service centers	As drone development is in a nascent stage, the connectivity to service centers for repairing and maintenance is not established in rural areas posing significant challenges of spatial accessibility.	[54]

participants were divided into smaller groups resulting in three focus groups. The discussion sessions were conducted separately, and the average duration of each session was nearly 42 min. All the focus group discussions were moderated, and the moderator ensured that the participants discussed same topic and got an equal opportunity to share their perceptions.

The moderator prepared a discussion guide and informed each group in the same manner about the nature of the focus group, and the same questions were addressed in each focus group discussion.

Each of the conducted focus group discussions started with a question, "What are the factors impeding the adoption of UAVs by the farmers in India to perform agricultural tasks?". Further, the list of barriers collected from the literature review is shared with each group for suggestions to ensure completeness. Moderator used virtual collaborator whiteboards for data collection. All the three-focus group discussions conducted were audiotaped, which were later analysed along with the whiteboard summaries. The identified list of factors through focus group discussions is then mapped with the barrier categories, as shown in Fig. 3.

Relevance of the barriers suggested by the experts is presented below.

(i) Navigational accuracy: Drone operations are subjected to regulations and airspace restrictions as per the Drone rules 2022, prescribed by DGCA, India. Navigational accuracy plays a crucial role in complying with these regulations, such as maintaining a safe distance from airports, avoiding sensitive areas, or adhering to altitude limitations. Precise navigation allows drones to reach designated waypoints, follow predefined flight paths, and capture accurate data or perform specific tasks with precision. Also, precise navigation allows drone to return to home point in case of emergencies which may be deviated in the drones with low accuracy navigation system. This minor deviation may lead to the drone crashing as the topography of agricultural farms is uneven.

(ii) Collision and crashing: Most of the affordable agro-UAVs that assist in spraying do not have advanced collision avoidance systems. Majority of them either sense the obstruction either in omni-directional or bi-directional, often leading to collision and crashing due to obstructions such as tall trees, electrical poles, birds, transmission lines may impede the flight, and unprofessional operation of the drone may lead to a collision and crashing.

(iii) Age group of farmers: The transition from conventional farming practices to the adoption of UAVs certainly depend on the age group of farmers, as traditional farmers are more inclined towards conventional practices.

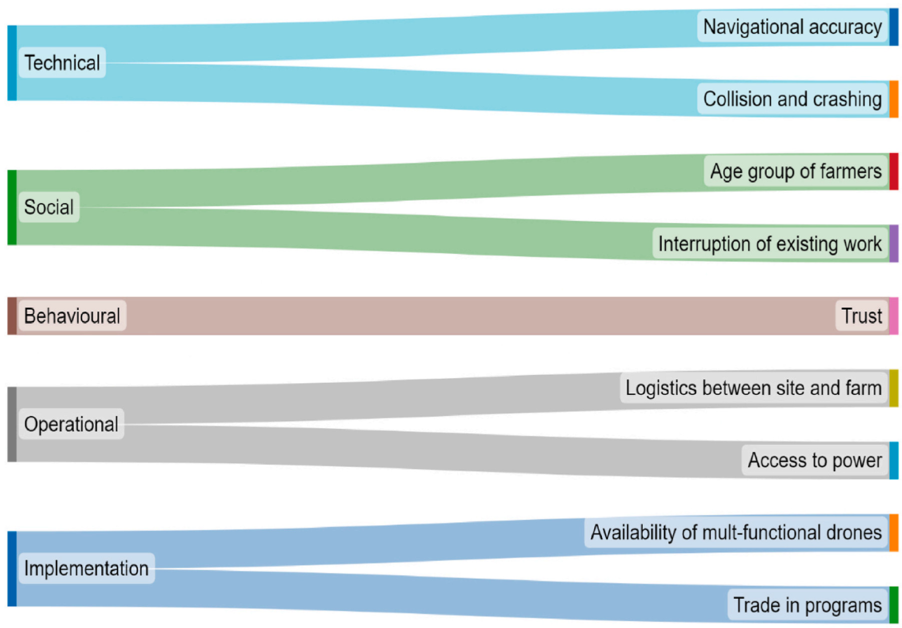

Fig. 3. Mapping of identified barriers to the barrier categories (viii) Availability of multi-functional drones: Nonavailability of multifunctional drones for various Agro-based applications. (ix) Trade in programs: There exist no such programs which exchange the old version of drones with the upgraded UAVs.

(iv) Interruption of existing work: Farmers view the transition from conventional techniques to adopting unmanned aerial vehicles (UAVs) as a significant hurdle in their ongoing and planned works. This perception stems from the concern regarding the time-consuming nature of adopting UAVs and its potential impact on their yield, which heavily relies on seasonal factors.
(v) Trust: Agro-based drones being electronic devices equipped with numerous sensors, the reliability of UAVs is also a major concern.
(vi) Logistics between site and farm: Transportation of UAVs between dwelling units and the farms is challenging as it requires dedicated vehicles. The problem is more prevalent in the case of Agro-Drones.
(vii) Access to power: The majority of the agricultural farms are isolated geographically and lack a power supply which is a challenge to charge the drone, which would be a mandatory requirement in view of the limited flight time of the drone.

3.3. Field visits to a village

To verify if the obtained responses from the experts translated the ground reality, a field visit was conducted in a nearby village, Karnal (Ref. Fig. 4), Haryana. The primary occupation in the chosen village is agricultural and it is one of the top producers of wheat. A team comprising researchers and students with preliminary training interacted with the group of farmers. A few of the participants own their own farm, and a few of them are involved in farming activities. The participants of the survey comprised males and females with age between 22 and 47 years.

As the first phase of interaction, an ice-breaking session (conducted in the local language) which was proven effective in making participants feel comfortable, was conducted. As an outcome, it was noted that drones are a popular term among the participants. However, they are popular for photography and videography videos, especially during marriages. After this session, they were asked about their awareness of drones in boosting yield and income levels. With this question, we observed that participants showed interest in knowing more about the capabilities of drones in the agricultural domain. Demo sessions were conducted using two different drones to elucidate the capabilities of drones. This helped the team to showcase all the steps involved in drone deployment.

As a final phase of the survey, a response to the question, i.e., “what does it take to adopt UAVs in their agricultural activities?” was posed. All the responses were audiotaped and later analysed by the team. The major concerns raised by the participants were initial investments, lack of knowledge to deploy the drones, fear of unemployment, and privacy concerns which were already identified by the literature review complemented with the expert suggestions, especially from the personnel from KVK centers who every day meet farmers in conducting activities that help to improve the agricultural practices. The series of exercises conducted as a part of the field visit affirms that the expert suggestions reflected the ground reality.

4. Analytical method

A hybrid multi-criteria framework is developed in this paper to evaluate the relevance of identified barriers and determine the hierarchy. The steps involved in the proposed framework are shown in Fig. 5.

The analysis first starts with the extant literature review to identify the barriers, followed by conducting focus group discussions to review and make additions to the list of barriers, ensuring completeness. Considering that the factors are identified using a literature review conducted in a global context, the relevance of each barrier in the Indian context is then assessed using the Fuzzy Delphi technique.

The outcomes of the Fuzzy Delphi analysis help to classify the barriers into selected and unselected groups. In the next phase of analysis, the list of selected barriers is floated among the expert panels, and their opinion on the relative dominance of each barrier is collected using a scale. Considering that the responses of each expert differ, the aggregated responses are combined into a fuzzy number. Thus, all the obtained responses are used to construct fuzzy pairwise decision matrix. These pair-wise matrices are further used to compute the overall dominance of each barrier an determine the hierarchy using the framework of the Fuzzy Analytical Hierarchy Process (AHP), which is only the methodology that aid to evaluate the hierarchy using the

Fig. 4. Field visit to Karnal, Haryana, (Latitude and Longitude 29.6857° N, 76.9905° E).

response obtained from decision makers. A detailed insight into the steps involved in the computations is presented in the subsequent sections.

4.1. Fuzzy set theory

The concept of fuzzy set theory is introduced by Zadeh (1965) with the objective of capturing the qualitative judgment of experts when dealing with a decision-making problem [56]. This theory gained popularity when conceptualizing real-life problem which is usually associated with uncertainty [57]. In the context of current research work, decision-making is complex since the subject of drones is fairly new in India, due to which the opinion of experts may differ. The framework of fuzzy set theory allows decision makers to share their opinions as a crips response when working with an unclear problem [58]. The generic representation of fuzzy set theory is shown below:

Say 'S' refers to a set of elements and is represented as $\{s_1, s_2, s_3, s_4 \cdots\cdots\cdots s_n\}$.

Then, a fuzzy set 'G' for S can be represented as $\{s, \mu_G(s) \mid s \in S\}$.

where, $\mu_G(s)$ is the membership function of fuzzy set S and the membership values range between 0 and 1.

In this paper, triangular fuzzy membership functions, which are proven suitable for dealing with pragmatic situations, are used. Let $\omega_1 = (\alpha_1, \beta_1, \gamma_1)$ and $\omega_2 = (\alpha_2, \beta_2, \gamma_2)$ are the two triangular fuzzy numbers, and Eq. (1) represents the membership function [57].

$$\mu_G(s) = \begin{Bmatrix} 0, & s \leq \alpha \\ \dfrac{s-\alpha}{\beta-\alpha}, & s \in [\alpha, \beta] \\ \dfrac{s-\gamma}{\beta-\gamma} & s \in [\beta, \gamma] \\ 0 & s \geq \gamma \end{Bmatrix} \quad (1)$$

4.2. Fuzzy Delphi

Delphi technique is a quantitative method used to collect the opinion of experts on a specific research question [59]. This technique is a reasonable approach to adopt when there is a lack of crisp guidelines on any aspect and explore the possible dimensions through discussion among a group of experts [60]. The concept of fuzzy set theory is integrated with the Delphi technique by Ishikawa to account for the vagueness associated with opinions while discussing an unpopular problem [61]. Since the adoption of drones is an unpopular area, this study adopted Fuzzy Delphi. The procedure involved in assessing the barriers is presented below:

Step-1 As a first step of analysis, the created list of barriers is floated among the experts.

Step-2 Experts are then allowed to evaluate the relevance of each identified barrier in the Indian context using the scale presented in Fig. 6. The judgment on a bth barrier by eth expert can mathematically be expressed as Eq. (2).

$$E_{eb} = (\alpha_{be}, \beta_{be}, \gamma_{be}) \quad (2)$$

where b ranges from 1,2,3,4 ….m, e ranges between 1,2,3,.. n, m is the total number of barriers. n is the total number of experts. The overall fuzzy weight corresponding to 'bth' barrier can be obtained using Eq. (3).

$$E_b^0 = \left[\min(\alpha_{be}), \quad \left(\prod_{e=1}^{n} \beta_{be} \right)^{1/n}, \quad \max\,(\gamma_{be}) \right] \quad (3)$$

Step-3 The fuzzified score of each barrier obtained using Eq. (3) is further defuzzified using mean method which can mathematically be represented using Eq. (4).

$$E_b^d = \left[\frac{\min(\alpha_{be}) + \left(\prod_{e=1}^{n} \beta_{be} \right)^{1/n} + \max\,(\gamma_{be})}{3} \right] \quad (4)$$

On the basis of the evaluated defuzzified score, the list of barriers is then classified into selected and unselected groups.

4.3. Fuzzy Analytical Hierarchy Process

Analysis using Fuzzy Delphi help decision-maker to evaluate the relevance of each barrier in the Indian context, but the relative dominance of each barrier remains unmapped. The theoretical framework of Fuzzy AHP is used to evaluate the overall dominance which is subsequently used to evaluate the hierarchy. Steps presented below gives a brief overview of the procedure to evaluate the overall dominance of a

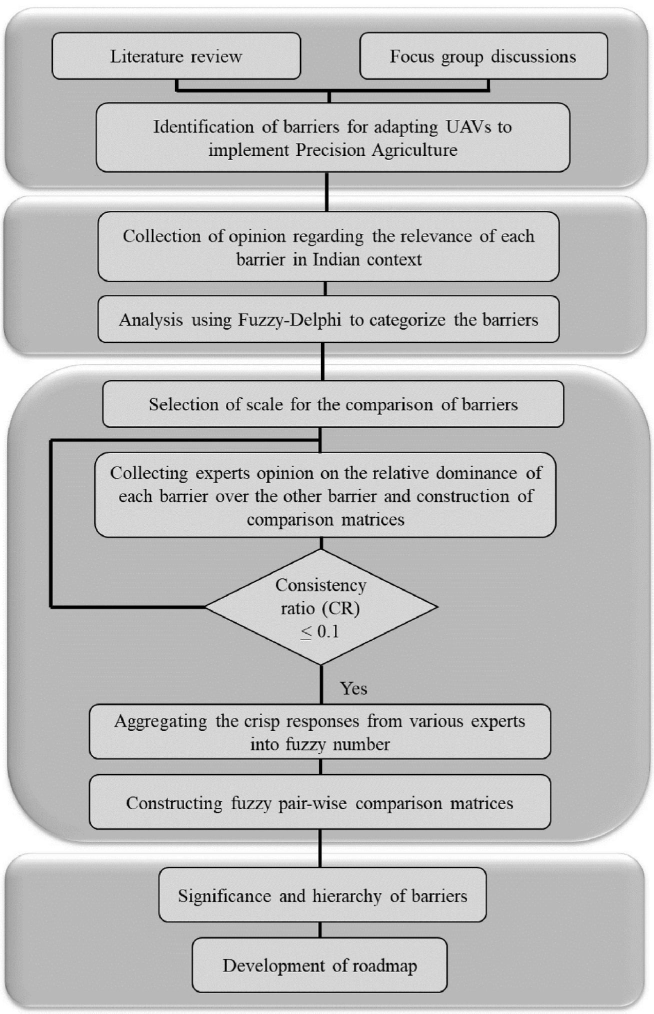

Fig. 5. Proposed framework to identify and analyse the barriers to adopt UAVs.

barrier.

Step-1 Selection of appropriate judgement scale

Saaty scale with scores ranging between 1 and 9 [62] is used in this study to evaluate the relative dominance of identified barriers. This scale also allows the decision maker to share their opinion using linguistic scale. The crisp score, corresponding linguistics judgements, and fuzzy score are shown in Fig. 7.

Step-2 Formulating decision matrix and evaluation of Consistency Ratio

The obtained responses from the decision maker based on the scale shown in Fig. 6 are further used to construct the decision matrix. Subsequently, consistency ratio is evaluated using Eq. (5) and is verified if it is less than 0.1 which is considered as the threshold limit.

$$CR = \frac{\left(\frac{\lambda_{max}-n}{n-1}\right)}{RI} \tag{5}$$

where, CR is the consistency ratio, and RI is the random consistency index.

Step-3 Constructing fuzzy decision matrix

Ratings given by all the experts of the panel is integrated and a fuzzy pairwise comparison matrix is developed. Interval consideration method [63], that provides a reliable result over the other aggregation techniques such as the average method [64], and geometric method [65], is used in this study to integrate the obtained responses. Eq. (6) presents the generic representation of the integration of combining the rating obtained from various experts.

$$E_{integrated} = \left(min(c_{be}), \frac{1}{n} \times \sum_{b=1}^{n} c_{be}, max(c_{be}) \right) \tag{6}$$

where b ranges between 1,2,3,4 ….m, and e ranges between 1,2, 3, n; m, n represents the total number of barriers and experts respectively.

Step-4 Computation of overall weights

This study used Chang's Extent Analysis [66] approach to determine the overall weight of each barrier. This approach aids the decision-maker in converting the fuzzy number into a crisp value, which easily helps in the relative comparison of barriers. The procedure to evaluate is presented below

Let $S = \{s_1, s_2, s_3, ...s_n\}$ represents object set and $G = \{g_1, g_2, g_3, ...g_n\}$ represents goal set. Then, as per the CEA, the extent of an object with respect to the goal is to be quantified using fuzzy numbers. For quantification, this study used fuzzy extent values using triangular fuzzy number (TFN).

The fuzzy extent with respect to the ith object can be represented using Eq. (7).

$$V_i = \sum_{j=1}^{t} T_{gi}^{j} \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{t} T_{gi}^{j} \right]^{-1} \tag{7}$$

where, T^j_{gi} represents the jth triangular fuzzy extent valuewhere, i = 1,2, 3, …,n; j = 1,2, 3, … …,t; and 't' represents the total number of extent analysis fields for a considered object.

To compute $\sum_{j=1}^{t} T^j_{gi}$, fuzzy addition operation, as shown in Eq. (8), is performed

$$\sum_{j=1}^{m} T_{gi}^{j} = \left(\sum_{j=1}^{t} \alpha_i, \sum_{j=1}^{t} \beta_i, \sum_{j=1}^{t} \gamma_i \right) \tag{8}$$

Further, to compute $\left[\sum_{i=1}^{n} \sum_{j=1}^{t} T^j_{gi}\right]^{-1}$, fuzzy addition operation, as shown in Eq. (9), is performed

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{t} T_{gi}^{j} \right]^{-1} = \left[\frac{1}{\sum_{i=1}^{n} \gamma_i}, \frac{1}{\sum_{i=1}^{n} \beta_i}, \frac{1}{\sum_{i=1}^{n} \alpha_{ii}} \right] \tag{9}$$

where, V_i is a normalized fuzzy number with medium values as unity and i = 1 … N (number of criteria).

Step-5 The normalized fuzzy number in step-4 is further defuzzified into a crips number using mean method which can be expressed using Eq. (10).

$$D = (\alpha + \beta + \gamma) / 3 \tag{10}$$

5. Empirical analysis and results

This section provides insight into the overall weight of barrier categories and the barriers to the adoption of UAVs in the rural areas of India. As per the proposed methodology, the list of identified barriers grouped under each barrier category is shared with the expert panel. Subsequently, their perception[2] on each of the identified barriers is

[2] Questionnaire used for collecting the responses is shown in Appendix-A.

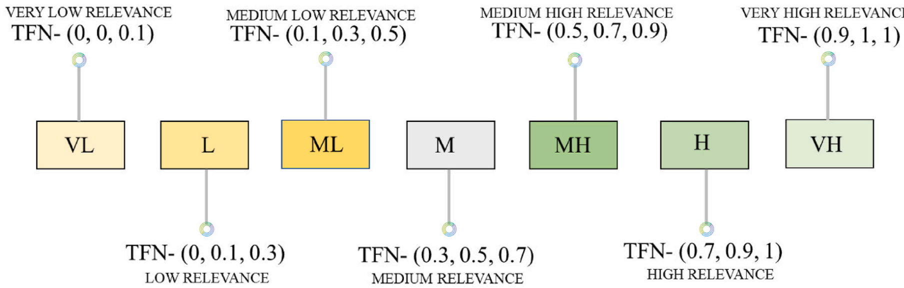

Fig. 6. Linguistic scale and the corresponding fuzzy score to collect the responses on relevance.

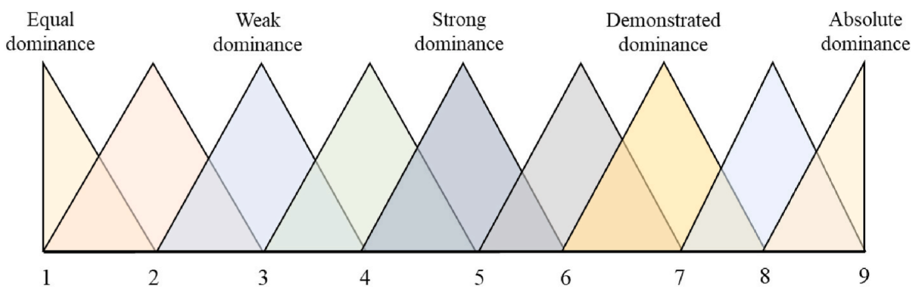

Fig. 7. Saaty scale used for collecting the responses from the expert panel.

collected using a linguistic scale shown in Fig. 6. Subsequently, the obtained linguistic responses are translated into fuzzy numbers a representative fuzzy score by accumulating the responses from all the experts is determined using Eq. (3). The defuzzified score corresponding to the barriers are presented in Table .2.

Considering the study of Puppala et al. (2022) [57], a threshold value of 0.6 is chosen as a cut-off value to classify the barriers into selected and un-selected categories. The list of barriers with a defuzzified score below 0.6 signifies that they are not relevant for adopting UAVs. Findings of Fuzzy Delphi as shown in Table .2 suggest that 'Educational background' and 'Reliability of report' are not relevant in the Indian context. These findings are coherent with the responses obtained in the survey conducted as it is noted that a fraction of participants with no higher education background expressed their willingness to adopt the technology. Further, the trust farmers have in technology, especially after the COVID-19 pandemic, as expressed in the survey, makes the 'reliability of report' obsolete. Though the first phase of analysis using Fuzzy Delphi helped in categorizing the barriers into selected and un-selected groups, the relative hierarchy of barriers remains unmapped. In this regard, the barriers grouped under the selected category are analysed using Fuzzy AHP in the next phase to determine the relative dominance of each barrier.

Excluding the barriers (n = 2) falling under an unselected group, a total of thirty barriers falling under technical, social, behavioural, operational, economic, and implementation are included to develop a hierarchy model containing three levels. Level 1 represents the goal of this study i.e., determining the hierarchy of the barriers, while level-2 and level-3 depict the barrier categories and barriers, respectively. Fig. 8 illustrates the developed hierarchy model.

Subsequent to developing the hierarchy model, the perception of experts on the relative dominance of each barrier is collected using the Saaty scale (ranging between 1 and 9). The collected responses are then further used to construct pairwise comparison matrices. A sample pairwise comparison matrix corresponding to the barrier categories is shown in Eq. (11). Equivalent matrices depicting the relative dominance of barriers in each category are also developed using the responses obtained. It is observed that the consistency ratio of all the formulated matrices is within 0.1.

$$E = \begin{bmatrix} & T & S & B & O & E & I \\ T & 1 & 6.0 & 7.0 & 4.0 & 3.0 & 3.0 \\ S & 0.17 & 1 & 0.25 & 0.20 & 0.17 & 0.13 \\ B & 0.14 & 4.0 & 1 & 0.25 & 0.17 & 0.14 \\ O & 0.25 & 5.0 & 4.0 & 1 & 0.50 & 5.0 \\ E & 0.33 & 6.0 & 6.0 & 2.0 & 1 & 0.50 \\ I & 0.33 & 8.0 & 7.0 & 0.2 & 2 & 1 \end{bmatrix} \tag{11}$$

It is observed that the deviation corresponding to specific assessment across all the decision makers is negligible, owing to which an offset value of 1 is adopted to determine the TFN. The crisp scores obtained from all the experts are fuzzified using the TFNs shown in Fig. 7, resulting fuzzy pairwise comparison matrix as shown in Eq.12. The attributes of the fuzzy pairwise comparison matrix are further used to determine the overall fuzzy weight of each barrier category and the barriers within each category using Eqs. (7)–(10). Table 3 presents the fuzzy weights of each barrier category.

For easy comparison of barrier categories, the fuzzy weights are defuzzified using Eq. (10). Results depict that 'Technical aspects' is the prime barrier for the adoption of UAVs in the Indian agriculture. Barriers under operational, economic, implementational, behavioural and social categories come next in the hierarchy.

A similar analysis is performed for each barrier category separately, and the relative crisp weights are determined. The weights thus obtained are used to derive the priority in each category, referred to as a local priority in this study. Besides this, considering the weight of each category, the overall weight of each barrier is also computed and is referred as global weights. Table .4 presents the local and global weight of each barrier. Local weight help to understand the priority of each category, while the global weights are helpful in getting a synoptic view and developing roadmaps to promote the adoption of UAVs in the Indian agricultural sector. For easy interpretation of relative hierarchy, the barriers as per the global ranks are presented in Appendix-B.

5.1. Sensitivity analysis

The variation of obtained hierarchy to the change in responses of experts is often considered as a basis to validate a considered framework [67]. Sensitivity analysis is usually performed by varying the responses

Table 2
Aggregated fuzzy score and the corresponding defuzzified.

Category	SF	Impeding factor	Fuzzy number	Defuzzified score	Category
Technical	T1	Internet connectivity	(0.5,0.76,1.0)	0.7537	S
	T2	Endurance time	(0.7,0.9,1.0)	0.8667	S
	T3	Collision and crashing	(0.7,0.9,1.0)	0.8667	S
	T4	Navigational accuracy	(0.7,0.96,1.0)	0.8885	S
	T5	R&D	(0.7,0.96,1.0)	0.8885	S
	T6	Payload weight	(0.7,0.93,1.0)	0.8774	S
Social	S1	Infringe of privacy	(0.5,0.82,1.0)	0.7759	S
	S2	Threat to property and animals	(0.5,0.7,0.9)	0.7000	S
	S3	Age group of farmers	(0.5,0.76,1.0)	0.7537	S
	S4	Educational background	(0.3,0.5,0.7)	0.5000	US
	S5	Interruption of existing work	(0.5,0.7,0.9)	0.7000	S
	S6	Noise Pollution	(0.5,0.76,1.0)	0.7537	S
Behavioural	B1	Attitude to adopt	(0.5,0.76,1.0)	0.7537	S
	B2	Awareness	(0.7,0.9,1.0)	0.8667	S
	B3	Perceived ease of use	(0.5,0.76,1.0)	0.7537	S
	B4	Fear of unemployment	(0.5,0.82,1.0)	0.7759	S
	B5	Perceived behavioural control	(0.5,0.7,0.9)	0.7000	S
	B6	Reliability of the report	(0.3,0.55,0.9)	0.5864	US
	B7	Trust	(0.5,0.7,0.9)	0.7000	S
Operational	O1	Skilled workforce	(0.7,0.96,1.0)	0.8885	S
	O2	Meteorological parameters	(0.7,0.93,1.0)	0.8774	S
	O3	Flying/non-flying zones	(0.5,0.76,1.0)	0.7537	S
	O4	Logistics between site and farm	(0.7,0.9,1.0)	0.8667	S
	O5	Access to power	(0.7,0.93,1.0)	0.8774	S
Economic	E1	High maintenance cost	(0.5,0.82,1.0)	0.7759	S
	E2	Cost of components	(0.5,0.7,0.9)	0.7000	S
	E3	Cost of skilled labour	(0.7,0.96,1.0)	0.8885	S
	E4	High investment cost	(0.7,0.96,1.0)	0.8885	S
Implementation	I1	Lack of Incentives	(0.5,0.82,1.0)	0.7759	S
	I2	Policy and regulations	(0.9,1,1.0)	0.9667	S
	I3	Availability of multi-functional drones	(0.7,0.93,1.0)	0.8774	S
	I4	Access to service centers	(0.9,1,1.0)	0.9667	S

Note: SF- Short form of barrier; S- selected category; US- unselected category.

of experts. As per the obtained hierarchy, the technical category is the first in priority, followed by other categories. This implies that a minor variation in the overall weight of technical category will impact the other categories and the global rankings. The approach suggested by Kumar et al. (2019) to perform sensitivity analysis is used in this study. As per the approach, a change in the weight of top criteria is induced manually using a multiplicative factor. Subsequently, the difference is distributed to the other criteria proportionally, followed by examining the variation of global rank corresponding to all the sub-criteria.

Accordingly, the weight of the technical barrier category is varied using a multiplicative factor. Ten different scenarios with 'm' vary between 0.9 and 0.1 with a step size of 0.1 are created. Later, the proportional weight of other barrier categories is evaluated, and the obtained weight are shown in Table .5. Using these weights, the global rank of each barrier is then evaluated as shown in Table .6 Sensitivity analysis suggests that for the minor variation in weights, the global ranks of barriers are not affected drastically, which depicts the validity of the derived hierarchy. A similar analysis is carried out by varying the weight of the implementation barrier, and identical observations are noted. Considering this, it can be conclusively stated that the derived hierarchy is reasonable and can be adopted to devise strategies.

6. Discussion

The proposed framework is used to analyse the hierarchy of barrier categories and the barriers to the adoption of UAVs in rural areas of India. The empirical results of this study highlight the importance of the technical category which is in line with the outcomes of Elijah et al. (2018) [53]. R&D is one of the key barriers within this category and the first in the priority list in terms of global rank. R&D can transform the capabilities of the existing drone and make UAVs a reasonable tool to perform tasks during different phases of agricultural. The need for R&D to improve the functionalities of agricultural drones and its role in enabling the adoption of drones for agricultural activities is also acknowledged in various other studies [40]. Even if farmers for the farmers to the currently available drones by compromising the capabilities of existing drones, attaining desired outcomes is inconceivable without precision in terms of spatial attributes. For these reasons, navigational accuracy, as second in the hierarchy of technical category is justifiable. The importance of navigational accuracy is also duly acknowledged by Boursianis et al. (2022) [68]. 'Payload weight,' third in the hierarchy with a relative dominance score of 0.168, is crucial especially for an agricultural drone as the payload is usually the spraying system filled with fertilisers. In the context of widely available drones, 'payload weight' is a major limitation owing to which the adoptability is restricted. If a drone can carry more payload weight, the chance of adoptability will increase which is also the observation made in the study by Khosta et al. (2022) [69]. Apart from these barriers in the technical category, 'collision and crashing' and 'internet connectivity', which are region specific, follow the priority order logically as these barriers are not a challenge in all of the scenarios.

The implementation barrier category is next in the hierarchy after the technical category. The results suggest that if farmers, after looking at the benefits and capabilities of UAVs, get convinced that UAVs can boost their income and think of adopting UAVs, 'Policy and Regulations' set by the Government of India can be major barriers to their adoption. This is justifiable as farmers may find the guidelines extremely technical. This observation is in line with the conclusions drawn by Haffez et al. (2022) [4]. Even if policies are supportive, the 'limited functionalities' of UAV do not allow the farmer to utilize it in all phases of harvesting making it second in the hierarchy. This observation is in line with the outcomes of Hsieh et al. (2020) [70]. If farmers adopt UAVs, there will be a need for service centers but is not well established in the current scenario, especially in India. Therefore, 'Access to service centers' is the third on the priority list. For instance, if farmers adopt UAVs, there will be a need for service centers but is not well established in the current

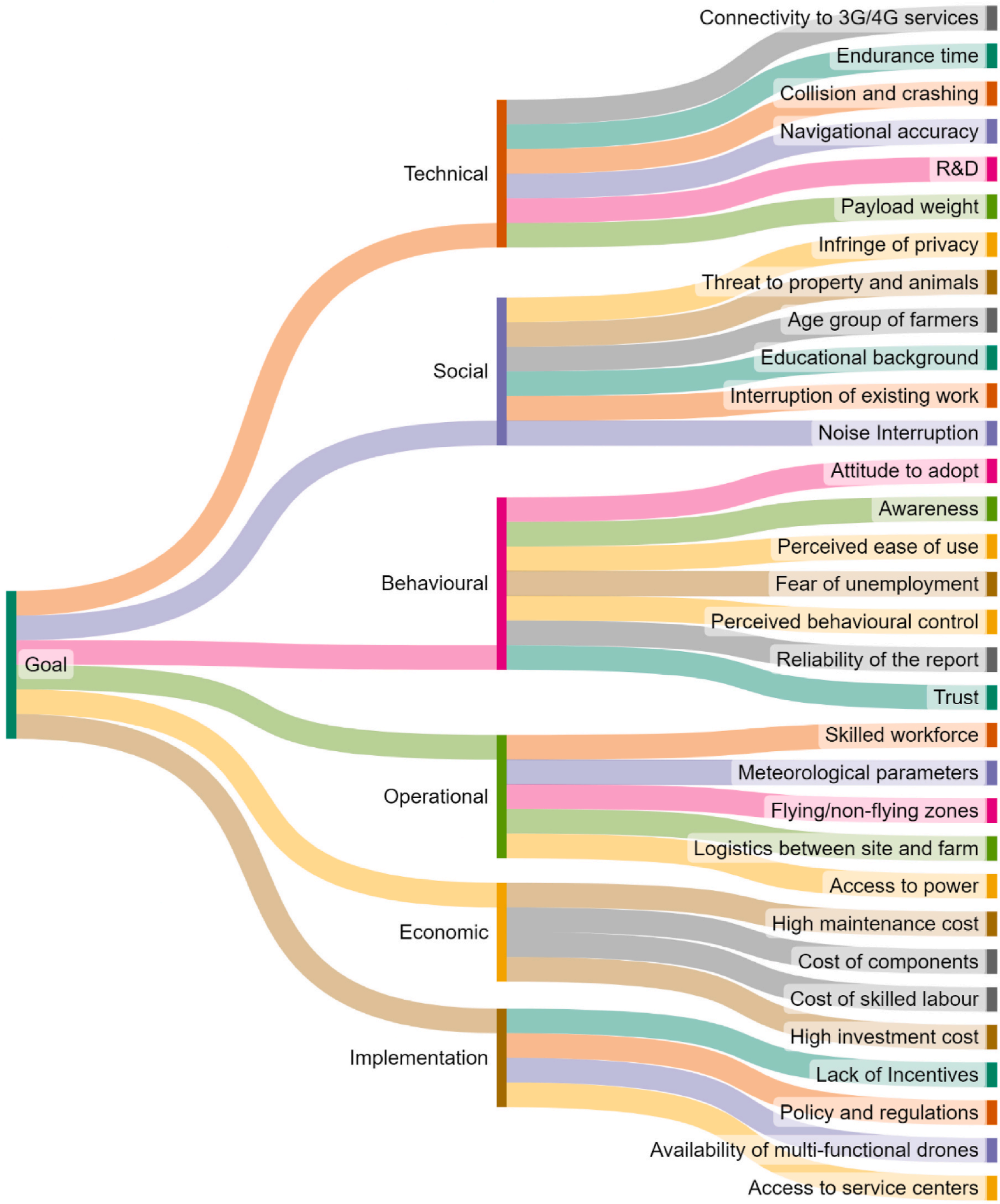

Fig. 8. Hierarchy model to evaluate the relative dominance of barrier to adopt UAV for PA.

$$E=\left[\begin{array}{ccccccccccccccccccc} & & T & & & S & & & B & & & O & & & E & & & I & \\ & \alpha & \beta & \gamma & \alpha & \beta & \gamma & \alpha & \beta & \gamma & \alpha & \beta & \gamma & \alpha & \beta & \gamma & \alpha & \beta & \gamma \\ T & 1 & 1 & 2 & 5.0 & 6.0 & 7.0 & 6.0 & 7.0 & 8.0 & 3.0 & 4.0 & 5.0 & 2.0 & 3.0 & 4.0 & 2.0 & 3.0 & 4.0 \\ S & 0.14 & 0.17 & 0.2 & 1.0 & 1.0 & 2.0 & 0.2 & 0.25 & 0.33 & 0.16 & 0.20 & 0.25 & 0.14 & 0.17 & 0.2 & 0.11 & 0.13 & 0.14 \\ B & 0.12 & 0.14 & 0.16 & 3.0 & 4.0 & 5.0 & 1.0 & 1 & 2.0 & 0.2 & 0.25 & 1.0 & 0.14 & 0.17 & 0.2 & 0.12 & 0.14 & 0.16 \\ O & 0.2 & 0.25 & 0.33 & 4.0 & 5.0 & 6.0 & 3.0 & 4.0 & 5.0 & 1.0 & 1.0 & 2.0 & 0.33 & 0.50 & 1.0 & 4.0 & 5.0 & 6.0 \\ E & 0.25 & 0.33 & 0.5 & 5.0 & 6.0 & 7.0 & 5.0 & 6.0 & 7.0 & 1.0 & 2.0 & 3.0 & 1.0 & 1.0 & 2.0 & 0.33 & 0.50 & 1.0 \\ I & 0.25 & 0.33 & 0.5 & 7.0 & 8.0 & 9.0 & 6.0 & 7.0 & 8.0 & 0.167 & 0.2 & 0.25 & 1.0 & 2.0 & 3.0 & 1.0 & 1.0 & 2.0 \end{array}\right] \quad (12)$$

Table 3
Fuzzy and defuzzified weight of barrier categories.

Barrier category	α	β	γ	Defuzzified score
Technical	0.18	0.29	0.46	0.289
Social	0.02	0.02	0.05	0.027
Behavioural	0.04	0.07	0.12	0.072
Operational	0.12	0.19	0.31	0.193
Economic	0.12	0.19	0.31	0.194
Implementation	0.15	0.23	0.35	0.224

scenario, especially in India. Experts' perception, translated in the form of scores, suggests that lack of monitory support is a barrier making 'lack of incentives. This is justifiable as the investment cost of currently available drones is considerably huge for a farmer and may be a barrier even if he is convinced to adopt to currently available UAVs. Analysing the type of costs associated with drones by explicitly dedicating a separate category i.e., 'economic category,' obtained the third rank among categories, depicting that investment cost is the prime barrier followed by cost of skilled labour, maintenance cost, and cost of components.

Subsequently, the operational barrier category follows next in the hierarchy. The most significant barrier in this category is 'skilled workforce', which limits the ability to adopt UAV technology in the Indian agricultural sector. Since this technology is a fairly new concept, there is a dearth of trained individuals who can harness the capabilities of drones, as acknowledged recently [71]. Despite the availability of skilled professionals, unfavourable working conditions can impede the adoption, which is reflected in the hierarchy of 'meteorological parameters' derived using the responses obtained from experts. For instance, high winds can drift the drones leading to a deviation from the prescribed path. Moreover, high temperatures and extensive rains can hinder drone deployment [72]. Following the 'meteorological parameters', 'access to power' is next in the hierarchy. Since conventional drones have limited endurance time, depending on the availability of surplus batteries and the area to be covered, there may be a requirement to charge the batteries to cover the entire farm. However, as some of the agriculture farms lack a power supply, charging the surplus batteries when one is in use is a challenge. 'Logistics between residence and farm' is fourth in the hierarchy within the operational category. In the context of India, the majority of the farmers either use a bicycle or two-wheel driven motor vehicle to travel between residence and farm. Agricultural drones are relatively big compared to surveillance drones and transporting them could be a barrier for many farmers. If the agricultural farms are within the vicinity of restricted zones, clearance to deploy is a challenge.

The Behavioural category is fifth in the rank hierarchy with a score of 0.07, which is relatively less compared to other considered categories. Although behavioural barriers are pivotal in technology adoption, as identified by Tarei et al. (2021) [73], the obtained ranking is justifiable in the context of India where the use of UAV for agricultural activities is hindered due to technical reasons. We expect that performing a similar analysis after substantial technological advancements may result in a higher weightage for behavioural factors. Among this category, 'Awareness' obtained the highest score, indicating it is a vital factor within behavioural category. This observation is in line with the observations of Smith et al. (2022) [74]. The barrier next in the priority list is 'fear of unemployment'. Since most farmers are primarily dependent on farming, adopting drones as a replacement to manual spraying was felt as a solution that brings unemployment. However, although it replaces the workforce in a few phases, it creates opportunities for skilled workforce and creates employment. Trust in the functionalities of UAVs, perceived ease of use, the attitude to adopt, and perceived behaviour control follow in the hierarchy with weights of 0.211, 0.151, 0.06, and 0.02, respectively.

The social barrier category holds the last rank in the priority among the identified categories. Our results suggest that 'infringe of privacy' is the prime barrier within this category, with a weight of 0.41. As per the farmers awareness in India, UAVs are popular for surveillance and event photography because of which a flying drone is perceived as a monitoring tool. Due to this perception, the adoptability of drones may be opposed in rural areas. Interruption of existing work, age group of farmers, threat to property and animals, and noise pollution follow the

Table 4
Local and global hierarchy of each barrier.

Category	Barrier	Local weight	Local rank	Global weight	Global rank
Technical	R&D	0.376	1	0.109	1
(w = 0.289)	Navigational accuracy	0.21	2	0.061	7
	Payload weight	0.168	3	0.049	10
	Collision and crashing	0.151	4	0.044	11
	Endurance time	0.076	5	0.022	14
	Internet connectivity	0.019	6	0.006	25
Social	Infringe of privacy	0.418	1	0.011	22
(w = 0.027)	Interruption of existing work	0.211	2	0.006	24
	Age group of farmers	0.178	3	0.005	26
	Threat to property and animals	0.146	4	0.004	28
	Noise Pollution	0.047	5	0.001	30
Behavioural	Awareness	0.284	1	0.021	15
(w = 0.072)	Fear of unemployment	0.264	2	0.019	16
	Trust	0.211	3	0.015	18
	Perceived ease of use	0.151	4	0.011	23
	Attitude to adopt	0.061	5	0.004	27
	Perceived behavioural control	0.028	6	0.002	29
Operational	Skilled workforce	0.386	1	0.075	4
(w = 0.193)	Meteorological parameters	0.263	2	0.051	9
	Access to power	0.183	3	0.035	12
	Logistics between site and farm	0.097	4	0.019	17
	Flying/non-flying zones	0.071	5	0.014	21
Economic	High investment cost	0.446	1	0.087	3
(w = 0.194)	Cost of skilled labour	0.351	2	0.068	5
	High maintenance cost	0.131	3	0.025	13
	Cost of components	0.072	4	0.014	19
Implementation	Policy and regulations	0.426	1	0.095	2
(w = 0.224)	Availability of multi-functional drones	0.279	2	0.062	6
	Access to service centers	0.233	3	0.052	8
	Lack of Incentives	0.062	4	0.014	20

Table 5
Variation of category weights to the change in weight of 'technical category'.

Barrier category	N	m = 0.9	m = 0.8	m = 0.7	m = 0.6	m = 0.5	m = 0.4	m = 0.3	m = 0.2	m = 0.1
Technical	0.29	0.26	0.23	0.20	0.17	0.14	0.12	0.09	0.06	0.03
Social	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.04
Behavioural	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Operational	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19
Economic	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19	0.19
Implementation	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22	0.22

Table 6
Sensitivity of global and local weight to the change in category weights.

	S	S = 0.9	S = 0.8	S = 0.7	S = 0.6	S = 0.5	S = 0.4	S = 0.3	S = 0.2	S = 0.1
T1	25	26	26	28	28	28	28	29	30	30
T2	10	10	10	11	11	12	13	17	21	24
T3	14	15	17	17	22	22	23	24	26	27
T4	11	11	12	12	12	13	16	21	22	25
T5	1	1	2	3	5	6	8	9	10	18
T6	7	7	9	9	9	10	11	14	19	22
S1	24	24	24	24	24	24	24	23	23	20
S2	28	28	28	26	26	26	26	26	25	23
S3	26	25	25	25	25	25	25	25	24	21
S4	22	22	22	22	21	20	18	16	15	13
S5	30	30	30	30	30	30	30	30	29	29
B1	29	29	29	29	29	29	29	28	28	28
B2	15	14	14	14	14	14	12	11	11	10
B3	23	23	23	23	23	23	22	22	20	19
B4	16	16	15	15	15	15	14	12	12	11
B5	27	27	27	27	27	27	27	27	27	26
B6	18	18	18	18	17	17	17	15	14	14
O1	21	21	21	21	20	21	21	20	18	17
O2	9	9	8	8	8	8	7	7	7	7
O3	4	4	4	4	3	3	3	3	3	3
O4	17	17	16	16	16	16	15	13	13	12
O5	12	12	11	10	10	9	9	8	8	8
E1	19	19	19	19	18	18	19	18	16	15
E2	13	13	13	13	13	11	10	10	9	9
E3	5	5	5	5	4	4	4	4	4	4
E4	3	3	3	2	2	2	2	2	2	2
I1	20	20	20	20	19	19	20	19	17	16
I2	2	2	1	1	1	1	1	1	1	1
I3	6	6	6	6	6	5	5	5	5	5
I4	8	8	7	7	7	7	6	6	6	6

hierarchy among the category of social barriers.

Considering the potential applications of UAVs in the agricultural sector, if considerable investments are made to carry out research activities it can help overcome T5. This can consequently aid in overcoming T2, T4, O5, O4, B7, and T6. It is also possible to reduce the cost of drones with the advent of new technology. Therefore, it is expected that all the barriers within the economic category can also be overcome with R&D. Majority of the existing drones have inbuilt ultrasonic sensors that can sense obstructions in the way. However, these obstructions are limited to specific directions. Giving special emphasis to fabricate drones that can sense obstructions in all directions can aid in overcoming T3. Furthermore, initiatives by the government such as providing incentives to farmers and making hustle-free policies can help to overcome I1 and I2. As farmers start adopting UAVs, it is anticipated that I4 will not be a barrier as companies compete to improve the level of service to the customers. Fabricating a multi-purpose drone that can perform various tasks in the pre-harvesting, harvesting, and post-harvesting phases can help overcome I3. Taking the initiative to conduct workshops in association with KVK can create trained personnel who help to overcome B2, O1, B3, and B1. Giving special emphasis to explain the capabilities and advantages of drones to farmers can help to overcome B7, B6, S1, S2, and S5.

7. Conclusions, limitations, and future scope

Rising demand for food is a major issue across the world. The mismatch in demand and supply of food, witnessed in several parts of the globe subject nearly 26% of the global population to food insecurity with severity ranging between moderate and extreme. The transformation of conventional agricultural practices through the adoption of advanced technological solutions is a compelling solution to overcome for food insecurity. Unmanned Aerial Vehicles also known as Drones can offer a significant modernisation of agricultural practices in emerging economies by allowing farmers to leverage technology for planting seeds, crop health monitoring, spraying fertilisers, weed detection and so on to increase crop yields. Although they are popular in many developed countries, their adoption in emerging economies can be associated with numerous barriers.

This study identified barriers impeding the adoption of drones through an extensive literature review, focus group discussions, and field visits. Using the proposed hybrid multi-criteria framework, the relative dominance of each barrier is evaluated to devise implementation strategies in India where the adoption of UAV is in the nascent stages, and the agriculture is considered as the backbone of the economy.

An exhaustive list of identified barriers (n = 32) is first analysed using Fuzzy Delphi to identify the barriers that are more relevant to the farmers of the Indian context. Fuzzy Analytical Hierarchy Process (FAHP) is used to evaluate the relative dominance of each barrier category and the barriers, which is further used to determine the local and global ranking of barriers. The empirical findings suggest that limited R&D, complex regulations, high investment costs, limited availability of skilled workforce, and the high costs of skilled labour are crucial barriers that inhibit Indian farmers from adopting UAVs.

The novel findings of this study suggest that conducting awareness camps, workshops, training sessions, monetary incentives to farmers, tax benefits to the drone-based companies, and investing in R&D can overcome the majority of the identified barriers. The hierarchy derived in this paper may change with time as the evolution of drone technology is taking place swiftly. For instance, R&D, which is the first in terms of global rank, may not be a barrier in the near future if the advancement meets the desired level. Endurance time, a significant barrier today, may not be a barrier in the future. Also, with new advances in technology, some of the chosen barriers may become obsolete with time. Owing to this, identifying the relevant barriers by considering the state of art technologies and performing the study using the framework proposed can lead to timely interventions. Potential new barriers can include path planning, the ability to form swarms efficiently, and the autonomous control of fertilizer discharge. In this regard, it is recommended to perform a similar study for other emerging economies, and the analysis should be revised periodically considering the advancements. This can lead to new strategies to enhance the adoption of new technologies in emerging economies

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Credit author statement

Harish Puppala: Conceptualization, Methodology, Formal analysis, Data curation, Writing- Original draft preparation, Writing- Original draft preparation, Validation. Pranav Peddinti: Conceptualization, Data curation, Writing- Original draft preparation, Validation. Jagannadha Pawan Tamvada: Conceptualization, Data curation, Writing- Original draft preparation, Validation. Jaya Ahuja: Data curation, Field visit, Focus group discussion, Writing – review and editing Byungmin Kim: Writing- Original draft preparation, Validation, Project Management.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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APPENDIX-A

Authors are thankful to each of the participant for accepting the invitation and participate in this survey. Authors appreciate the interest of each participant in this survey. The prime objective of this study is mentioned below for your reference.

This study aims at identifying the significant barriers impeding the adoption of agricultural drones in implementing precision agriculture in India. A total of 32 barriers falling under Technical, Social, Behavioural, Operational, Economic, and Implementation.

Kindly use the following linguistic scale to evaluate the relevance of each barrier.

Table
Linguistic scale to evaluate the relevance of each barrier.

Linguistic scale	Score
Very low (VL)	1
Low (L)	2
Medium low (ML)	3
Medium	4
Medium high	5
High	6
Very high	7

Questionnaire Form And Sample Response

	Barrier	VL	L	ML	M	MH	H	VH
1	Internet connectivity	☐	☐	☐	☐	☒	☐	☐
2	Endurance time	☐	☐	☐	☐	☐	☒	☐
3	Collision and crashing	☐	☐	☐	☐	☐	☒	☐
4	Navigational accuracy	☐	☐	☐	☐	☐	☐	☒
5	R&D	☐	☐	☐	☐	☐	☐	☒
6	Payload weight	☐	☐	☐	☐	☐	☒	☐
7	Infringe of privacy	☐	☐	☐	☐	☒	☐	☐
8	Threat to property and animals	☐	☐	☐	☐	☒	☐	☐
9	Age group of farmers	☐	☐	☐	☐	☒	☐	☐
10	Educational background	☐	☐	☐	☒	☐	☐	☐
11	Interruption of existing work	☐	☐	☐	☐	☒	☐	☐
12	Noise Pollution	☐	☐	☐	☐	☒	☐	☐
13	Attitude to adopt	☐	☐	☐	☐	☒	☐	☐
14	Awareness	☐	☐	☐	☐	☐	☒	☐
15	Perceived ease of use	☐	☐	☐	☐	☒	☐	☐
16	Fear of unemployment	☐	☐	☐	☐	☐	☒	☐
17	Perceived behavioural control	☐	☐	☐	☐	☒	☐	☐
18	Reliability of the report	☐	☐	☐	☒	☐	☐	☐
19	Trust	☐	☐	☐	☐	☒	☐	☐
20	Skilled workforce	☐	☐	☐	☐	☐	☐	☒
21	Meteorological parameters	☐	☐	☐	☐	☐	☒	☐
22	Flying/non-flying zones	☐	☐	☐	☐	☒	☐	☐
23	Logistics between site and farm	☐	☐	☐	☐	☐	☒	☐
24	Access to power	☐	☐	☐	☐	☐	☒	☐
25	High maintenance cost	☐	☐	☐	☐	☐	☒	☐
26	Cost of components	☐	☐	☐	☐	☒	☐	☐
27	Cost of skilled labour	☐	☐	☐	☐	☐	☐	☒

(*continued on next page*)

(*continued*)

	Barrier	VL	L	ML	M	MH	H	VH
28	High investment cost	☐	☐	☐	☐	☐	☐	☒
29	Lack of Incentives	☐	☐	☐	☐	☒	☐	☐
30	Policy and regulations	☐	☐	☐	☐	☐	☐	☒
31	Availability of multi-functional drones	☐	☐	☐	☐	☐	☐	☒
32	Access to service centers	☐	☐	☐	☐	☐	☐	☒

APPENDIX-B

Global rank	Barrier
1	R&D
2	Policy and regulations
3	High investment cost
4	Skilled workforce
5	Cost of skilled labour
6	Availability of multi-functional drones
7	Navigational accuracy
8	Access to service centers
9	Meteorological parameters
10	Payload weight
11	Collision and crashing
12	Access to power
13	High maintenance cost
14	Endurance time
15	Awareness
16	Fear of unemployment
17	Logistics between site and farm
18	Trust
19	Cost of components
20	Lack of Incentives
21	Flying/non-flying zones
22	Infringe of privacy
23	Perceived ease of use
24	Interruption of existing work
25	Internet connectivity
26	Age group of farmers
27	Attitude to adopt
28	Threat to property and animals
29	Perceived behavioural control
30	Noise Pollution

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