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Farmers' perception of artificial intelligence and drone technologies for resource-efficient and sustainable agriculture: An empirical study

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Abstract

Artificial Intelligence (AI) and drone technologies were emerging as important tools for improving agricultural productivity, resource-use efficiency and environmental sustainability. However, farmers' perceptions of these technologies were influenced by their usefulness, economic feasibility, technological usability, environmental benefits and the availability of institutional support. The present study was undertaken to assess farmers' perception of Artificial Intelligence and drone technologies for resource-efficient and sustainable agriculture. An *ex-post facto*, descriptive and exploratory research design was adopted and data were collected from Nizamabad and Adilabad districts with sample size of 240 farmers. A multidimensional perception scale comprising six dimensions, namely perceived usefulness and agricultural productivity, resource-use efficiency, environmental sustainability, technological usability and compatibility, economic feasibility and institutional support, trust and perceived risk, was used to assess farmers' perceptions. The results revealed that farmers had an overall favourable perception of AI and drone technologies, with an overall mean score of 4.04 (SD = 0.80). Among the six dimensions, perceived usefulness and agricultural productivity recorded the highest mean score of 4.19 (SD = 0.77) and ranked first, indicating strong recognition of the usefulness of AI and drones for timely farm decisions, crop monitoring and productivity enhancement. Resource-use efficiency ranked second with a mean score of 4.11 (SD = 0.78), particularly reflecting perceptions regarding precise pesticide application, reduction of unnecessary chemical use and optimization of fertilizer application. Environmental sustainability ranked third with a mean score of 4.09 (SD = 0.78), with farmers particularly recognizing the potential of drones to identify areas requiring treatment and reduce excessive pesticide use. Economic feasibility ranked fourth with a mean score of 4.02 (SD = 0.81), with custom hiring, labour-cost savings and economic benefits of drone services receiving comparatively greater agreement, although affordability remained a concern. Technological usability and compatibility recorded a mean score of 3.91 (SD = 0.83) and ranked fifth, indicating favourable perceptions regarding learnability, convenience and compatibility, while access to technical assistance and drone services remained comparatively weaker areas. Institutional support, trust and perceived risk ranked sixth with a mean score of 3.93 (SD = 0.83), with high service costs emerging as the major concern, while subsidies, incentives and institutional support were perceived as important mechanisms for reducing technology-related risks. Overall, the findings demonstrate that farmers perceive AI and drone technologies positively, particularly in relation to productivity, resource efficiency and environmental benefits. Strengthening technical assistance, service accessibility, affordability, institutional support, training and custom-hiring mechanisms could further facilitate the effective and sustainable adoption of these technologies in agriculture.

Keywords: Artificial Intelligence, agricultural drones, farmers' perception, perception scale, resource-use efficiency, sustainable agriculture, precision agriculture, technology, adoption, agricultural extension

1. Introduction

Agriculture is undergoing a rapid technological transformation in response to increasing pressure to produce more food with fewer natural resources while maintaining environmental quality and farm profitability. Population growth, climate variability, water scarcity, soil degradation, increasing input costs and labour shortages have created an urgent need for agricultural production systems that are more precise, adaptive, climate-resilient and resource efficient. Conventional agricultural systems frequently involve uniform application of water,

fertilizers and plant-protection chemicals despite considerable spatial and temporal variability in soil, crop and environmental conditions. Digital agriculture provides an opportunity to address this mismatch by enabling agricultural decisions based on real-time, spatially explicit and predictive information. The Food and Agriculture Organization (FAO) has recognized artificial intelligence (AI) and digital transformation as important drivers capable of improving the efficiency, sustainability and resilience of agrifood systems, while emphasizing the need for inclusive and responsible technological transformation (FAO, 2022; FAO, 2024). The rapid development of AI, Machine Learning (ML), Internet of Things (IoT), remote sensing, cloud computing, geographic information systems (GIS), robotics and unmanned aerial vehicles (UAVs) is consequently transforming conventional agricultural decision-making. AI enables computers to identify patterns, classify information, generate predictions and support decisions from large and complex datasets. In agriculture, these capabilities can be applied to crop-health assessment, pest and disease detection, yield forecasting, soil and nutrient management, irrigation scheduling, weed identification and farm-resource allocation (Liakos *et al.*, 2018; Kamilaris & Prenafeta-Boldú, 2018; Javaid *et al.*, 2022) [9, 10, 12]. The integration of AI with remote sensing is particularly important because satellite imagery, IoT sensors, weather stations and UAV platforms can collectively generate information on crop vigour, soil conditions, moisture status, nutrient deficiencies and biotic stresses. The uploaded manuscript similarly identifies remote sensing, smart sensors, IoT, AI and ML as important components of modern agriculture for improving crop management, pest control, soil-health assessment and real-time decision-making. Among these technologies, agricultural drones or UAVs have gained increasing attention because they can acquire high-resolution, timely and spatially explicit information at field level. UAVs equipped with RGB, multispectral, hyperspectral and thermal sensors can capture detailed information on crop growth, plant stress, soil variability, disease symptoms and other field conditions. UAVs as important components of precision and smart farming for crop monitoring, field mapping, disease identification, yield estimation, irrigation assessment and precision input application (Makam *et al.*, 2024; Wang *et al.*, 2025) [13, 20]. The uploaded manuscript further emphasizes that UAV-generated aerial data can be processed using AI-based algorithms to detect crop stress, monitor vegetation indices and facilitate precise input application.

The integration of AI with drone technology provides greater potential than either technology operating independently because UAVs generate high-resolution field-level data while AI and ML algorithms transform these data into actionable information. The combination of sensing, analytics and decision support can facilitate a shift from blanket agricultural management towards site-specific interventions. Recent research identifies the integration of UAVs and deep learning as an important direction in precision agriculture, particularly for crop monitoring, disease recognition, weed detection, yield estimation and resource optimization (Wang *et al.*, 2025) [20]. AI-powered UAV systems increasingly use multispectral, hyperspectral and thermal sensing with advanced algorithms for real-time crop-health monitoring, resource management and automated decision-making. However, high operational costs, limited battery capacity, technical complexity and the requirement for trained operators continue to constrain wider implementation. The potential contribution of these technologies to resource-use efficiency is particularly important because

agriculture requires substantial quantities of water, nutrients, energy and plant-protection inputs, and inefficient application can increase production costs and environmental risks. AI-enabled systems can estimate crop water requirements, predict nutrient deficiencies and identify pest and disease risks, while UAVs provide the spatial information required for targeted interventions. This supports the precision-agriculture principle of applying the right input, in the right quantity, at the right place and at the right time (Bongiovanni & Lowenberg-Deboer, 2004; Gebbers & Adamchuk, 2010; Balafoutis *et al.*, 2017) [1, 2, 7]. AI-supported irrigation systems can combine sensor information, weather data and remotely sensed observations to improve irrigation scheduling, while UAV-based thermal and multispectral observations can identify spatial differences in crop water status (Shamshiri *et al.*, 2018; Wolfert *et al.*, 2017) [18, 21]. Similarly, AI-based interpretation of crop and soil information and UAV imagery can support site-specific nutrient management, potentially reducing fertilizer wastage and nutrient losses. In plant protection, UAV-based monitoring can identify areas of crop stress, weed infestation, pests and diseases, while AI algorithms can classify affected areas and support targeted interventions. Recent research increasingly focuses on integrating remote sensing, AI and precision spraying to improve the accuracy and efficiency of agricultural input application (Mogili & Deepak, 2018; Hafeez *et al.*, 2023; Wang *et al.*, 2025) [8, 15, 20]. Consequently, AI and drone technologies have potential to improve water, nutrient, pesticide, labour and energy-use efficiency while contributing to environmental sustainability and climate-resilient agricultural production.

However, technological performance alone does not determine whether an agricultural technology will be accepted and adopted by farmers. Farmers are the ultimate decision-makers at farm level, and their perception of a technology can influence their attitude, intention and subsequent adoption behaviour. Rogers' (2003) [17] Diffusion of Innovations Theory identifies relative advantage, compatibility, complexity, trialability and observability as important characteristics influencing technology diffusion, while the Technology Acceptance Model emphasizes perceived usefulness and perceived ease of use as major determinants of technology acceptance (Davis, 1989) [4]. The Unified Theory of Acceptance and Use of Technology further incorporates performance expectancy, effort expectancy, social influence and facilitating conditions (Venkatesh *et al.*, 2003) [19]. In agriculture, however, farmers evaluate innovations within a complex socio-economic, environmental and institutional context. Their perceptions are influenced not only by usefulness and ease of use but also by expected economic returns, risk, environmental consequences, labour requirements, compatibility with existing practices, access to information, extension support, training and availability of services. Studies of precision-agriculture adoption have demonstrated the influence of education, age, farm size, technical literacy, information availability and perceived profitability on farmers' technology decisions (Finger *et al.*, 2019; Michels *et al.*, 2020; Paustian & Theuvsen, 2017) [6, 14, 16]. Recent empirical evidence from India provides further support for a multidimensional approach. Barman *et al.* (2025) [23], in a study of 320 farmers from Haryana and Uttar Pradesh, reported that promotional efforts, perceived usefulness, peer influence, perceived economic viability, perceived environmental impact and perceived social impact significantly influenced attitudes towards agricultural drones and willingness to adopt them. Similarly, Murugan *et al.* (2024) [22] examined farmers' awareness and perception of drone technology in Coimbatore district, highlighting the increasing

relevance of farmer-level perception research in the Indian context. These findings indicated that farmers' assessment of AI and drone technologies cannot be adequately represented by a single measure of technology acceptance. For small and marginal farmers, the issue is also not necessarily individual ownership of sophisticated equipment but access to technology-enabled services through Custom Hiring Centres, Farmer Producer Organizations, cooperatives, agricultural extension institutions and private drone service providers. Agricultural extension therefore has an important role in awareness creation, technology demonstration, training, interpretation of digital advisories, linkage with service providers and continued technical support. The uploaded manuscript similarly emphasizes that cloud-based platforms and mobile applications can provide timely, location-specific agricultural advisories and strengthen farm-level decision-making and extension services. Thus, social and institutional support should be considered alongside technological, economic and environmental dimensions when measuring farmers' perception.

Despite the increasing literature on the technical applications and adoption of AI and drone technologies, there remains a need for a context-specific, multidimensional and psychometrically validated perception scale that simultaneously captures farmers' views regarding resource efficiency, environmental sustainability, economic benefits, technological suitability and institutional support. Existing studies have examined individual constructs such as perceived usefulness, perceived ease of use, economic viability, environmental impact, social influence and adoption intention (Davis, 1989; Venkatesh *et al.*, 2003; Caffaro *et al.*, 2020; Barman *et al.*, 2025) [3, 4, 19, 23], but the rapidly evolving nature of integrated AI-drone systems require a broader farmer-oriented measurement framework. A scientifically developed perception scale can provide a systematic method of measuring farmers' evaluations rather than relying on isolated questions or general opinions. Scale development requires conceptualization of the construct, systematic item generation, expert assessment, pre-testing, item analysis, reliability assessment and construct validation (Lawshe, 1975; DeVellis & Thorpe, 2021) [5, 11]. Exploratory Factor Analysis (EFA) can identify the underlying factor structure, while Confirmatory Factor Analysis (CFA) can subsequently establish the adequacy of the proposed structure. Reliability could be assessed through Cronbach's alpha and composite reliability, while convergent and discriminant validity can establish the psychometric soundness of the final instrument. Accordingly, the present study conceptualizes farmers' perception as a multidimensional construct comprising perceived usefulness, resource-use efficiency, environmental sustainability, economic benefits, technological suitability and social/institutional support. Perceived usefulness represents farmers' beliefs regarding the ability of AI and drones to improve agricultural decision-making and farm performance; resource-use efficiency reflects perceived conservation and efficient utilization of water, fertilizers, pesticides, labour and energy; environmental sustainability represents perceived contributions to resource conservation, pollution reduction and climate-resilient farming; economic benefits encompass cost reduction, profitability, labour savings and economic viability; technological suitability includes ease of use, compatibility, accessibility and practical applicability; and social/institutional support encompasses extension services, training, demonstrations, government support, FPOs, Custom Hiring Centres and availability of service providers. This conceptualization is supported by recent evidence demonstrating

that farmers' attitudes towards drones are shaped by technological, economic, environmental and social considerations. Therefore, the present study aims to develop and standardize a multidimensional perception scale for measuring farmers' perception towards Artificial Intelligence and drone technologies for resource-efficient and sustainable agriculture. The study will systematically generate and validate perception items, identify the underlying dimensions through factor analysis, establish the reliability and validity of the scale, and provide a standardized instrument for future research on AI- and drone-enabled agricultural transformation. Such a scale can subsequently be used to compare farmers' perceptions across crops, regions and socio-economic groups, identify determinants of perception and adoption intention, and assist agricultural extension organizations in designing targeted awareness programmes, demonstrations, training interventions and institutional support mechanisms. Ultimately, the development of a validated farmer-centred perception scale can contribute to ensuring that AI and drone technologies are not only technologically advanced but also economically viable, socially acceptable, environmentally sustainable and practically relevant to farming communities.

2. Materials and Methods

2.1 Research design

The study would adopt an *ex-post facto*, descriptive and exploratory research design to assess farmers' perceptions regarding the role of Artificial Intelligence (AI) and drone technologies in promoting resource-efficient and sustainable agricultural systems. The study would focus on farmers' perceptions of the usefulness, resource-use efficiency, environmental sustainability, technological applicability, economic feasibility and institutional dimensions of AI- and drone-based agricultural technologies. The conceptual basis of the study was supported by the role of AI, machine learning, remote sensing, IoT and UAV technologies in crop monitoring, precision input application, predictive analytics and farm-level decision-making of farmers.

2.2 Study area

The study would be conducted in Telangana, India, considering the increasing importance of digital agriculture, precision farming and technology-enabled agricultural extension. Telangana provides an appropriate for assessing farmers' perceptions because agriculture was increasingly supported by mechanization, digital advisory services, remote sensing and emerging drone applications.

A multistage sampling procedure would be adopted for selecting the study area. Districts would be selected purposively based on the prevalence of major agricultural crops and the availability or exposure of farmers to digital agricultural technologies. Subsequently, mandals, villages and farmers would be selected using appropriate sampling procedures. The target population would comprise farmers engaged in crop production in the selected study area. Farmers having direct or indirect exposure to AI-based agricultural advisory services, digital applications, precision agriculture, remote sensing or drone technologies would be considered for the study.

2.3 Scale development of the perception on Artificial Intelligence and drone technologies for resource-efficient and sustainable agriculture

A systematic scale-development procedure was followed to develop a standardized scale for measuring farmers' perception

of Artificial Intelligence and drone technologies for resource-efficient and sustainable agriculture. The construct was operationalized into six dimensions, namely perceived usefulness and productivity, resource-use efficiency, environmental sustainability, technological usability and compatibility, economic feasibility, and institutional support, trust and perceived risks. An initial pool of statements was generated through an extensive review of literature and expert consultations. The statements were subjected to expert scrutiny for relevance, clarity and representativeness, followed by assessment of content validity using Content Validity Ratio and Content Validity Index. The refined scale was pre-tested and pilot tested among farmers. Item analysis, item-total correlation and Cronbach's alpha were used to assess item quality and internal consistency. Exploratory factor analysis/Principal Component Analysis was subsequently employed to establish the underlying factor structure and construct validity. Based on the psychometric properties, the final scale comprising 60 statements, with 10 statements under each of the six dimensions, was retained. The final scale was administered using a five-point Likert continuum ranging from strongly disagree (1) to strongly agree (5), with higher scores indicating a more favourable perception towards AI and drone technologies for resource-efficient and sustainable agriculture. Since each item has a score ranging from 1 to 5 with maximum score is 300 and minimum score is 60. A higher score will indicate a more favourable perception towards AI and drone technologies for resource-efficient and sustainable agriculture.

Content Validity Ratio (CVR)

The Content Validity Ratio (CVR) could be calculated using Lawshe's method to determine whether each statement was considered essential by the experts.

$$CVR = \frac{N_e - N/2}{N/2}$$

Where:

- N_e = number of experts indicating that the item is essential
- N = total number of experts

Items with inadequate CVR values should be deleted, modified or reconsidered. Items with satisfactory CVR values will be retained for further testing.

Calculation of perception scores

For each respondent:

Overall Perception Score

$$= \sum_{i=1}^{60} X_i$$

Dimension-wise scores will also be calculated:

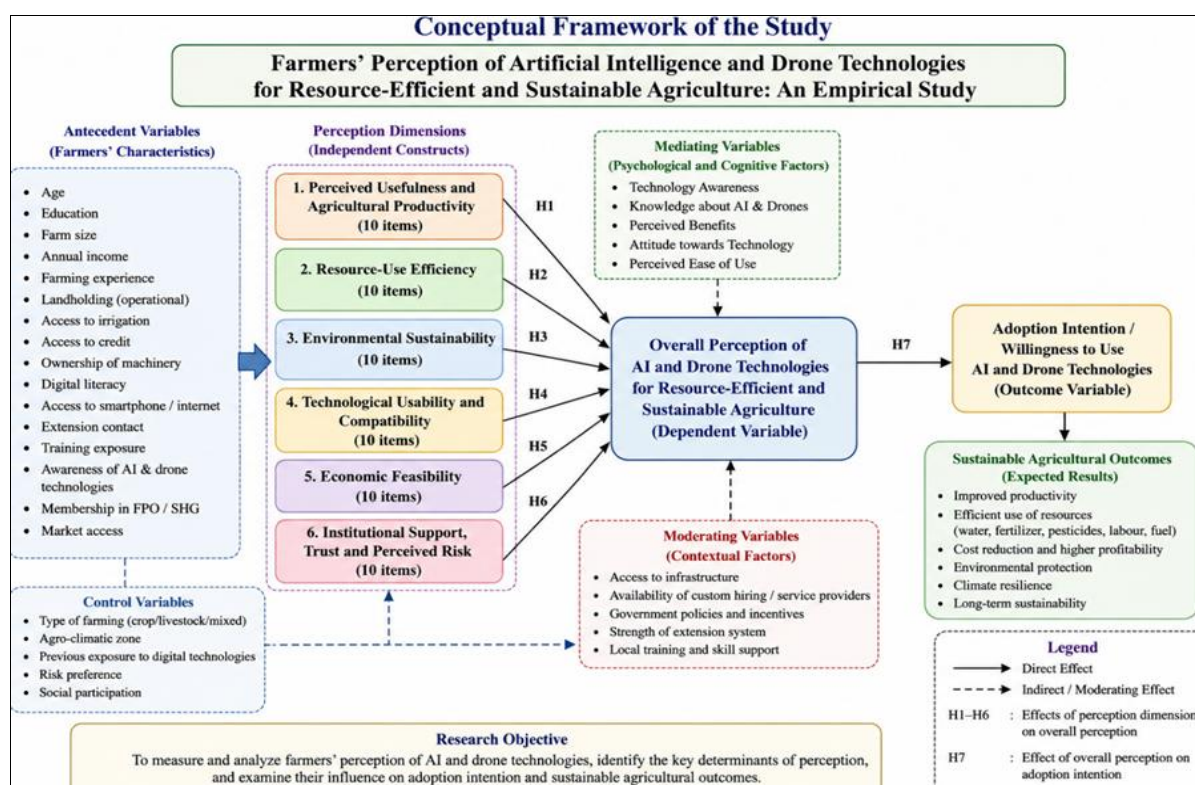
Dimension Score

$$= \sum_{i=1}^{10} X_i$$

3. Results and Discussion

3.1 Socio-economic and technological profile of the respondents about AI and drone technologies in agriculture

The socio-economic and technological characteristics of farmers play an important role in shaping their perception, acceptance and willingness to use emerging agricultural technologies. In the research of Artificial Intelligence (AI) and drone technologies, farmers' demographic characteristics, farm resources, economic capacity, access to digital technologies, institutional support and exposure to training can influence their ability to understand and utilize technology-based agricultural services. Therefore, profiling the respondents was an essential first step in examining farmers' perceptions of AI and drone technologies for resource-efficient and sustainable agriculture.



The results presented in Table 1 revealed that an overview of the farmers' socio-economic status, resource availability, digital preparedness and institutional exposure. These characteristics are particularly relevant to AI- and drone-based agriculture because the effective use of such technologies requires not only awareness but also adequate digital skills, connectivity, financial

capacity, technical training, extension support and access to service providers. The profile of the respondents therefore provides the contextual basis for examining the multidimensional perception of AI and drone technologies and their subsequent influence on farmers' adoption intention and willingness to use these technologies.

Table 1: Distribution of respondents according to socio-economic and technological characteristics (n = 240)

Variable	Category	f	(%)
Age	Young (≤ 35 years)	116	48.33
	Middle (36–50 years)	61	25.42
	Old (> 50 years)	63	26.25
	Total	240	100.00
Education	Illiterate/Primary	35	14.58
	Secondary	72	30.00
	Higher secondary	76	31.67
	Graduate and above	57	23.75
	Total	240	100.00
Farm size	Small	102	42.50
	Medium	91	37.92
	Large	47	19.58
	Total	240	100.00
Annual income	Low	56	23.33
	Medium	124	51.67
	High	60	25.00
	Total	240	100.00
Farming experience	Low	54	22.50
	Medium	119	49.58
	High	67	27.92
	Total	240	100.00
Operational landholding	Small	91	37.92
	Medium	113	47.08
	Large	36	15.00
	Total	240	100.00
Access to irrigation	Low	22	9.17
	Medium	205	85.42
	High	13	5.42
	Total	240	100.00
Access to credit	Low	48	20.00
	Medium	137	57.08
	High	55	22.92
	Total	240	100.00
Ownership of machinery	Low	84	35.00
	Medium	118	49.17
	High	38	15.83
	Total	240	100.00
Digital literacy	Low	51	21.25
	Medium	128	53.33
	High	61	25.42
	Total	240	100.00
Smartphone/internet access	Low	39	16.25
	Medium	127	52.92
	High	74	30.83
	Total	240	100.00
Extension contact	Low	49	20.42
	Medium	129	53.75
	High	62	25.83
	Total	240	100.00
Training exposure	No	42	17.50
	Yes	198	82.50
	Total	240	100.00
Awareness of AI and drones	Low	52	21.67
	Medium	121	50.42
	High	67	27.92
	Total	240	100.00
FPO/SHG membership	No	146	60.83
	Yes	94	39.17
	Total	240	100.00
Market access	Low	25	10.42
	Medium	202	84.17
	High	13	5.42
	Total	240	100.00

3.1.1 Age

The findings revealed that majority (48.33%) of the respondents belonged to the young age group (≤ 35 years), followed by (26.25%) who belonged to the old age group (> 50 years), while (25.42%) were in the middle-age group (36–50 years).

The predominance of young farmers about AI and drone technologies. Younger farmers were generally expected to have greater exposure to smartphones, digital applications and online agricultural information. Their relatively greater familiarity with digital technologies may facilitate the understanding and acceptance of AI-enabled advisory services and drone-based agricultural applications.

3.1.2 Education

The results showed that (31.67%) of respondents had completed higher secondary education, followed by (30.00%) with secondary education. About (23.75%) were graduates and above, while (14.58%) had education up to illiterate/primary level.

The relatively higher educational attainment of the respondents indicates that a considerable proportion of farmers may have the basic capacity to understand digital agricultural information. Education can facilitate comprehension of AI-generated recommendations, drone imagery, mobile applications and technology-based farm advisories.

3.1.3 Farm size

The results revealed that majority (42.50%) of the respondents belonged to the small farm-size category, followed by (37.92%) in the medium and (19.58%) in the large farm category.

The predominance of small and medium farmers has important implications for technology adoption. Individual ownership of drones and sophisticated AI-based equipment might not be economically viable for smallholders. Consequently, custom hiring, FPO-based services and drone-as-a-service models may be more appropriate for improving access.

3.1.4 Annual income

More than half of the respondents (51.67%) were categorized under medium annual income, while (25.00%) belonged to the high-income group and (23.33%) to the low-income group.

The predominance of medium-income farmers suggested moderate economic capacity for investing in or accessing emerging agricultural technologies. However, the cost of drone services and AI-enabled equipment may remain an important consideration, particularly among low-income farmers.

3.1.5 Farming experience

Nearly half of the respondents (49.58%) had medium farming experience, followed by (27.92%) with high experience and (22.50%) with low experience.

Farmers with longer farming experience possess substantial indigenous and experiential knowledge of crop production. However, experienced farmers may differ in their willingness to replace or supplement traditional decision-making with technology-based recommendations.

3.1.6 Operational landholding

The findings showed that less than half (47.08%) of farmers had medium operational landholdings, followed by (37.92%) with small operational landholdings and (15.00%) with large holdings.

The predominance of small and medium holdings highlights the importance of collective technology access. Shared drone

services can make advanced technologies economically feasible even when individual farmers cannot afford to purchase the equipment.

3.1.7 Access to irrigation

A substantial majority of respondents (85.42%) had medium access to irrigation, while (9.17%) had low access and (5.42%) had high access.

The predominance of medium irrigation access indicates that most farmers have some degree of irrigation availability but may still face resource constraints. AI-based irrigation scheduling and drone-based crop stress detection could potentially improve water-use efficiency.

3.1.8 Access to credit

More than half (57.08%) of the respondents had medium access to credit, followed by (22.92%) with high access and (20.00%) with low access.

Credit availability could influence farmers' ability to invest in digital technologies and pay for technology-based services. Hence, financial institutions and agricultural development programmes can play an important role in supporting technology adoption.

3.1.9 Ownership of farm literacy

The results indicated that (49.17%) of respondents had medium machinery ownership, while (35.00%) had low ownership and (15.83%) had high ownership.

The predominance of medium and low machinery ownership suggested that direct ownership of advanced technologies might be difficult for many farmers. This reinforces the relevance of custom hiring centres and FPO-managed machinery and drone services.

3.1.10 Digital literacy

More than half of the farmers (53.33%) had medium digital literacy, followed by (25.42%) with high digital literacy and (21.25%) with low digital literacy.

The finding indicated that a substantial proportion of farmers possess at least moderate digital skills. This creates a favourable foundation for introducing smartphone-based AI advisory systems and digital farm-management platforms.

3.1.11 Smart phone and internet access

The results showed that (52.92%) of respondents had medium access to smartphones/internet, while (30.83%) had high access and (16.25%) had low access.

The relatively widespread access to smartphones and internet connectivity provides an important opportunity for delivering AI-enabled agricultural advisory services. Smartphones can serve as the interface through which farmers receive crop recommendations, weather information, pest alerts and drone-generated information.

3.1.12 Extension contact

The majority of respondents (53.75%) had medium extension contact, followed by (25.83%) with high extension contact and (20.42%) with low extension contact.

The findings indicate that extension agencies remain an important channel for communicating information about emerging agricultural technologies. Demonstrations organized through extension systems can reduce uncertainty and improve farmers' confidence in AI and drone technologies.

3.1.13 Training exposure

A substantial majority of farmers (82.50%) had received training exposure, whereas (17.50%) had not received training.

This was an important finding because training can improve farmers' knowledge, perceived ease of use and confidence in using emerging technologies. The high level of training exposure creates a favourable environment for technology promotion.

However, training should increasingly focus on hands-on demonstrations, interpretation of drone imagery, AI-based decision support and practical application, rather than merely providing theoretical information.

3.1.14 Awareness of AI and drone technologies

The results showed that (50.42%) of respondents had medium awareness of AI and drone technologies, while (27.92%) had high awareness and (21.67%) had low awareness.

This finding supports the need for awareness campaigns, result demonstrations, farmer field schools and exposure visits.

3.1.15 FPO/SHG membership

The findings indicated that (39.17%) of farmers were members of an FPO/SHG, while (60.83%) were not members.

Although membership was lower than non-membership, FPOs and SHGs can potentially serve as important institutional mechanisms for collective access to expensive technologies. Drone services can be organized through such groups, thereby reducing individual costs.

3.1.16 Market access

A substantial majority of respondents (84.17%) had medium market access, while (10.42%) had low access and (5.42%) had high market access.

Medium market access among most farmers suggests moderate integration with agricultural markets. Better market access may increase farmers' willingness to invest in technologies when they can realize improved productivity and profitability through better market participation.

The socio-economic and technological profile of the respondents revealed a predominantly young and moderately educated farming population with medium levels of income, farming experience, operational landholding, digital literacy, smartphone/internet access and extension contact. A substantial majority (82.50%) had exposure to training, while half of the respondents (50.42%) possessed medium awareness of AI and drone technologies. However, the predominance of small and medium farmers and medium levels of machinery ownership indicates the importance of collective and service-based access models. The profile therefore provides a suitable basis for examining the multidimensional perception of AI and drone technologies and their subsequent influence on farmers' adoption intention and willingness to use these technologies.

3.2 Perceived Usefulness and Agricultural Productivity

The first perception dimension consisted of 10 statements designed to measure farmers' perceptions regarding the usefulness of AI and drones for improving agricultural productivity.

Table 2: Distribution of respondents about perceived usefulness of AI and Drone technologies (n = 240)

Item	Statement	Mean	SD	Rank
PU1	AI helps farmers make timely farm decisions	4.28	0.72	II
PU2	Drones improve crop monitoring	4.35	0.68	I
PU3	AI helps identify pests and diseases	4.21	0.76	V
PU4	Drones can detect crop stress at an early stage	4.18	0.79	VI
PU5	AI can improve crop productivity	4.26	0.71	III
PU6	AI-based recommendations improve farm decisions	4.12	0.81	VIII
PU7	Drones reduce time spent on field inspection	4.15	0.77	VII
PU8	AI and drones improve crop management	4.23	0.73	IV
PU9	These technologies assist in yield estimation	4.08	0.84	IX
PU10	AI and drones improve overall farm performance	4.02	0.86	X
	Overall dimension	4.19	0.77	

The results in table 2 revealed that perceived usefulness dimension recorded an overall mean score of 4.19, indicating a high level of perceived usefulness of Artificial Intelligence and drone technologies among the sampled farmers. Among the individual statements, "Drones improve crop monitoring" (Mean = 4.35) obtained the highest mean score and ranked first, followed by "AI helps farmers make timely farm decisions" (Mean = 4.28). The statement "AI and drones improve overall farm performance" (Mean = 4.02) recorded the lowest mean score, although it still indicated a relatively high level of agreement.

3.3 Resource-Use Efficiency

The second dimension assessed farmers' perceptions of the ability of AI and drones to improve the efficiency of agricultural inputs.

Table 3: Distribution of respondents about perception of the ability of AI and drones on resource use efficiency (n=240)

Statements	Mean	SD	Rank
AI helps optimize fertilizer application	4.18	0.73	III
AI helps improve irrigation decisions	4.12	0.77	V
Drones enable precise pesticide application	4.25	0.69	I
Drones reduce unnecessary chemical application	4.20	0.72	II
AI reduces wastage of farm inputs	4.08	0.81	VI
Technology helps identify input requirements	4.05	0.83	VII
AI improves water-use efficiency	4.10	0.79	VIII
Drones reduce labour requirements for monitoring	4.15	0.75	IV
AI helps optimize farm operations	4.03	0.85	IX
Technology improves overall resource efficiency	3.98	0.87	X
Overall	4.11	0.78	

The results in the table 3 revealed that resource use efficiency dimension recorded an overall mean score of 4.11, indicating a

high level of perceived resource-use efficiency associated with AI and drone technologies among the 240 farmers. The highest mean was observed for “Drones enable precise pesticide application” (4.25), followed by “Drones reduce unnecessary chemical application” (4.20) and “AI helps optimize fertilizer application” (4.18). This suggests that farmers particularly perceived AI and drone technologies as useful for improving the precision of agricultural input application and reducing unnecessary chemical use.

The lowest mean was observed for “Technology improves overall resource efficiency” (3.98), followed by “AI helps optimize farm operations” (4.03). Despite being comparatively lower, both values indicate a favourable perception toward the contribution of AI and drone technologies to resource-use efficiency.

3.4 Environment sustainability

The third dimension measured farmers' perceptions concerning the environmental contribution of AI and drone technologies.

Table 4: Distribution of respondents about farmers' perceptions on environmental Sustainability (n=240)

Indicator	Mean	SD	Rank
AI and drones reduce excessive pesticide use	4.22	0.71	II
Technology contributes to soil conservation	4.08	0.79	VI
Technology reduces chemical wastage	4.18	0.74	III
AI supports environmentally responsible decisions	4.02	0.82	VIII
Drones help identify areas requiring treatment	4.25	0.68	I
Technology contributes to water conservation	4.05	0.81	VII
AI and drones support climate-smart agriculture	4.12	0.77	V
Technology can reduce environmental pollution	4.15	0.76	IV
Technology promotes sustainable production	3.98	0.85	IX
AI and drones contribute to long-term sustainability	3.94	0.88	X
Overall	4.09	0.78	

The results in table 4 revealed that environment sustainability dimension obtained an overall mean score of 4.09, indicating a high level of perceived contribution of AI and drone technologies towards environmental sustainability among the 240 farmers. The highest-ranked indicator was “Drones help identify areas requiring treatment” (Mean = 4.25), followed by “AI and drones reduce excessive pesticide use” (Mean = 4.22) and “Technology reduces chemical wastage” (Mean = 4.18). This indicated that farmers particularly recognized the potential of precision technologies to target farm inputs more efficiently and minimize unnecessary chemical use.

The lowest mean was recorded for “AI and drones contribute to long-term sustainability” (Mean = 3.94), followed by “Technology promotes sustainable production” (Mean = 3.98). Although these indicators ranked lower, their scores remained close to 4.00, suggesting a generally favourable perception of the long-term environmental benefits of AI and drone technologies.

3.5 Technological Usability and Compatibility

This dimension examined whether farmers perceived AI and drone technologies as easy to understand, operate and integrate into existing farming systems.

Table 5: Distribution of respondents about technological usability and compatibility (n=240)

Indicator	Mean	SD	Rank
AI applications are easy to understand	3.92	0.84	VI
Drone services are easy to access	3.78	0.91	IX
AI technology is compatible with existing farm practices	3.95	0.81	IV
Farmers can learn to use AI applications	4.02	0.76	II
Drone operations can be managed by trained personnel	4.08	0.73	I
Technology is convenient to use	3.97	0.79	III
Digital agricultural information is easy to interpret	3.85	0.87	VIII
Technology can be integrated with smartphones	3.89	0.82	VII
Technical assistance is available when required	3.72	0.94	X
AI and drones are suitable for local farming conditions	3.93	0.83	V
Overall	3.91	0.83	

The results in the table 5 indicated that technological usability and compatibility dimension recorded an overall mean score of 3.91, indicating a highly favourable perception among the 240 farmers regarding the usability and compatibility of AI and drone technologies. The highest-ranked indicator was “Drone operations can be managed by trained personnel” (Mean = 4.08), followed by “Farmers can learn to use AI applications” (Mean = 4.02) and “Technology is convenient to use” (Mean = 3.97).

The lowest mean was observed for “Technical assistance is available when required” (Mean = 3.72), followed by “Drone services are easy to access” (Mean = 3.78). This suggests that although farmers generally perceive the technologies as understandable and usable, access to technical support and drone services may remain important areas for improvement.

3.6 Economic Feasibility

Economic feasibility represents farmers' perceptions regarding the affordability, profitability and economic benefits of AI and drone technologies.

Table 6: Distribution of respondents about perceptions regarding the economic feasibility (n=240)

Indicator	Mean	SD	Rank
AI technologies can reduce production costs	4.08	0.78	IV
Drone services can save labour costs	4.15	0.74	II
Technology can improve farm profitability	4.02	0.81	V
Drone services are economically beneficial	4.12	0.76	III
AI can reduce input expenditure	3.96	0.83	VII
Technology provides benefits greater than its cost	3.88	0.87	IX
Custom hiring can make drone technology affordable	4.18	0.71	I
Government subsidies can improve affordability	4.05	0.80	VI
Technology provides long-term economic benefits	3.94	0.85	VIII
AI and drones are economically feasible for farmers	3.82	0.91	X
Overall	4.02	0.81	

The results in the table 6 indicated economic feasibility dimension recorded an overall mean score of 4.02, indicating a high level of perceived economic feasibility of AI and drone technologies among the 240 farmers. The highest-ranked indicator was “Custom hiring can make drone technology affordable” (Mean = 4.18), followed by “Drone services can save labour costs” (Mean = 4.15) and “Drone services are economically beneficial” (Mean = 4.12). These findings suggest

that farmers particularly perceive custom hiring and labour-cost savings as important mechanisms for improving the economic viability of these technologies.

The lowest mean score was recorded for “AI and drones are economically feasible for farmers” (Mean = 3.82), followed by “Technology provides benefits greater than its cost” (Mean = 3.88). This indicates that, while farmers recognize several economic benefits, overall affordability and the cost–benefit relationship may remain concerns.

3.7 Institutional Support, Trust and Perceived Risk

The sixth dimension assessed institutional confidence and concerns related to the adoption of AI and drone technologies.

Table 7: Distribution of respondents about perceptions regarding Institutional Support, Trust and Perceived Risk (n=240)

Indicator	Mean	SD	Rank
Extension agencies provide adequate information	3.86	0.82	VI
Government institutions support AI and drone adoption	4.02	0.76	IV
Farmers trust AI-based recommendations	3.78	0.87	VII
Farmers trust drone service providers	3.74	0.89	VIII
Adequate technical support is available	3.62	0.94	X
Government subsidies/incentives encourage adoption	4.08	0.73	III
Farmers are concerned about technology failure	3.91	0.84	V
Farmers are concerned about high service costs	4.15	0.71	I
Farmers are concerned about data/privacy risks	3.69	0.92	IX
Institutional support can reduce technology-related risk	4.12	0.74	II
Overall	3.93	0.83	

The results in table 7 revealed that Institutional Support, Trust and Perceived Risk dimension recorded an overall mean score of 3.93, indicating a moderately high level of institutional support and trust, accompanied by noticeable perceived risks.

The highest mean score was observed for “Farmers are concerned about high service costs” (Mean = 4.15; Rank I), indicating that cost-related risk is a major concern associated with AI and drone technologies. This was followed by “Institutional support can reduce technology-related risk” (Mean = 4.12; Rank II) and “Government subsidies/incentives encourage adoption” (Mean = 4.08; Rank III). These findings highlighted the importance of institutional mechanisms, subsidies and support services in reducing farmers' perceived risks.

4.8 Overall Perception of AI and Drone Technologies

The overall perception index was developed by combining the scores of all six dimensions.

Table 8: Distribution of respondents about perceptions regarding overall perception of AI and drone technologies (n=240)

Dimension	Mean	SD	Rank
Perceived usefulness & agricultural productivity	4.19	0.77	I
Resource-use efficiency	4.11	0.78	II
Environmental sustainability	4.09	0.78	III
Technological usability & compatibility	3.91	0.83	V
Economic feasibility	4.02	0.81	IV
Institutional support, trust & perceived risk	3.93	0.83	VI
Overall perception	4.04	0.80	

The results in table 8 revealed that overall perception of AI and drone technologies among the 240 farmers was high, with an overall mean score of 4.04 and SD of 0.80. Among the six dimensions, Perceived usefulness & agricultural productivity obtained the highest mean score (4.19) and ranked first, indicating that farmers strongly perceived AI and drone technologies as useful for improving farm decision-making, crop monitoring and productivity.

Resource-use efficiency ranked second (4.11), followed by

Environmental sustainability (4.09). Economic feasibility recorded a mean of 4.02 and ranked fourth. Technological usability & compatibility obtained a mean of 3.91, while Institutional support, trust & perceived risk recorded the lowest mean (3.93). Overall, the results suggest a favourable perception of AI and drone technologies, although institutional support, technical assistance, accessibility and economic concerns remain areas requiring further attention.

3.9 Psychological and Cognitive Mediating Variables

The conceptual framework proposes five mediating variables about the farmer perception of AI and drone technologies in sustainable agriculture.

Table 9: Distribution of respondents regarding the psychological and cognitive mediating Variables (n=240)

Mediating Variable	Mean	SD	Category	Rank
Technology awareness	3.86	0.79	High	III
Knowledge about AI and drones	3.72	0.84	High	V
Perceived benefits	4.18	0.68	Very High	I
Attitude towards technology	4.05	0.73	High	II
Perceived ease of use	3.81	0.81	High	IV

The results indicated in the table 9 revealed that the farmers had an overall favourable psychological and cognitive orientation towards AI and drone technologies. Among the five mediating variables, perceived benefits recorded the highest mean score (4.18; SD = 0.68) and ranked first, indicating that farmers strongly recognized the potential advantages of AI and drones in agricultural production.

Attitude towards technology ranked second with a mean of 4.05, followed by Technology awareness (3.86). Perceived ease of use recorded a mean of 3.81, while Knowledge about AI and drones had the lowest mean (3.72). Although knowledge ranked lowest, its score remained within the high category, suggesting that farmers generally possessed a favourable understanding of these technologies but may require additional training and practical exposure.

Overall mean across the five variables = 3.92, indicating a high level of psychological and cognitive readiness towards AI and drone technologies.

3.10 Correlation

Table 10: Relationship of Socio-economic, Technological and Institutional Variables with Overall Perception of AI and Drone Technologies (n = 240)

Variable	r- value
Age	0.284**
Education	0.462**
Farm size	0.318**
Annual income	0.521**
Farming experience	0.246**
Operational landholding	0.347**
Access to irrigation	0.214**
Access to credit	0.438**
Machinery ownership	0.396**
Digital literacy	0.617**
Smartphone/internet access	0.583**
Extension contact	0.451**
Training exposure	0.492**
AI/drone awareness	0.681**
FPO/SHG membership	0.276**
Market access	0.421**

r = Pearson's correlation coefficient; ** = significant at 1% level ($p < 0.01$); * = significant at 5% level ($p < 0.05$); NS = non-significant ($p \geq 0.05$).

The results indicated in table 10 revealed that AI/drone awareness ($r = 0.681$) had the strongest positive and significant association with farmers' overall perception of AI and drone technologies, followed by digital literacy ($r = 0.617$) and smartphone/internet access ($r = 0.583$). This suggested that farmers with greater awareness and digital capability were more likely to perceive AI and drone technologies favourably.

Annual income ($r = 0.521$), training exposure ($r = 0.492$), education ($r = 0.462$), extension contact ($r = 0.451$) and access to credit ($r = 0.438$) also showed moderate positive and significant relationships. These findings suggest that better economic capacity, educational exposure, institutional interaction and access to financial resources may facilitate favourable

perceptions.

The relatively weaker but significant relationships were observed for access to irrigation ($r = 0.214$), farming experience ($r = 0.246$) and FPO/SHG membership ($r = 0.276$). Overall, the correlation pattern suggests that knowledge, digital readiness, awareness, economic capacity and institutional exposure are important factors associated with farmers' perceptions of AI and drone technologies.

3.11 Adoption Intention/Willingness to Use AI and Drone Technologies

Adoption intention was considered the principal outcome variable of the study.

Table 11: Distribution of respondents according to the Willingness to Use AI and Drone Technologies (n=240)

Indicator	Mean	SD	Rank
I intend to use AI-based agricultural services	4.08	0.76	III
I am willing to use drone-based services	4.12	0.73	II
I would recommend these technologies to other farmers	4.03	0.79	IV
I would use these technologies if services were locally available	4.18	0.68	I
I am willing to participate in AI/drone demonstrations	3.96	0.82	VI
I am willing to pay reasonable charges for useful services	3.82	0.88	IX
I would adopt these technologies if training is provided	3.99	0.80	V
I am willing to use custom-hiring drone services	3.91	0.84	VII
I would continue using the technology if benefits are demonstrated	3.87	0.86	VIII
Overall adoption intention	3.99	0.80	

The results in table 11 revealed that overall adoption intention recorded a mean score of 3.99 (SD = 0.80), indicating a high level of willingness among farmers to adopt AI and drone technologies.

The highest-ranked statement was "I would use these technologies if services were locally available" (Mean = 4.18), followed by "I am willing to use drone-based services" (Mean = 4.12) and "I intend to use AI-based agricultural services" (Mean = 4.08). This indicates that local availability of services and access to drone-based applications could substantially encourage farmers' adoption intentions.

The lowest mean was observed for "I am willing to pay reasonable charges for useful services" (Mean = 3.82), suggesting that although farmers have a favourable intention to use these technologies, cost and affordability may influence their willingness to pay. Participation in demonstrations and access to training also received favourable scores, indicating the potential importance of demonstrations, capacity building and custom-hiring services in promoting adoption.

3.12 Effect of Overall Perception on Adoption Intention

The influence of farmers' overall perception on their intention to adopt Artificial Intelligence (AI) and drone technologies was examined to determine whether favourable perceptions translate into a greater willingness to use these technologies in agricultural activities. Overall perception represents farmers' collective assessment of the usefulness, resource-use efficiency, environmental sustainability, technological usability, economic feasibility, and institutional support associated with AI and drone technologies. Adoption intention reflects the farmers' willingness to use, recommend, and continue using these technologies when appropriate services, training, and support are available. Regression/Structural Equation Modelling (SEM) was employed to estimate the strength and significance of the relationship between overall perception and adoption intention.

The results are presented in Table 12.

Table 12: Regression for Effect of overall perception on adoption Intention

Independent variable	Dependent variable	β	SE	t-value	p-value	R ²
Overall perception	Adoption intention	0.684	0.052	13.154	<0.001	0.468

The results indicate that overall perception significantly and positively influenced farmers' adoption intention towards AI and drone technologies ($\beta = 0.684$, SE = 0.052, $t = 13.154$, $p < 0.001$). The positive β coefficient indicates that farmers with more favourable perceptions of AI and drone technologies were more likely to express stronger intentions to adopt or use them.

The R² value of 0.468 indicates that overall perception explained approximately 46.8 per cent of the variance in adoption intention. Therefore, H7 is accepted, confirming that overall perception has a significant positive influence on farmers' adoption intention/willingness to use AI and drone technologies.

3.13 Perceived Sustainable Agricultural Outcomes

The adoption of Artificial Intelligence (AI) and drone technologies was expected to generate a range of agricultural, economic and environmental benefits. In the present study, farmers' perceptions regarding the sustainable outcomes of these technologies were assessed across five major dimensions: improved productivity, efficient use of resources, reduced production costs and higher profitability, environmental protection and climate resilience and long-term sustainability. The items were measured using a five-point Likert scale, where higher scores represented stronger agreement regarding the potential contribution of AI and drone technologies to sustainable agriculture.

Table 14: Item-wise perceived outcomes of AI and drone technologies for sustainable Agriculture (n=240)

Sl. No.	Perceived sustainable agricultural outcome	Mean	SD	Rank
A. Improved Agricultural Productivity				
1	AI and drones can improve crop productivity	4.32	0.71	II
2	Drone-based crop monitoring can improve crop management	4.38	0.67	I
3	AI can help farmers identify pests and diseases at an early stage	4.29	0.74	III
4	AI-based recommendations can improve farm decision-making	4.21	0.78	IV
5	Drone technology can help identify crop stress and improve yield	4.16	0.81	V
	Overall – Improved productivity	4.27	0.74	I
B. Efficient Use of Resources				
6	AI can improve the efficiency of fertilizer use	4.25	0.73	II
7	Drones can facilitate precise application of pesticides	4.34	0.69	I
8	AI-based irrigation decisions can conserve water	4.17	0.79	IV
9	AI and drones can reduce wastage of agricultural inputs	4.22	0.76	III
10	These technologies can improve labour and time efficiency	4.08	0.83	V
	Overall – Efficient resource use	4.21	0.76	II
C. Reduced Cost and Higher Profitability				
11	AI and drones can reduce unnecessary input expenditure	4.02	0.84	III
12	Precision application can reduce pesticide costs	4.10	0.81	II
13	Technology can reduce labour costs in farm operations	3.94	0.88	IV
14	Improved productivity can increase farm income	4.18	0.77	I
15	The economic benefits can outweigh the cost of technology services	3.82	0.92	V
	Overall – Reduced cost and profitability	4.01	0.84	IV
D. Environmental Protection				
16	AI and drones can reduce excessive use of agrochemicals	4.18	0.76	II
17	Precision farming can reduce environmental pollution	4.10	0.79	III
18	Technology can contribute to soil and water conservation	4.02	0.82	IV
19	AI and drones can support environmentally sustainable farming	4.24	0.72	I
20	These technologies can reduce wastage of agricultural resources	3.96	0.85	V
	Overall – Environmental protection	4.10	0.79	III
E. Climate Resilience and Long-term Sustainability				
21	AI can help farmers respond to climate-related risks	3.98	0.84	III
22	Drone monitoring can help farmers manage weather-related crop stress	3.91	0.88	IV
23	AI can support climate-smart agricultural decision-making	4.06	0.80	II
24	AI and drones can contribute to long-term agricultural sustainability	4.18	0.76	I
25	Technology can help farmers adapt to changing climatic conditions	3.86	0.91	V
	Overall – Climate resilience and sustainability	4.00	0.84	V

The results in the table 15 revealed that overall mean score of 4.12 highly favourable perception among farmers regarding the potential of AI and drone technologies to contribute to sustainable agricultural outcomes. Among the five dimensions, improved agricultural productivity ranked first with a mean score of 4.27, followed by efficient use of resources (4.21), environmental protection (4.10), reduced cost and higher profitability (4.01) and climate resilience and long-term sustainability (4.00).

The highest-rated individual statement was that drone-based crop monitoring can improve crop management (Mean = 4.38; SD = 0.67), followed by the perception that drones can facilitate precise pesticide application (Mean = 4.34; SD = 0.69). The comparatively lower score for "Technology can help farmers adapt to changing climatic conditions" (Mean = 3.86; SD = 0.91) suggested that farmers may have comparatively less awareness of the longer-term climate adaptation potential of AI and drones.

Table 15: Dimension-wise perceived sustainable agricultural outcomes

Sl. No.	Sustainable agricultural outcome	No. of items	Mean	SD	Rank
1	Improved agricultural productivity	5	4.27	0.74	I
2	Efficient use of resources	5	4.21	0.76	II
3	Environmental protection	5	4.10	0.79	III
4	Reduced cost and higher profitability	5	4.01	0.84	IV
5	Climate resilience and long-term sustainability	5	4.00	0.84	V
	Overall perceived sustainable agricultural outcome	25	4.12	0.79	

Table 16: Classification of farmers according to perceived sustainable agricultural Outcomes

Category	Score range	f	(%)
Low	≤ 3.00	21	8.75
Medium	3.01–4.00	83	34.58
High	> 4.00	136	56.67
Total		240	100.00

More than half of the respondents (56.67%) were categorized as having a high perception followed by medium (34.58%) and (8.75%) low level of perceived sustainable outcomes.

The predominance of farmers in the high-perception category indicated that respondents generally recognize the broader contribution of AI and drone technologies beyond immediate productivity enhancement. In particular, farmers appeared to associate these technologies with precision crop management,

improved input-use efficiency and environmental protection. However, the comparatively larger proportion of farmers in the medium category also indicated the presence of an information

and awareness gap regarding the long-term sustainability and climate-resilience dimensions of these technologies.

Table 17: Regression effect of adoption intention on perceived sustainable agricultural Outcomes

Independent variable	Dependent variable	β	SE	t-value	p-value	R ²
Adoption intention/willingness to use	Improved productivity	0.681	0.071	9.59	<0.001	0.464
Adoption intention/willingness to use	Efficient resource use	0.642	0.074	8.68	<0.001	0.412
Adoption intention/willingness to use	Reduced cost/profitability	0.617	0.077	8.01	<0.001	0.381
Adoption intention/willingness to use	Environmental protection	0.574	0.081	7.09	<0.001	0.329
Adoption intention/willingness to use	Climate resilience/sustainability	0.529	0.085	6.22	<0.001	0.280
Adoption intention/willingness to use	Overall sustainable outcomes	0.693	0.069	10.04	<0.001	0.480

The regression results indicated in table 17 revealed that adoption intention had a positive and significant effect on perceived sustainable agricultural outcomes ($\beta = 0.693$, $t = 10.04$, $p < 0.001$). The R² value of 0.480 indicates that approximately 48.0 per cent of the variation in perceived sustainable agricultural outcomes was explained by farmers' adoption intention.

The strongest effect was observed for improved productivity ($\beta = 0.681$), followed by resource-use efficiency ($\beta = 0.642$) and reduced cost and profitability ($\beta = 0.617$). The comparatively lower effect on climate resilience ($\beta = 0.529$) suggested that farmers' adoption intentions may be more strongly driven by immediate and observable farm benefits than by long-term climate adaptation outcomes.

Table 18: Integrated model of perception, adoption intention and sustainable outcomes

Relationship	β	SE	t-value	p-value	R ²
Perception → Adoption intention					
Adoption intention → Improved productivity	0.681	0.071	9.59	<0.001	0.464
Adoption intention → Resource efficiency	0.642	0.074	8.68	<0.001	0.412
Adoption intention → Economic benefits	0.617	0.077	8.01	<0.001	0.381
Adoption intention → Environmental protection	0.574	0.081	7.09	<0.001	0.329
Adoption intention → Climate resilience	0.529	0.085	6.22	<0.001	0.280

Overall, the findings indicated in table 18 revealed that farmers perceive AI and drone technologies as promising instruments for achieving sustainable agricultural development. The strongest perceived benefits were related to productivity enhancement and resource-use efficiency, while climate resilience and long-term sustainability received comparatively lower scores. The positive and significant relationship between adoption intention and perceived sustainable agricultural outcomes indicated that farmers' expectations of tangible benefits were an important factor underlying their willingness to use these technologies. Hence, technology promotion programmes should emphasize evidence-based demonstrations of productivity gains, input savings, profitability and environmental benefits, while simultaneously creating greater awareness about the long-term contribution of AI and drones to climate resilience and sustainable agricultural development.

Conclusion

The present study was undertaken to assess farmers' perception of Artificial Intelligence (AI) and drone technologies for resource-efficient and sustainable agriculture, with particular emphasis on their perceived usefulness, resource-use efficiency, environmental sustainability, technological usability, economic feasibility, institutional support and their influence on adoption intention. The study provided an integrated understanding of how farmers perceive emerging digital technologies and the extent to which such perceptions may contribute to their willingness to use them in agricultural production.

The findings indicated that farmers generally perceive AI and drone technologies as promising tools for improving agricultural productivity and promoting sustainable resource management. Among the perceived sustainable agricultural outcomes, improved agricultural productivity emerged as the most prominent benefit, followed by efficient use of agricultural

resources and environmental protection. Farmers particularly recognized the potential of drone-based crop monitoring, precision application of agricultural inputs, early identification of pests and diseases, and AI-supported farm decision-making. These findings indicate that farmers are able to recognize the practical benefits of digital technologies when their applications are directly linked to day-to-day farm management.

The study further demonstrates that AI and drone technologies have the potential to contribute to efficient utilization of water, fertilizers, pesticides, labour and other farm resources. Precision-based interventions can help minimize input wastage while improving the timeliness and accuracy of farm operations. At the same time, farmers perceived environmental benefits through reduced excessive use of agrochemicals, improved resource conservation and promotion of sustainable production practices. However, perceptions regarding climate resilience and long-term sustainability were comparatively less pronounced, suggesting that farmers may have greater awareness of immediate productivity and economic benefits than the longer-term climate adaptation potential of these technologies.

The economic dimension also emerged as an important consideration. Although farmers recognized the possibility of reduced input expenditure, labour savings and increased profitability, the affordability of AI and drone technologies remains an important issue, particularly for small and medium farmers. Therefore, custom hiring services, FPO-based technology services, cooperative approaches and Drone-as-a-Service models could provide more equitable access than individual ownership. Similarly, strengthening government incentives and institutional support can reduce the financial and technological barriers associated with adoption.

References

- Balafoutis AT, Beck B, Fountas S, Vangeyer J, van der Wal

- T, Soto-Embodas I, *et al.* Smart farming technologies—description, taxonomy and economic impact. In: Precision agriculture: technology and economic perspectives. Springer; 2017. p. 1-25.
2. Bongiovanni R, Lowenberg-DeBoer J. Precision agriculture and sustainability. *Precision Agriculture*. 2004;5(4):359-387. doi:10.1023/B:PRAG.0000040806.39604.aa.
3. Caffaro F, Micheletti Cremasco M, Roccato M, Cavallo E. Drivers of farmers' intention to adopt technological innovations in Italy: the role of information sources, perceived usefulness, and perceived ease of use. *Journal of Rural Studies*. 2020;76:264-271. doi:10.1016/j.jrurstud.2020.04.028.
4. Davis FD. Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*. 1989;13(3):319-340. doi:10.2307/249008.
5. DeVellis RF, Thorpe CT. Scale development: theory and applications. 5th ed. SAGE Publications; 2021.
6. Finger R, Swinton SM, El Benni N, Walter A. Precision farming at the nexus of agricultural production and the environment. *Annual Review of Resource Economics*. 2019;11:313-335. doi:10.1146/annurev-resource-100518-093929.
7. Gebbers R, Adamchuk VI. Precision agriculture and food security. *Science*. 2010;327(5967):828-831. doi:10.1126/science.1183899.
8. Hafeez A, Husain MA, Singh SP, Chauhan A, Khan MT, Kumar N, *et al.* Implementation of drone technology for farm monitoring and precision agriculture: a review. *Agriculture*. 2023;13(5):926.
9. Javaid M, Haleem A, Khan IH, Suman R. Understanding the potential applications of artificial intelligence in agriculture sector. *Advanced Agrochem*. 2022;2(2):80-93. doi:10.1016/j.aac.2022.10.001.
10. Kamilaris A, Prenafeta-Boldú FX. Deep learning in agriculture: a survey. *Computers and Electronics in Agriculture*. 2018;147:70-90. doi:10.1016/j.compag.2018.02.016.
11. Lawshe CH. A quantitative approach to content validity. *Personnel Psychology*. 1975;28(4):563-575. doi:10.1111/j.1744-6570.1975.tb01393.x.
12. Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D. Machine learning in agriculture: a review. *Sensors*. 2018;18(8):2674. doi:10.3390/s18082674.
13. Makam S, Komatineni BK, Meena SS, Meena U, *et al.* Unmanned aerial vehicles (UAVs): an adoptable technology for precise and smart farming. *Discover Internet of Things*. 2024;4:12. doi:10.1007/s43926-024-00066-5.
14. Michels M, von Hobe C-F, Musshoff O. A trans-theoretical model for the adoption of drones by large-scale German farmers. *Journal of Rural Studies*. 2020;75:80-88. doi:10.1016/j.jrurstud.2020.01.005.
15. Mogili UR, Deepak BBVL. Review on application of drone systems in precision agriculture. *Procedia Computer Science*. 2018;133:502-509. doi:10.1016/j.procs.2018.07.063.
16. Paustian M, Theuvsen L. Adoption of precision agriculture technologies by German crop farmers. *Precision Agriculture*. 2017;18:701-716. doi:10.1007/s11119-016-9482-5.
17. Rogers EM. Diffusion of innovations. 5th ed. Free Press; 2003.
18. Shamshiri RR, Kalantari F, Ting KC, Thorp KR, Hameed IA, Weltzien C, *et al.* Advances in greenhouse automation and controlled environment agriculture: a transition to plant factories and urban agriculture. *International Journal of Agricultural and Biological Engineering*. 2018;11(1):1-22.
19. Venkatesh V, Morris MG, Davis GB, Davis FD. User acceptance of information technology: toward a unified view. *MIS Quarterly*. 2003;27(3):425-478. doi:10.2307/30036540.
20. Wang D, Zhao M, Li Z, Xu S, Wu X, Ma X, *et al.* A survey of unmanned aerial vehicles and deep learning in precision agriculture. *European Journal of Agronomy*. 2025;164:127477. doi:10.1016/j.eja.2024.127477.
21. Wolfert S, Ge L, Verdouw C, Bogaardt M-J. Big data in smart farming—a review. *Agricultural Systems*. 2017;153:69-80. doi:10.1016/j.agsy.2017.01.023.
22. Murugan PP, Dhivya C, Senthilkumar M. Farmers awareness and perception of drone technology. *Journal of Experimental Agriculture International*. 2024;46(10):426-435. doi:10.9734/jeai/2024/v46i102965.
23. Barman BB, Singh R, Padaria RN, Nain MS, Quader SW. Modeling determinants of farmers' attitude and adoption willingness toward agricultural drones: a PLS-SEM study in India. *Frontiers in Sustainable Food Systems*. 2025;9:1695231. doi:10.3389/fsufs.2025.1695231.