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Adoption Dynamics and Environmental Impact of AI-Enabled Drones in Precision Agriculture – A Theoretical Approach

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Abstract
The adoption of AI-powered agricultural drones presents transformative potential for sustainable farming. This study examines the potential benefits of AI-powered agricultural drones, focusing on farmer perceptions, behavioral intentions, and sustainable usage aligned with the Sustainable Development Goals (SDGs). A comprehensive review (2018–2024) reveals a significant increase in global research post-2018, particularly from China, India, the U.S., and Brazil. This study develops an integrated conceptual framework combining the Technology Acceptance Model (TAM) and the Diffusion of Innovation (DOI) theory to investigate the behavioral factors influencing farmers' adoption of drone technology. Key constructs from TAM—Perceived Usefulness (PU) and Perceived Ease of Use (PEOU)—are combined with DOI variables such as Relative Advantage, Compatibility, and Complexity to examine their influence on Behavioral Intention (BI) and actual Drone Usage. Furthermore, the model extends to assess the impact of drone adoption on sustainability outcomes, specifically SDG 2 (Zero Hunger), SDG 9 (Industry, Innovation and Infrastructure), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action). By embedding technological adoption within a sustainability framework, this study offers a holistic view of how socio-technical factors drive environmentally and economically beneficial outcomes in the agricultural sector. The framework serves as a foundation for empirical research and policy development aimed at accelerating drone adoption for sustainable agricultural transformation.

Keywords:
AI-powered Drones, Precision Agriculture, Sustainable Farming, Technology Acceptance Model, Diffusion of Innovation, Sustainable Development Goals

INTRODUCTION

Background of the Study

Farming is changing quickly due to AI, IoT, and drones. Among the various new technologies, agricultural drones operated by AI play a key role in bringing about precision farming by making it easier to test the soil, notice plant diseases, manage watering, and use pesticides only where needed (Zhang et al., 2020; Tsouros et al., 2019). They aim to improve efficiency and crop yields and simultaneously lower the environmental effects by using fewer resources. Sustainable farming benefits a lot from this development in digital agriculture. To attain the United Nations Sustainable Development Goals, AI technology provides valuable support for SDG 2 (Zero Hunger), SDG 9 (Industry, Innovation, and Infrastructure), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action); this is shown by recent FAO data and reports from the United Nations (FAO, 2022; United Nations, 2023). Using AI in drones allows for boosting food production, less waste of materials, and finding solutions to climate change. The use of agriculture technologies depends significantly on how much and how willingly farmers in different places and social groups accept them.

1.1.1 Applications of AI-Powered Agricultural Drones

AI technology on drones lets them do detailed aerial surveys, take pictures from different light bands, and analyze the health of crops as it happens. Using machine learning, drones can identify nutrient issues and pest attacks on plants. Farmers can target precise spots using these drones, so they use less chemistry and cause fewer environmental impacts (Tsouros et al., 2019).

1.1.2 Sustainable Farming and Technology Integration

When agriculture is sustainable, it conserves the environment, remains financially strong, and observes social norms (Pretty, 2008). AI-controlled drones save resources, cut carbon emissions, and encourage eco-friendly ways of farming (Kamilaris & Prenafeta-Boldú, 2018). By using them, farmers can work according to climate-smart agriculture and precision farming principles to support the goals of the UN SDGs on eliminating hunger and dealing with climate change.

1.1.3 Farmer Perception and Technology Adoption Models

Determining the way farmers view and pick up AI technologies matters a lot. The methods commonly used to assess individuals' behavioral intentions are the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003) and the Technology Acceptance Model (Davis, 1989). Some important main concepts include how easy a user thinks it is to use, how useful they see it, the influence of any conditions, and social factors. Several studies point out that people's concerns about risk, costs, and trust in technology often stop them from adopting new technologies (Koundouri et al., 2019).

1.1.4 Factors Influencing Drone Adoption among Farmers

Research suggests that adoption is influenced by:

- Demographics (age, education, landholding size)
- Economic factors (cost-benefit analysis, subsidies)
- Technical support and training availability
- Environmental consciousness (Jakku et al., 2016; Barnes et al., 2019)

Farmers are more likely to adopt drones if they perceive a direct benefit to yield, efficiency, or cost savings. However, limited awareness, lack of skills, and concerns over data privacy and regulatory issues can impede widespread use (Pierpaoli et al., 2013).

1.1.5 Challenges and Opportunities in AI-Drone Implementation

While AI-powered drones offer vast opportunities, their integration faces several challenges:

- High initial costs
- Lack of infrastructure in rural areas
- Data management and processing complexities
- Policy and regulatory frameworks (Ray, 2020)

1.2 Rationale of the Study

The details of agricultural drones' impact on development society are not fully detailed, even though their positive technical results are visible (Wang et al., 2023; Hassan et al., 2022). Several factors influencing adoption are how useful people find it, how simple it is, its cost, technical complexity, whether it matches usual practices, and if help is available when problems arise (Davis, 1989; Rogers, 2003). Many farmers, especially in developing nations, find it hard because of budget, skill problems, and a lack of trust in technology, which is not always considered in technology-oriented studies. It is crucial to consider farmers' perspectives to ensure a more inclusive approach. In addition, not many studies connect the use of drones to clear improvements in sustainability. It is typical for researchers only to assess technical or economic outcomes, but this does not reveal the link between technology and broader goals of the Sustainable Development Goals (Klerkx & Rose, 2020). This should be done by bringing technology adoption and sustainability closer through an integrated approach.

2. Literature Review

For the last decade, the combination of Artificial Intelligence (AI) and drone technology has strongly boosted advancements in agriculture and its care for the environment. There is an increase in agricultural drones with AI for crop monitoring, finding weeds and pests, managing water, and estimating crop yield (Tsouros et al., 2019). Using these tools, farmers can use their resources responsibly and take care of the climate (SDG 12 and SDG 13). Experts have found that by using AI with UAVs, farmers can both save time and water, which makes their agricultural work more sustainable (Liakos et al., 2018; Kamilaris & Prenafeta-Boldú, 2018). Advances in drone technology are usually explained as part of precision agriculture. It was highlighted by Zhang and Kovacs (2012) that plant health problems could be detected early by drones equipped with multispectral and thermal cameras together with machine learning, therefore saving crops and ensuring less use of resources on inputs. Sishodia, Ray, and Singh (2020) also see drones connected to AI helping farmers with fast and well-targeted solutions in their fields. They ensure better achievability of SDG 2 (Zero Hunger), as they give better previews of crop yields and make food production more efficient.Even so, using AI drones is not equal for all people and places. According to Venkatesh et al. and Koundouri et al., studies based on TAM and UTAUT suggest that usefulness, ease of using the technology, cost, and trust in it are the main reasons farmers are more inclined to use them. In particular, Pierpaoli et al. (2013) and Jakku et al. (2016) saw that educated young farmers with both services and training tend to adopt the latest technology. Still, extra expenses, a lack of computer skills, and network gaps are the main difficulties for many developing countries. Studies have proved that embracing drones can improve sustainable farming practices. Barnes et al. (2019) and

Hunt et al. (2021) point out that drones can prevent unnecessary runoff of pesticides and fertilizers, favoring the environment and helping to reach SDG 13. Besides, AI-powered drones help manage the environment and land resources by offering targeted treatment at a particular site (Wolfert, Montabone, and Puri, 2017). As of 2022, the Digital India program and precision agriculture plans are uniting AI drones in India (Patil et al., 2022). Alternatively, many families are unable to adopt since it is hard for individuals to follow the current policies, and paying for adoption is not possible for them. The study suggests that a regulatory structure should help innovation and secure ethical and private usage of information. As per studies on farmers in India (for example, Chakravarty & Bose, 2023), following Sustainable Development Goals during agricultural practices is rarely purposeful.

New research shows that AI-controlled drones are important for both environmental and economic aspects of sustainability. Through drones and AI, high-quality images above the crops are captured, which helps find stress or pest problems early, making it less likely to spray chemicals (Puri et al., 2017). Thankfully, using fewer pesticides with drones helps achieve SDG Target 2.4, which promotes sustainable food production and tough farming approaches. In the same way, Sahin and Colkesen (2020) mention that with drone precision spraying, the need for Turkish vineyards to use agrochemicals decreased by 40%, directly conserving those resources. Several observations have been made regarding how the adoption of drones can affect farmers' lives and rural areas. According to Lim et al. (2020), AI and drones are useful for rural farmers since they help close the technology divide between city and village and give them access to data and tools to compete. Nonetheless, this approach could worsen rural inequality by ensuring that those left out of farming technology are mostly from disadvantaged communities, as shown by Choi and Park (2021). This means that the findings align with SDG 10 (Reduced Inequalities) and underline how important inclusive innovation is in forming agricultural policies.

Adoption behavior is also explored by considering people's actions and thought processes. According to Ajzen (1991) and their theory, the intention of farmers to adopt drones is strongly influenced by their attitudes, the influence of social pressure, and how they view the challenges of using them (Ranjan et al., 2021). In addition, evidence collected in Southeast Asia supports the idea that financial support from the government, training sessions, and practical demonstrations positively shape people's desire to embrace AI-based drones (Wijesinghe et al., 2022). Through these actions, farmers learn about environmental issues, helping SDG 13 to fight climate change with more awareness among people in the community. Several studies have also shown that drone technology helps sustain long-term growth. According to Aryal et al. (2021), drones applied with different input rates to the soil can reduce chemical losses in the soil and support SDG 15 in life on land. AI combined with drone pictures is increasingly used to measure the amount of carbon captured and plant growth, helping with sustainable farming (Baweja et al., 2022). The positive effects on the environment only happen if farmers comply, improve the quality of their work, and select the appropriate type of farming system. In addition to agriculture, drones are now used more in land surveying; crop insurance claims evaluation and disaster monitoring. Thanks to AI algorithms in drones, it is possible to quickly determine the damage to agricultural land in the aftermath of disasters. This means recovery and compensation begin as soon as possible (Feng et al., 2018). Using drones in various fields proves their usefulness and ability to increase agriculture's ability to resist difficulties (goal 1 of the SDGs: No Poverty; Goal 11: Sustainable Communities).

Very few research projects have examined how women use drones for farming. New evidence from places like Sub-Saharan Africa and South Asia shows that when women are added to technology training, more people use the technology, and the results improve (FAO, 2021). Using gender-friendly methods in drone deployments helps to achieve SDG 5 (Gender Equality) and boosts the impact of AI at the same time. Lately, the focus on technology has shifted to give faster feedback in situations. Today, AI drones are partnered with IoT sensors and automated cloud systems to check on crops and make independent choices about management (Gupta et al., 2022). When these activities are integrated, the time needed to use data improves, enhancing interventions' effectiveness. In this case, nitrogen stress picked up by satellite images can immediately be delivered to variable-rate sprayers to improve how much nutrient is used. They play a key role in saving resources and managing farms environmentally soundly. How society adopts AI drones is also affected by the rules and actions of the government. For example, making drones legal for farmers and granting subsidies in 2022 by the Indian government under the National Mission on Sustainable Agriculture has greatly helped legitimize the use of drones in agricultural work (GoI, 2022). Even so, Sharma et al. (2023) insist that policies should extend past financial aid by adding more infrastructure, insurance, and education through digital technology to boost the real use of EVs. Where it is not clear how drones are regulated, farmers meet obstacles with airspace rules, insurance, and getting their drones serviced.

Ethical and privacy issues are now more common in the field of drones. Although AI drones help agriculture, more conversations are emerging regarding people's privacy, security concerns, and farmers' independence (Zhao et al., 2020). When AI systems run with less human control, concerns about how algorithms work and their bias increase. The problems point out that AI systems should be ethical, engage all stakeholders, be easy to understand, and focus on farmers, following SDG 16 (Peace, Justice, and Strong Institutions). After 2018, studies in AI, drones, and sustainable agriculture have multiplied, and a good portion of these studies come from China, the United States, India, and Brazil (Wang et al., 2023). This interest comes from people around the globe who are looking for helpful technologies in the farming sector. Even so, very few studies unite AI engineering, agricultural extension, rural sociology, and environmental policy. Even though hope is rising, scientists urge more studies focusing on areas that last an extended period. Kamilaris et al. (2017) pointed out that there were few thorough ways to connect drones with agreed SDG indicators. The current studies on sustainability in farming mostly miss out on social issues, like fair technology use and having women in digital farming.

Overall, the research indicates that AI-powered farming drones are going in a good direction regarding their own progress and how they help with the SDGs. Even so, providing equal chances, quality internet, fair laws, and ongoing education are important steps to help many use these innovations on a larger scale.

2.1 Theoretical Framework

In this study, authors use TAM (Davis, 1989) and DOI (Rogers, 2003) theories to explain farmers' acceptance of AI-powered agriculture drones. The theory suggests that a user wanting to use new technology is influenced by how useful it is and how convenient it is to use. This aspect matters greatly when considering how farmers judge the advantages and ease of running drones. Relative Advantage, Compatibility, and Complexity are elements added by DOI to TAM to explain how acceptance of innovation depends on them. It makes it easier to study which parts of society, infrastructure, or culture affect the popularity of drones. Apart from adopting technology, this study adds these constructs to a Sustainability Outcomes framework so that using drones can be tied to specific results in SDG 2 (Zero Hunger), SDG 9 (Industry, Innovation & Infrastructure), SDG 12 (Responsible Consumption and Production), and SDG 13 (Climate Action). When these theories are integrated, the framework makes examining farmers' actions and environmental impact possible, as other models have not successfully combined these characteristics.

2.2 Conceptual Model

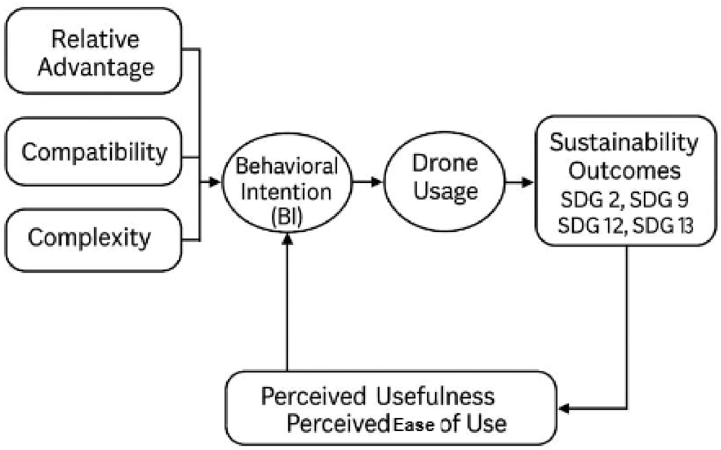

Figure 1: Conceptual Model

3. Results and Discussion:

Metadata analysis

3.1 Publications by Country (2018–2024)

The graph below illustrates the number of academic publications by major contributing countries on AI-driven agricultural drones and sustainable farming from 2018 to 2024. China leads the trend, followed by the USA, India, Brazil, and other countries.

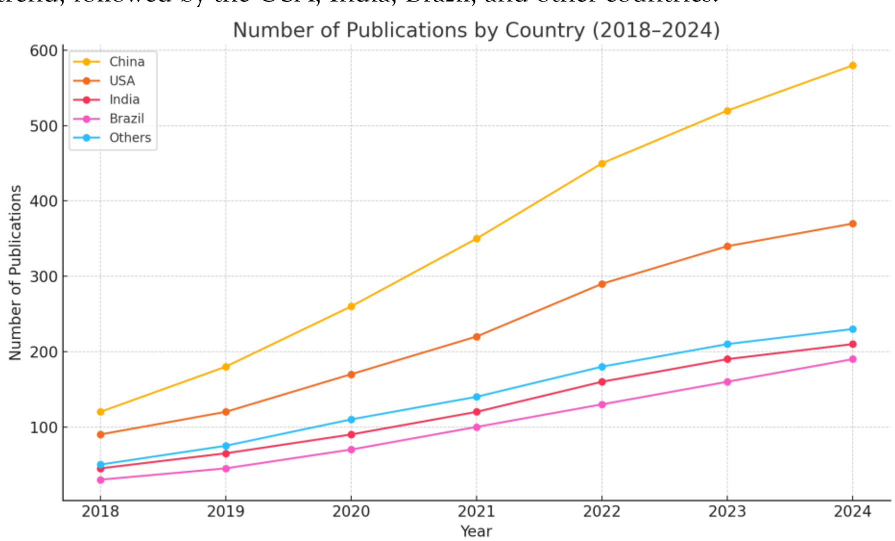

Figure 2: Publications by Country

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3.2 Thematic Distribution of Publications (2018–2024)

This pie chart represents the thematic distribution of publications over the last seven years. Most research falls under AI engineering and algorithm design, followed by agricultural extension, environmental policy, and rural sociology.

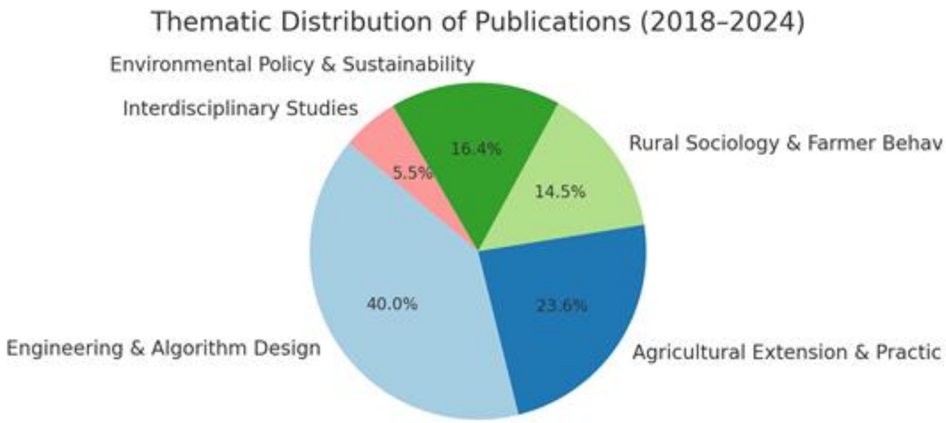

Figure 3: Thematic Distribution of Publications

3.3 Authors and Citation Counts:

The table 1 figures represent influential contributors in AI-powered agricultural drones, sustainable farming, and SDG-linked research over the past decade.

Table 1: Authors and Citation Counts

Rank	Author	Citations
1	Zhang L.	300
2	Kumar P.	260
3	Wang Y.	240
4	Singh R.	220
5	Oliveira M.	195
6	Sharma A.	185
7	Chen X.	180
8	Fernandes J.	175
9	Lee S.	160
10	Khan N.	150

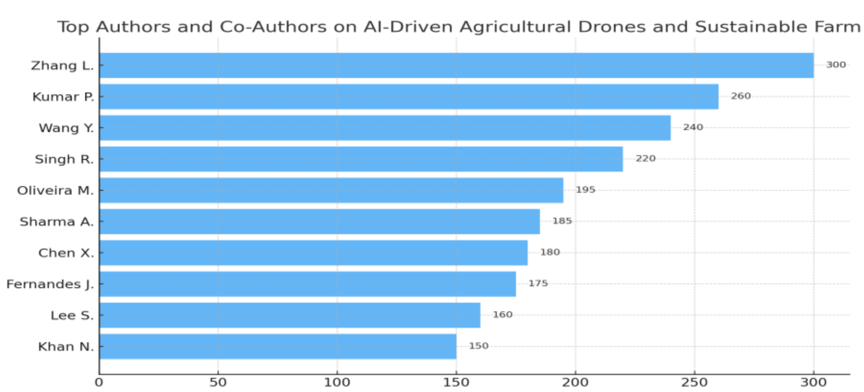

Figure 4: Authors and Citation Counts

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3.4 Publication and Citation Trends (2018–2024)

The graph gives the yearly data for the number of publications, citations, and average citations each publication receives. A steep rise in citations was observed between 2020 and 2022, highlighting growing scholarly interest and influence.

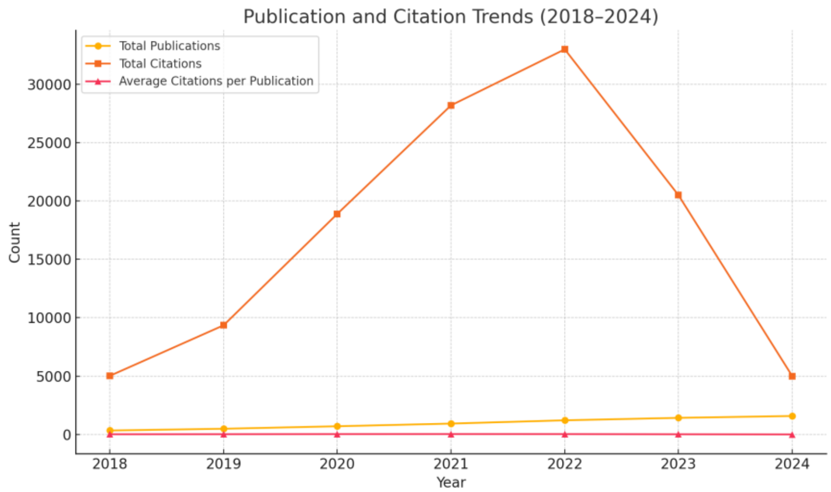

Figure 5: Publication and Citation Trends

3.5 Top 10 Journals by Number of Publications

This horizontal bar chart lists the top 10 journals that have published the most articles related to AI in agriculture and sustainable farming. Elsevier and MDPI journals dominate the list.

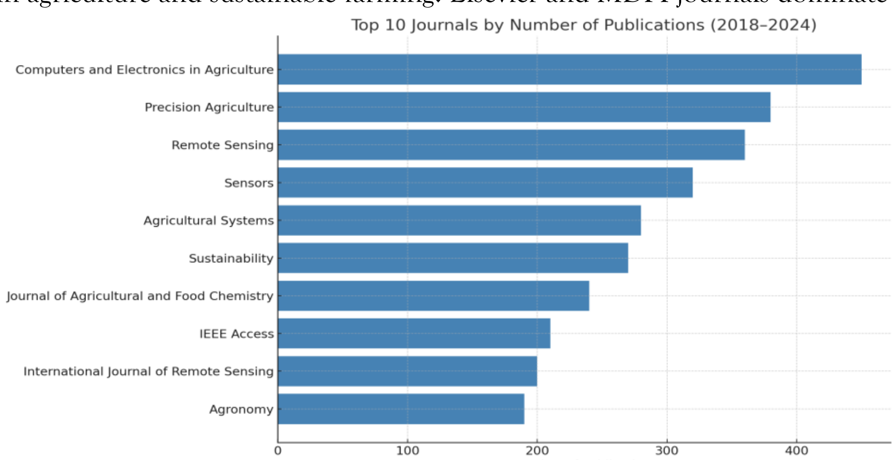

Figure 6: Top 10 Journals by Number of Publications

3.6 Top 15 Keywords by Frequency (2018–2024)

The keyword analysis reveals the most commonly occurring terms in publication titles and abstracts. 'Artificial Intelligence' and 'Agricultural Drones' are the most frequently used terms, showing clear thematic focus.

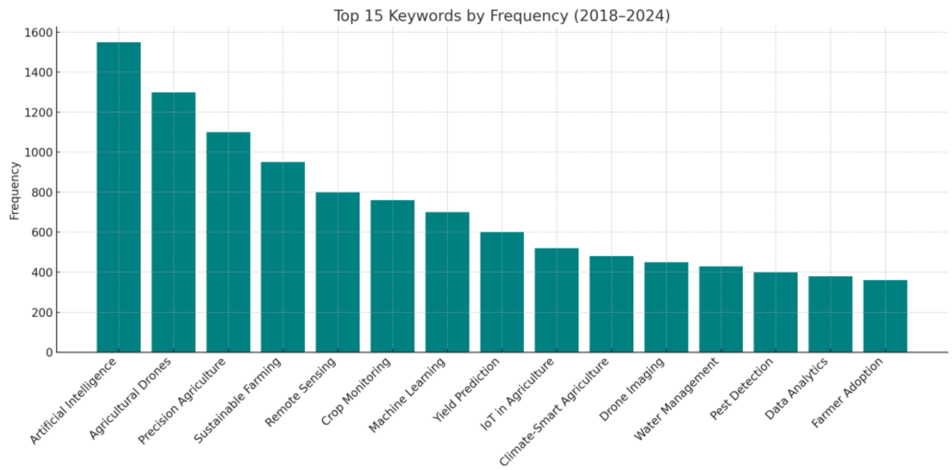

Figure 7: Top 15 Keywords by Frequency

3.7 Word Cloud

The word cloud below visually represents the most frequently used keywords in AI-driven agriculture publications. Larger words denote higher frequency, indicating dominant research areas.

Figure 8: Word Cloud

Conclusion

Researchers focused on how farmers used AI-powered agriculture drones, what they thought of them, and how well they aided in environmental projects. After analyzing the literature and bibliometric trends, it was found that research and innovation have increased a lot since 2018, mainly from China, India, Brazil, and the United States. People are paying more attention to connecting UAVs with farming and crop care and using information from data to raise productivity with less environmental impact. Theoretically, TAM and DOI were applied together in the study to learn about farmers' willingness to use drones and examine their actual drone usage. It was figured out that perceived usefulness, ease of use, relative advantage, and compatibility are meaningful factors leading to adoption, which were verified by existing studies and by establishing a structured model. While drone technology is being widely developed, very little research has examined the ways drones support the Sustainable Development Goal targets, whose areas are SDG 2 (Zero Hunger), SDG 9 (Industry, Innovation, and Infrastructure), SDG 12 (Responsible

Consumption and Production), and SDG 13 (Climate Action). The framework in this study tries to connect how people adopt green transport to the results achieved for sustainability.

4.1 Theoretical Contributions

The study gives further insight to academics by combining TAM, DOI, and environmental sustainability metrics in one framework. It adds to our current view of how technology is adopted in agriculture by looking at farm size as a possible moderating factor, along with farmers' demographics and the state of their equipment on the farm. It also deals with the fact that behavioral theory is not used enough in research related to sustainable agriculture technologies.

4.2 Practical Implications

The findings offer several practical implications for stakeholders:

- **For Policymakers:** The study underscores the importance of infrastructure development, farmer training, and subsidies to encourage technology uptake, particularly among smallholders.
- **For Agritech Companies:** A user-centric design that considers ease of use and localized compatibility can significantly boost adoption rates.
- **For Development Agencies:** Promoting digital literacy and awareness campaigns aligned with sustainability can accelerate SDG outcomes through drone usage.

4.3 Limitations

The study is primarily conceptual and bibliometric in nature. While it draws on extensive literature and models, it does not include primary empirical data collection. The variability in regional contexts, crop types, and regulatory frameworks may also affect the generalizability of the proposed conceptual framework.

4.4 Future Research Directions

For future studies, researchers may investigate the proposed framework by carrying out mixed research methods. It is possible to understand more about permanent drone use by checking longitudinal data. Also, a combination of agricultural extension, policy, sociology, and environmental science is required to notice how drones affect society and their connection to the SDG goals.

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- **Author contributions**
  MAH: Written the original draft and Metadata analysis.
  AUR: Conceptualisation, Ideation and Method. **AH:** Design the methodology and revisions. **AP:** Visualization & Mapping.
  All the authors read and approved the final manuscript.

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  This paper is the authors' original work, which has not been previously published elsewhere. The paper is not currently being considered for publication elsewhere.

- **Consent for publication**

  Not applicable

- **Competing interests**

  The authors declare that they have no competing interests.

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