International Journal on Food, Agriculture, and Natural Resources
Volume 7, Issue 2, Page 15-24
ISSN: 2722-4066
http://www.fanres.org

Original Paper

Factors Influencing the Adoption of Smart Farming Unmanned Aerial Vehicles among Emerging Farmers in Gauteng

Sikhosonke Manyela[1], Alfred Thaga Kgopa[1]*
1) School of Computing, University of South Africa, South Africa
**) Corresponding Author: 38951355@mylife.unisa.ac.za*

Received: 17 April 2026; Revised: 20 June 2026; Accepted: 28 June 2026
DOI: *https://doi.org/10.46676/ij-fanres.v7i2.650*

***Abstract*—Unmanned Aerial Vehicles (UAVs) or drones promise to improve crop growth while increasing crop yields leading to sustainable agriculture. However, the adoption of this technology among emerging farmers in the Sedibeng District, Gauteng, is inert due to innumerable factors. The main objective of the study was to examine the factors that influence the acceptance of smart farming technology (SFT) drones among emerging farmers in Sedibeng District, Gauteng. This research study employed a qualitative research method with constructs of the technology acceptance model (TAM) theory. The data analysis was conducted using thematic analysis. Data collection utilised interviews, field visits, and observations. This study found that UAV technology is a recent phenomenon in the agricultural context in Sedibeng District, Gauteng Province, and there are knowledge and practical gaps. The findings of this research study were positive as emerging farmers in Sedibeng District, Gauteng, perceived the benefits of UAVs in increasing crop yields in a predictable and profitable manner. These research results will potentially help and empower emerging farmers in Sedibeng District, Gauteng to detect crop problems early by accepting UAV technology to boost crop growth and contribute to future research on SFT adoption. This research study will add to the paucity of literature in UAVs adoption among emerging farmers in Sedibeng District, Gauteng while providing insights for policymakers, SFT vendors and mitigating risks on food security problems.**

Keywords*—*crops, drones, emerging farmers, sustainable agriculture, smart farming

I. Introduction

Emerging farmers in Gauteng recurrently experience multifarious obstacles such as crop damage from heat waves, inclement weather conditions, and flooding leading to crop losses [1], [2]. Notably, emerging farmers in Gauteng lack the appropriate technology to cope with crop losses. As a result, unpredictable crop yield methods are frequently used [3]. Gauteng which is the smallest province in South Africa by land area out of nine provinces, has the highest rising population estimated at 16 million. As a result, Gauteng faces a food inadequacy problem and about 20% or 500 000 people are food insecure [4]. Thus, the South African government identified emerging farmers to help in initiating innovative ways to mitigate against the risk of malnutrition and food insecurity [5]. This research study was conducted among emerging farmers in the Sedibeng District, Gauteng Province, South Africa maize triangle. Currently in South Africa, there are limited literature studies that show UAVs usage and adoption among emerging farmers in Gauteng [6]. The recent research suggested that this could be due to rigid government policies on UAVs and potentially relatively modern technology in agriculture [7]. Inspired by recent UAVs innovative technology in agriculture aimed at improving crop yields. This study aims to increase the visibility of the literature in this growing research domain [3]. To examine the slow uptake and underutilisation of UAVs by emerging farmers, it is imperative to investigate the factors affecting the adoption [8]. This study selected the technology acceptance model (TAM) as a theoretical construct. This study identified the existing knowledge gap among emerging farmers on the adoption of UAVs in Gauteng [9]. Moreover, this research opted for interviews in data collection. This could aid in the research foci aimed at transforming emerging farmers into commercial farmers by considering UAVs [10]. This study can provide insights into crop yields, and crop health monitoring among emerging farmers despite the limited sample size of less than 30 farmers.

Emerging farmers in Sedibeng District, Gauteng Province, often face drought and water scarcity problems [1]. This problem regularly poses threats to maize crop production that impact crop yields [11]. The lack of adequate technology implies that maize crop damage triggered by El-Nino climate phenomena, water stress, pests, and disease infestation problems negatively impact emerging farmers in Gauteng with a loss of revenue [3]. Unmanned aerial vehicles (UAVs) or drones, which are an emerging technology, have been employed in advanced countries with remarkable success. Scholarly work indicates that UAVs are useful in crop trait modelling and provide an improved method to predict crop yields [12]. Built-in UAV cameras and sensors have been used successfully to identify the presence of pests and crop diseases that lead farmers to make effective decisions through the availability of real-time data analysis [13].

Multispectral UAV images have been impactful in water stress observability, mapping, and crop health monitoring

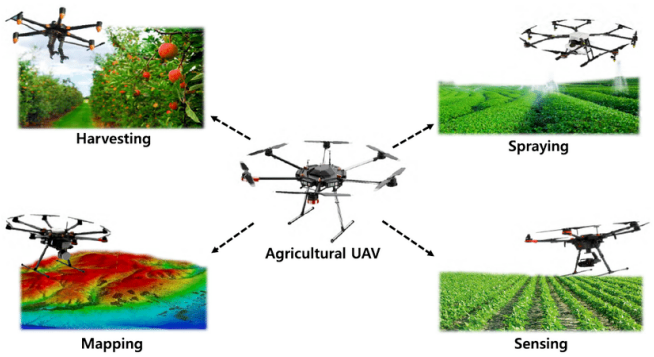


Fig. 1. Agriculture UAVs in Field Crops [20]

leading to improved crop yields with amplified profits for farmers [14]. Although climate variability is a major problem in all parts of South Africa, including Gauteng [10]. The lethargic uptake of UAVs or drone technology adoption among emerging farmers in Gauteng is an ongoing issue which threatens agricultural sustainability, and food security with low crop productivity. On the other hand, smart farming technologies (SFT) such as UAV promise to revolutionise agriculture while mitigating food security risks [15]. This study is guided by the following research objectives.

- To investigate factors influencing smart farming unmanned aerial vehicles (UAV) adoption among emerging farmers.
- To examine the perceptions of emerging farmers and their views on the utilisation of UAVs in the farming context in Gauteng province of South Africa.
- To use findings and formulate recommendations on the suitable method in utilising UAVs among the emerging farmers.

II. Literature Review

A. *Unmanned Aerial Vehicle Types and Payload*

The demand for quality food worldwide has positively impacted the drone market with forecasts of the UAV market size projected at 5.7 billion USD by 2030 [16]. Moreover, recent scholarship indicates that the agricultural drone market is dominated mainly by DJI and Skydio drone manufacturers [17]. According to [18], popular and widely used drones in agriculture constitute fixed-wing, rotary, and hybrid UAVs. The fixed-wing UAV flight system is significantly simpler with effective battery usage, longer flight time, and can fly at high speeds and altitudes, while its drawbacks being the costs.

These UAVs could be used for aerial mapping and land surveying [13]. For example, the rotary-wing UAV provides a complex flight system with varying propeller speeds to move with less weight, travel at a lower speed with in-depth crop health monitoring and analysis, and pest' infestation observability [19]. However, hybrid UAVs combine features of the rotary and fixed-wings and are impactful in crop yield estimation due to crop monitoring and mapping. However, research has established that prohibitive cost remains the major drawback [8].

TABLE I. Drone Data Crop Protection [21]

Crop Spraying/Spreading Drone	**DJI AGRAS T30**	**DJI AGRAS T40**	**DJI AGRAS T50**
Weight	52 kg	50 kg	52 kg
Max Take-off Weight Spraying	92Kg	90Kg	92Kg
Max Take-off Weight Spreading	35 KG	101 KG	103 KG
Wind Resistance	6 m/s	6 m/s	6 m/s
Propulsion System - Motors	Size :100*18 mm, KV: 77 rpm/V, Power: 3600 W/rotor	Size :100*33 mm, KV: 48 rpm/V, Power: 4000 W/rotor	Size :100*33 mm, KV: 48 rpm/V, Power: 4000 W/rotor
Propellers	Quantity: 8, Dimension: 54 inches	Quantity: 8, Dimension: 54 inches	Quantity: 8, Dimension: 54 inches
Spray Tank	Volume: 40 L, Payload: 30 kg, Material: Plastic	Volume: 40 L, Payload: 40, Material: Plastic	Volume: 40 L, Payload: 40, Ma terial: Plastic
Sprinklers	Spray width 4 – 11m at 3m height above	Spray width 4 – 11m at 2.5m height above, quantity: 2	Spray width 4 – 11m at 3m height above
Array Radar System	Obstacle sensing range 1- 50m multidirectional	Obstacle sensing range 1- 50m multidirectional	Obstacle sensing range 1- 50m multidirectional
Binocular Vision	FOV 129 degrees horizontal and vertical is 82 degrees	FOV 90 degrees horizontal and vertical is 106 degrees	FOV 90 degrees horizontal and vertical is 106 degrees
Remote Controller	Max distance: 7KM FCC, Wi-Fi: Wi-Fi Direct, 802.11/a/g/n/ac Bluetooth: 4.2, Internal battery: 2 hours	Max distance: 7KM FCC, Wi-Fi: Wifi-6, Bluetooth: 5.1, Internal battery: 3 hours	Max distance: 7KM FCC, Wi-Fi: Wifi-6 Bluetooth: 5.1, Internal battery: 3 hours
Battery	Capacity: 29000 mAh	Capacity: 30000 mAh	Capacity: 30000 mAh
Inverter battery charge time	9-12 minutes	9-12 minutes	9-12 minutes

TABLE II. Drone Sensing [21]

	DJI Mavic 3 Enterprise	**Skydio X10**	**Quantum Trinity F90**
Max Weight	1050 g	2.49 kg	5 kg
Max Ascent Speed	6 m/s	6 m/s	17 m/s
Wide Camera Sensor	Pixels 48 MP	Pixels 50.3 MP	Pixels 42.4 MP
Tele Camera Sensor	Pixels 10 MP	Pixels 48 MP	
Thermal camera temperature measurement	-20 to 150 degrees Celsius	-40 to 150 degrees Celsius	-12 degrees to 50 degrees Celsius
Sensing	Binocular vision, infrared sensors		RGB, LiDAR

The feature-rich functionalities of the DJI Agras drone range are aimed primarily at crop protection. Table 2 illustrates the evolution of these crops spraying UAVs.

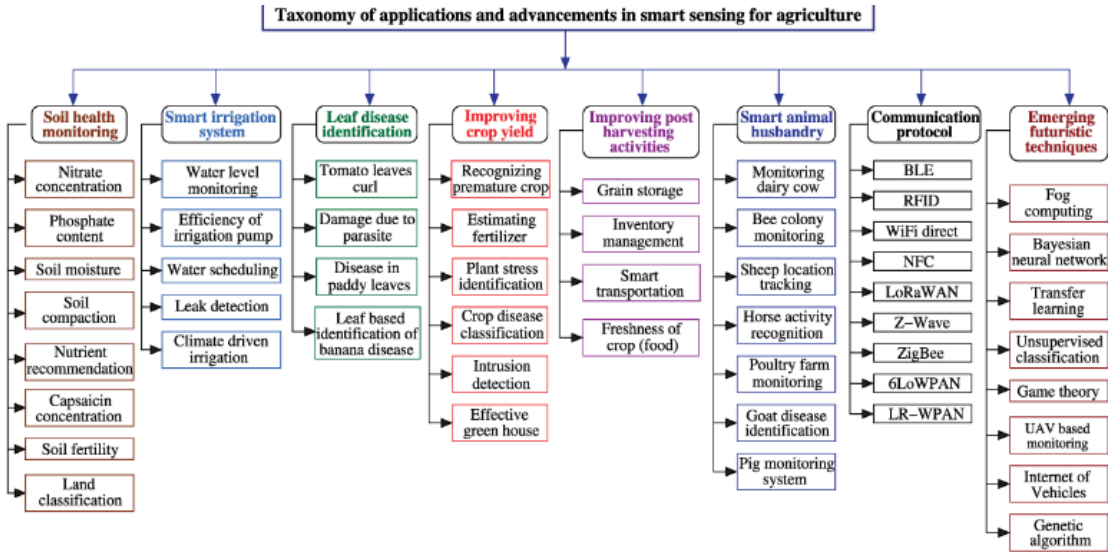


Fig. 2. Smart Sensing [24]

B. *Unmanned Aerial Vehicle Sensors in Agriculture*

Reference [13] asserted that UAV sensors are critical in remote sensing whilst providing insights into crop health up to the post-harvest stage. The study by [6] asserted that there are multiple categories of UAV sensors, including image-based RGB, multi-hyperspectral, thermal infrared and laser-enabled LIDAR. The LIDAR sensor technology UAV provides accuracy and precision, high-resolution 3D mapping, and crop canopy structure analysis [22]. Reference [23] inferred that one major drawback of the LIDAR sensor is the cost factor. Fig. 2 illustrates different use cases for smart sensing in agriculture.

Thermal imaging sensors provide heat detection in crops, whilst showing insights into potential crop diseases and water stress levels [25]. Reference [3] conducted research on crop analysis. The results indicated that the thermal imaging sensors were effective in row-by-row crop analysis. In a similar study, the results indicated that multispectral and hyperspectral UAV sensor technology provides soil mapping optimised for irrigation, crop health observability, weed detection, and harvest planning, leading to impactful yield prediction [12]. Recently [26] reported that UAV sensors were important in crop data collection, influencing effective decision-making [27].

C. *Related Work*

In Gauteng, [1] asserted that water deficit is one of the obstacles faced by emerging farmers that hinder their success. Reference [13] proposed an SFT IoT-powered smart irrigation system instead of flood-centric irrigation due to effective and lower water usage that crop losses and soil preservation. Currently, South Africa has a problem of interruptions in power supply that affect agricultural activities [28]. The solar-enabled UAV, in addition to increasing flight time, could be beneficial to emerging farmers in addressing the power disruptions that currently impact agricultural production [29]. The literature on the use of solar-enabled drones in South African agriculture is currently sparse [7]. This research could potentially contribute to the development of environmentally friendly, energy-efficient solar-powered UAVs in the agricultural sector [29].

Drone swarming enables numerous UAVs to be used concurrently [30]. Recent scholarship indicated that despite security attacks, drone swarming could be impactful in agricultural tasks due to efficiency and enhanced productivity [30]. The literature indicated that currently emerging farmers employ manual knapsack spraying techniques. As a result, this method is ineffective in the management of new weeds that cause crop loss [6]. The drone-derived data could help address the weed management gap. Consequently, this could help emerging farmers apply effective smart fertilisers through optimal UAV crop spraying and improving crop health [20]. Recent studies reported that emerging farmers lack real-time crop analysis. Recent research found that AI-enabled UAVs could enhance decision-making through data-driven agricultural practices [31].

III. Methodology

This section provides the research methodology undertaken in this study.

A. *Study Design*

The interprevists philosophy guided this research, emphasising an understanding of subjective experiences and contextual factors that influence farmers' views. An inductive approach was adopted to allow patterns and themes to emerge directly from the data [32]. The phenomenological strategy was employed to deeply explore farmers lived experiences with UAVs, focusing on their practical and perceptual implications.

The mono-method qualitative approach ensured a comprehensive, and focused exploration of the perspectives of the participants. A cross-sectional time horizon was chosen, capturing a snapshot of perceptions at a specific time [32]. Semi-structured interviews served as the primary data collection method, allowing flexibility to probe farmers' nuanced insights. Purposive sampling ensured that participants were selected based on their relevance to UAV use in farming,

ensuring rich contextual data. The data analysis employed thematic analysis, enabling the identification of recurring patterns, attitudes, and barriers related to UAV adoption [32]. This methodology facilitated a holistic understanding of farmers' views on UAVs, integrating their unique contexts and challenges, which are essential to tailor adoption strategies.

B. Study Setting

This study started with the retrieval of profiles of emerging farmers in the Sedibeng District, Gauteng Province, who were available to be interviewed by phone calls and Microsoft Teams. This was done to accurately screen farmers who might have been exposed to precision agriculture or SFT and to increase the response rate. The difficult part was setting up the interview schedule, as the number of farmers were busy because it was during the planting season November-December. Another difficult aspect was contacting farmer organisations that declined to participate in the study, and others opted not to respond to emails.

C. Data Collection, Population and Sampling

The semi-structured interviews conducted on MS Teams or WhatsApp were undertaken with consent to share study information with the farmers. A total of 20 semi-structured interviews were conducted with emerging farmers who expressed interest or willingness to participate in the study. In addition, 10 drone service providers were interviewed to provide insights on how emerging farmers can address the challenges they face when adopting UAVs in their farming practices.

The demographic profiles of the emerging farmers were determined and established based on the gender constructs and the age of the farmer. The Gauteng department of agriculture (GDARD) database indicated a total of 50 emerging farmers in Gauteng. The smaller sample size of only 20 emerging farmers in Sedibeng, Gauteng Province reflects this database. Emerging farmers in Sedibeng, Gauteng Province, were coded (EF1-EF20) for confidentiality. Sedibeng District, Gauteng Province, was chosen due to maize and livestock production. The sample included a diverse mix of males and females**,** aged 22 to 60 years**,** with varying educational levels, high school, diploma, degree, and farming experience ranging from 4 to 37 years. This systematic approach ensured detailed contextual insights into participants' backgrounds, enriching the analysis of UAV adoption perspectives across different demographic profiles. The drone service provider sample was expanded to provide rigour in the findings.

D. Data Analysis

The data analysis followed the process to organise the data, identify significant information, conceptualise code names, categorise and link codes, thematise, reporting, and interpretation. Table 3 presents data collected from 20 emerging farmers. Table 4 presents the interviews conducted with ten drone service providers specialising in agricultural technology. Surprisingly, the participants in these companies were transparent in terms of their exact age, despite being asked to only reveal age groups. The interview transcripts were uploaded to Atlas.ti version 25, and two documents were selected for analysis [33]. The findings of Atlas.ti version 25

TABLE III. GENDER CONSTRUCT CATEGORY

Emerging Farmer Code	Gender	Age	Education	Farm Experience
EF1	Female	32	Diploma/Degree	12
EF2	Female	47	Diploma/Degree	17
EF3	Male	54	High School	25
EF4	Female	58	Diploma/Degree	30
EF5	Female	55	High School	33
EF6	Male	55	Diploma/Degree	25
EF7	Male	30	Diploma/Degree	6
EF8	Male	46	Diploma/Degree	15
EF9	Male	60	High School	37
EF10	Female	26	Diploma/Degree	6
EF11	Male	27	Diploma/Degree	5
EF12	Male	29	Diploma/Degree	6
EF13	Female	47	High School	15
EF14	Male	22	Diploma/Degree	4
EF15	Male	52	Diploma/Degree	18
EF16	Male	44	Diploma/Degree	14
EF17	Male	58	Diploma/Degree	35
EF18	Male	52	Diploma/Degree	30
EF19	Male	48	Diploma/Degree	15
EF20	Male	58	Diploma/Degree	22

TABLE IV. DRONE SERVICE PROVIDER PROFILE

Drone Service Provider Code	Gender	Age	Education	Drone Experience
DSPC1	Male	26	Diploma/Degree	7
DSPC2	Male	37	Diploma/Degree	9
DSPC3	Female	42	Degree	3
DSPC4	Male	55	Diploma	5
DSPC5	Male	47	High School	2
DSPC6	Female	55	Degree	5
DSPC7	Male	60	Diploma	6
DSCP8	Female	25	Degree	7
DSPC9	Male	31	Degree	4
DSPC10	Male	37	High School	3

showed fascinating insights when performing concept analysis [33]. The analysis in Fig. 3 showed 94 concepts, 1657 phrases from Atlas.ti version 25 and the participants names, the interviewer and academics were excluded, and only concepts related to the topic were considered [33].

In Fig. 3, the drone concept carried 158 tokens, followed by the farmer with 90 tokens, indicative of the positive links and importance of the topic in contemporary agriculture. It must be noted that, Atlas.ti version 25 uses machine learning to extract relevant tokens or concepts. In Figure 3, the tokens related to crops showed positive results with 33 tokens and technology at 58, and training at 38. The results indicated that in relation to loadshedding, power and generator were tied at 11 tokens. The fertiliser and tractors each showed 12 tokens, chemicals 17, market and remote sensing were tied at 7 tokens, and these concepts were explored in confirming the legitimacy of the emerging themes in UAVs among small or medium farms in Sedibeng, Gauteng, confirming constructs in the literature [7], [27], [34].

In Fig. 3 there were 48 codes **a**uto generated from the drone service provider, two documents and using a single code group from Atlas.ti version 25 [33]. The Sankey Chart Diagram in Fig. 4. showed the code co-occurrence analysis with three

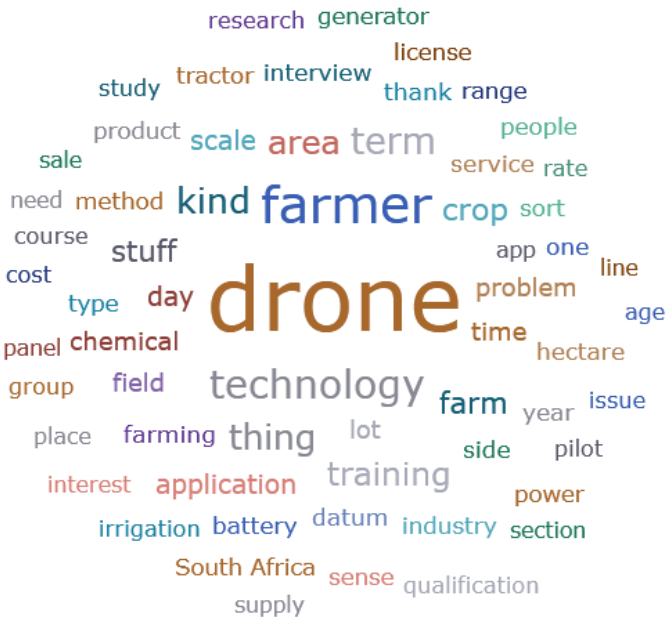


Fig. 3. Atlas.ti version 25 UAV Concepts

sentiment analysis negative, positive, and neutral from Atlas.ti software [33]. The professional services in Fig. 4. showed the relationship between academic, training, certification its links to business, innovation, technology, and agriculture supporting findings in the literature [27]

In the findings, we then explored Atlas.ti version 25 shows the ad-hoc network in Fig. 5. The findings in Fig. 5 reveal team dynamics from layout selection of hierarchical left-right and orthogonal routing, despite the absence of groundedness and density, close links with smart farming technology. Moreover, the network diagram findings in Fig. 5 indicated that adaptability, training, education, certification, business, and ties to smart farming technologies within agriculture confirm similar constructs in the literature [27]. The literature indicates that saturation in qualitative studies could be reached within 6 interviews. Therefore, this study found that by the 9th interview there were no new themes emerging from the data and content validity was established.

E. *Thematic Analysis*

This study used thematic analysis to identify, analyse and report themes emerging from datasets. The observations were made on the patterns arising from the data. The interviews of the emerging farmers and drone service providers were transcribed into two distinct documents and populated in data coding. The data coding used recurring words and phrases and assigned codes based on the research objectives and populated in the codebook. The overlapping keywords were merged for code reduction and data classification and cleaning. The Atlas.ti version 25 was used to refine codes in the Code Manager. This study used the inductive reasoning. The use of this method was to determine concepts pertinent to this research. Moreover, the data coding was used to structure data systematically and increase validity and reduce bias.

TABLE V. THEME, SUB-THEME AND THEORETICAL MODEL

Theme	Sub-theme	Theoretical Framework
Psychological, behavioural factors positively influence acceptance and adoption SFT	Attitude	TAM
	Motivation	TRA
	Subjective Norms	TPB
	Awareness	TAM
	Perceived Behaviour Control	TPB
	Behavioural Beliefs	TAM
	Perceived Risk	TAM
Barrier Factors – Rising Input Costs, UAV costs	Risk Input Cost	TAM
	Crop Spraying Dorne Cost	TAM

IV. RESULTS

The section provides the results of the study. The emerging two themes and subthemes were coded based on the research objectives presented in the Introduction section of this study. Table 5 illustrates the themes and subthemes and the associated theoretical frameworks. TAM model emerges as the key framework indicating impact in this study. Although not dominant in the overall results, TRA and TPB construct emerged in sub-themes.

A. *Attitude*

"I'm not afraid to ask if I don't know anything, I ask someone who has done it so that I can do it, and if I have done it and failed, I will go and ask again". [EF1-17]

The results subtheme showed that future-oriented emerging farmers in Sedibeng District, Gauteng expressed positive attitudes and behaviour towards unmanned aerial vehicles in the domain of crop protection and early disease detection. The findings indicated that emerging farmers expressed cheerful outlook behaviour in UAVs that showed maize traits susceptible to diseases confirming findings in recent studies. The findings suggested that emerging farmers views were based on understanding that GLS disease is prevalent in high humidity and warm temperatures and is closely related to limited maize crop yields. The findings were correlated with the previous literature that indicated emerging farmers felt that the triability of the UAVs could give them direct experience and potentially influence adoption in line with TAM construct of PEOU [35]. Affective responses could trigger an influential attitude, emerging farmers felt positive about UAVs confirming PEOU and PE in TAM actual use behaviour. In the construct of attitudinal ambivalence farmers showed more interest in UAVs than disliking the technology [35]. The results highlighted emerging farmers modalities of different attitude ranging from cognitive, behavioural, and affective could be used and likely to influence UAVs acceptance behaviour in line with [36].

B. *Motivation*

"Always be eager to learn. Talk to farmers around, old farmers. Old people have been around in this". [EF1-13]

The findings demonstrated that emerging farmers were motivated by the fact that they can be empowered to become commercial farmers confirming literature in [15]. The findings showed that emerging farmers SFT intrinsic motivation behaviour appear to be driven by

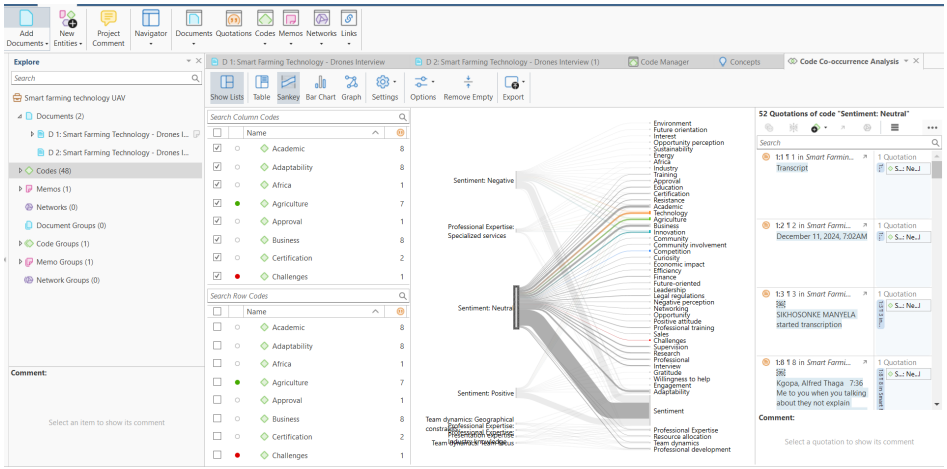


Fig. 4. Atlas.ti Sankey Diagram from Code Analysis

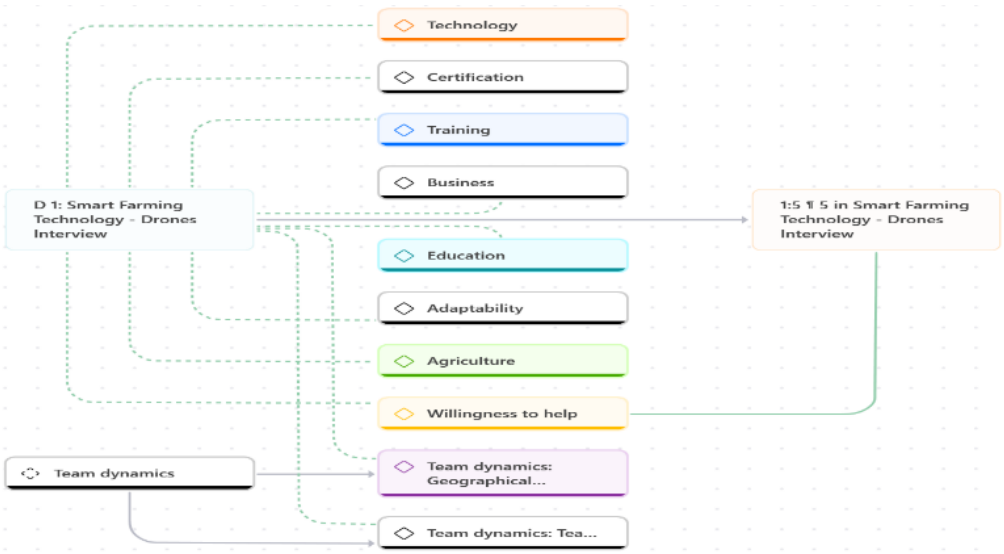


Fig. 5. Ad-Hoc Network Diagram Atlas.ti version 25

self-determination, self-realisation, self-actualisation, sense of achievement, competency traits in farming validating TPB in literature [37]. The findings indicated that emerging farmers SFT extrinsic motivation behaviour was underlined by the social rewards in agriculture practices, profit, feeding community, social building constructs [38]. In Sedibeng incentive motivation was viewed higher by emerging farmers due to possibility to positively participate in the economy with SFT at the core [3]. The findings revealed that most emerging farmers were driven by the need to belong to a structure or organisation, and precision agriculture or SFT provides and contributes to affiliation motivation. Fear motivation emerged among farm workers due to the issue of job losses.

C. *Subjective Norms*

"On the farm when you put fertilizer, you can program it to how many bags you put in this land". [EF5-20]

The results subtheme pointed out that emerging farmers who had UAV data at hand were more likely to apply appropriate fertilisers to combat pests and diseases in maize crop plants, validating TAM perceived use [3]. The findings highlighted that the ability among emerging farmers to make formidable decisions about which fertilisers were linked to descriptive norms. The results established that emerging farmers cognitive effort behaviour was interlinked maize crop savings confirming literature [26]. The results indicated that emerging farmers perceived dry weather and soil degradation as a potential threat hazard that impact agricultural output, injunctive norms confirming findings [1]. The emerging farmers perceived water or air pollution negatively contributes to crop growth imposing further risks on environment in line [1]. This study did not find correlations between group norms and subjective norms among the emerging farmers in Sedibeng.

D. *Awareness*

"*Precision farming is adopted throughout the world to increase the yield". [EF5-15]*

The findings highlighted that emerging farmers have heard about the existence of UAVs but have not taken advantage of

the technology to the maximum extent in producing quality crops [3]. Awareness about UAVs appeared to be driven by social media [39]. As a result, the Internet was the leading medium in creating awareness about UAVs. The farmer workshops, TVs, radio also contribute positively to UAVs awareness [39]. Awareness emerged as key theme to influence factors for TAM perceived ease of use (PEOU).

E. Perceived Behavioural Control

The findings showed that emerging farmers who demonstrated conviction to produce quality crops had a deep sense of readiness in line with previous research [27]. The self-capability of the emerging farmer was inextricably linked to self-efficacy, thus indicative of the behaviour to perform farming tasks in accordance with [27].

F. Behavioural Beliefs

The results showed that behaviour intention represents antecedents and positive indicator in actual use behaviour [40]. Emerging farmers perceived UAVs positive since the technology provided a certain level of predictability in agriculture practices supporting [41], [42]. Among the emerging farmers positive behaviour towards UAVs appeared to influence attitude in acceptance of UAV confirming TAM PE [26]. The results showed that farmers who had a great exposure, and awareness of UAVs were likely to consider and accept the UAV confirming TAM literature in PEOU and PE [34]. The results indicated that the correlation between behaviour and attitude was significantly greater in emerging farmers who had accessibility to UAVs supporting [35], [43]. The findings highlighted that the TRA and TPB theories combined in TAM are valid and useful in showing how attitudes predict behaviour to accept UAVs [38].

In the construct behaviour and habit, among emerging farmers accessibility of UAV was viewed higher and provided some predicate in stimulus situations particular among maize farmers supporting [43]. The findings indicated that individual farmers showed a positive belief that they perform UAVs tasks without a necessary reward mechanism in line with TAM PE. The results indicated that among emerging farmers behavioural skill was intricately linked to self-efficacy in farming with intent to produce quality crops confirming TAM perceived usefulness (PE) in literature [27], [42]. This study found that the belief that drones could provide crop health data has to a larger degree positive connection to behaviour performance in line TAM constructs [15]. This study did not find cultural beliefs impede or barrier to the intent to accept and adopt UAVs in line with [35]. In contrast, emerging farmers showed shared cultural beliefs and perceived attractiveness to UAVs confirming previous studies [35]. This study did not find a dominant culture acculturation over a minor group among emerging farmers in Sedibeng, rather the heritage culture was much more prominent.

G. Perceived Risks

"*Diversification helped me to reduce the risks of the business". [EF5-17]*

Emerging farmers viewed and perceived UAVs risks being inclined in operational aspects supporting [27]. The farmers viewed drone flight autonomy to be as risky when the optimal route has been determined upfront confirming TAM perceived usefulness [27]. The farmers perceived fierce winds as potential risks to fly UAVs [42]. The perceived UAVs risks in extreme weather conditions has not been a deterrent or a negative influential factor in drone acceptance among emerging farmers [3].

TABLE VI. FERTILISER PRICES [44]

Month to Month Change	**Jul-24**	**Aug-24**	**% Change**
Fertiliser	Rand/ton	Rand/ton	%
Ammonia	6497	6514	0,3
Urea 46	6351	6081	-4,2
DAP	10695	10902	1,2
KCL	5092	5108	0,3

"But I must say that the only issue that small scale farmers face is generally to get their finances in place even though the drone technology is far less than your traditional tractors and things like that, they do still struggle to get finances to actually adopt the technology". [DSP1-2]

The results indicated that emerging farmers views, and perceptions were unanimous in that the UAVs provides immense efficiency in farming task and enhanced crop production confirming TAM PE [34]. Farmers viewed the SFT to be significantly expensive, particularly upfront UAV costs similar findings [36].

H. Rising Input Costs

"He has a drone and then he taught us how to use the drone to spray here pesticides. I managed to cut down a lot on the diesel costs and labour costs". [EF3,5,7]

Recent studies indicated that in 2022 alone, South Africa farming fertilisers prices surged to over 100 percent, seeds by 5 percent, fuel by more than 30% and agrochemicals at 18 percent [44].

"We apply fertiliser and soil samples, reduce soil salinity recommendations that we get from the results of the soil samples". [EF2, EF3, EF5, EF6, EF9, EF11, EF14, EF16]

This issue alone may be one of the factors that contribute to destabilising the supply-demand mechanism that affects food security. The variable costs fluctuating annually among emerging farmers could have contributed negatively with low agriculture outputs [44]. In other words, emerging farmers invested far less than expected. The problems in Table 6 could be beyond the control of emerging farmer, but a competitive approach is needed to help and aid farmers in producing quality crops.

I. Crop Spraying Drone Costs

In Table 7, the figures from the service providers indicated that the latest crop protection UAV DJI Agras was estimated at R144 000 in 2024 [45]. This study concurs with [7] that the Dollar/Rand exchange rate contributed to the exorbitant UAV costs. The figure in Table 7 showed that the cost could be one of the factors contributing to the resistance to the acceptance and adoption of UAVs among emerging farmers [45]. This study viewed UAV rental services as an alternative approach to maize crop projection. For example, in advanced countries, this

TABLE VII. CROP DRONE COST PRICE FIGURES BY [45]

Crop Spraying/Spreading UAV	DJI Agras T40	DJI Agras T50	DJI Agras T50 with charger and three batteries
Price	R144 299 excl. VAT	R176 520 excl. VAT	R309 211 excl. VAT

TABLE VIII. UAV ACCESSORIES PRICING [45]

Accessory Description	Price
DJI Agras T40 Battery	R35, 912 excl. VAT
Agras T40/T50 Remote	R28, 799 excl. VAT
Agras T50 Spreading	R20, 086.00 excl. VAT
D12000iEP Generator	R47 999.13 excl. VAT
Propeller CCW	R699.00 excl. VAT

has been explored and priced competitively at $10 per hectare in line with TAM perceived usefulness to influence actual use behaviour [34].

The results in Table 8 indicated that the price proposition for UAV accessories varied from the cheapest propeller at R699 excluding VAT to the expensive generator estimated at R47 999.13 [45]. Table 8 indicated that the precision spraying drone sector in SA was growing at a rapid rate despite a significant cost in the technology.

V. DISCUSSION

The findings of this study showed that the prevalent problems emerging farmers face serious issues that constrain agriculture production [15]. This study found that the increasing input costs limit production output among emerging farmers [35], [36]. This study found that limited access to credit affects agriculture crop production [3], [15]. This study highlighted that UAVs target farm sizes from small plots, medium and large estate. This could benefit emerging farmers to provide sustainable agriculture in comparison with results in studies by [34]. This study found in line with previous studies that attitudes, subjective norms, age, farm sizes, skills, and cost constraints influence the behaviour to adopt and accept UAVs [26], [27], [34]. This study established that direct training could help farmers build confidence in accepting UAVs [27], [43]. Previous studies reported inert levels of UAVs adoption in South Africa among emerging farmers. and this has been under-investigated in Sedibeng [3], [41]. The findings indicated that UAVs awareness can be driven by agronomists as emerging farmers trust their input and views [15].

The findings suggested that peer-led learning was preferred among the emerging farmers [27], [43]. To increase SFT adoption, a consideration on social media driven information dissemination about climate variability, water shedding, and food security is needed. On the other hand, a personalised drone training for agriculture can be used to accelerate UAVs acceptance among emerging farmers [39]. This study pointed out that the availability of UAV-based data is effective in predicting maize variability. Therefore, this could be critical in assessing crop health [15]. This study in line with other previous studies viewed rapid phenotyping founded on drone data as much more accurate and beneficial in crop growth and yield estimation [43].

The findings are consistent with other studies [26], [41] that UAV sensors can be effective in the detection of crop water status. Therefore, this allowed an accurate calculation of crop water stress index (CWSI). The findings supported previous studies that precision spraying UAVs allows aerial treatments with input savings. As a result, crops were not disturbed during the droplet deposition [34], [36]. This study viewed that UAV based differentiated fertilisation leads to fertiliser savings. Therefore, this positively impact yields without harming the environment [6], [35]. The UAV technology could provide emerging farmers with opportunities in dynamic crop health monitoring with the possibility to make effective decisions. This study revealed that UAV technology is a recent phenomenon in the agricultural context in Sedibeng. Therefore, knowledge gaps and practical gaps need further in-depth investigation.

A. Expected Contribution

This research will add to the paucity of literature on the adoption of unmanned aerial vehicles among emerging farmers in the context of South Africa. This research added to the knowledge gap on improving crop yields and offered sustainable agriculture practices among emerging farmers in Sedibeng District, Gauteng employing the TAM framework. This research study contributed to the key factors that influence emerging farmers in adopting and accepting UAVs. The conclusion and results of this research provided novel methods for legislators, farmers, and UAV service providers with information to accelerate the adoption of SFT among emerging farmers.

B. Future Research

Future research should examine solar-enabled drones due to the remoteness of emerging farmers and disruptions in power supply that contribute negatively to agriculture. Future research should also consider the UAVs manufacturing sector in Gauteng with favourable price propositions for Sub-Saharan countries facing rampant poverty and food insecurity. Future research should examine the behavioural and psychological factors that impact the adoption of robotics and UAVs among emerging farmers and delineate on the benefits and barriers [43]. Future research should consider UAV-derived soil elemental analysis as emerging farmers lack insights into soil erosion or land degradation. In future research investigations in AI-enabled UAVs [46], crop health observability [22], [43], crop trait modelling [19], [47], weed and disease detection [6], and drought forecasting techniques will be helpful to adequately prepare emerging farmers. Future research should induce drone data to inform effective water management among emerging farms through smart irrigation [22], [48]. The sampling of only 20 emerging farmers limits the mathematical study generalisation. Therefore, a quantitative study should supplement this research.

C. Recommendations

This study recommends that awareness and knowledge constructs about smart farming technologies should be undertaken inside the farmer networks to reshape attitudes, perceptions, and behaviours towards the innovative agriculture climate-smart technologies [39]. These workshops should be targeted at direct training, demonstrations, and peer learning

to heighten self-efficacy in UAVs usage in accordance with previous research [36], [43]. The information dissemination about UAVs should be aimed at knowledge sharing with social media WhatsApp, YouTube, Facebook, and TikTok at the center of awareness campaigns [39].

The emerging farmers trust and value input from agronomists and learning that was driven by the agricultural advisors in a conducive environment. As a result, this could help accelerate the UAVs adoption [27], [43]. The study recommends the establishment of a youth farmer organisation and women-affiliated institutions aimed at precision agriculture and UAVs. The emerging farmers and to a greater degree small-scale farmers might have been inadvertently left out of SFT participation due to a lack of capital [26]. In addition, broad knowledge and skills on the SFT among emerging farmers in Sedibeng District were found to be lacking. This study recommends public and private partnerships, particularly in financial instruments, green taxonomy, collaboration with banks enabling emerging farmers financial inclusion and enhance participation in the agriculture value chain [15]. Previous studies [34], [36] indicated that strong partnerships between academia, scholars, universities, industry, and government facilitate effective adoption in technology. We recommend that this should be encouraged particularly in the constructs of food security and sustainable agriculture [49]. This study recommends that the quantitative method should be explored to supplement this research to arrive at conclusive findings and results.

VI. CONCLUSION

This study investigated the factors influencing UAV acceptance and adoption among emerging farmers in Sedibeng, Gauteng. The findings indicated that the UAVs usage in maize crop among emerging farmers Sedibeng District was limited [3], [41]. A concerted campaign effort and awareness driven by government, academia, and industry is needed to increase the UAVs adoption among small to medium farms in Sedibeng District to improve agricultural outputs predictably. In reducing the gender gap, this study suggests that women's empowerment in climate-smart agriculture acceptance in Sedibeng will be much more effective if it is state-driven and female-led. The findings indicated that UAVs could help emerging farmers reduce crop losses and effectively predict yields.

The findings highlighted that emerging farmers were willing to use UAVs despite current challenges [3]. The theoretical and practical insights in this study complement the existing literature on UAVs as a critical technology in addressing challenges in food and nutritional security risks. This study understands that acceptance is a complex, and dynamic process, fluctuates over time, and individual views could change depending on contextual factors. The readiness of the emerging farmer in Sedibeng District to consider UAV was positive. However, in this study, we could not determine whether the lack of SFT contributes to the high stress levels of the emerging farmers in Sedibeng emerging farmers or poor mental health state.

This study viewed autonomous drone surveillance as impactful in the path of law enforcement and in reducing livestock theft. This study concurs with previous studies that asserted that agricultural UAVs usage in Sub-Saharan Africa is long overdue [3], [6], [26], [41]. In conclusion, this study viewed and observed that the government-driven SFT policies, strategies, and adoption are at their weakest at present and the implications of ending poverty and zero hunger by 2030 may not be met [49].

References

[1] S. Ruwanza, G. Thondhlana, and M. Falayi, "Research Progress and Conceptual Insights on Drought Impacts and Responses among Smallholder Farmers in South Africa: A Review," *Land (Basel).*, vol. 11, no. 2, p. 159, Jan. 2022, doi: 10.3390/land11020159.

[2] H. Chikoore and M. R. Jury, "South African drought, deconstructed," *Weather Clim. Extrem.*, vol. 33, p. 100334, Sep. 2021, doi: 10.1016/j.wace.2021.100334.

[3] M. Sibanda *et al.*, "EXPLORING THE PROSPECTS OF UAV-REMOTELY SENSED DATA IN ESTIMATING PRODUCTIVITY OF MAIZE CROPS IN TYPICAL SMALLHOLDER FARMS OF SOUTHERN AFRICA," *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, vol. X-1/W1-2023, pp. 1143–1150, Dec. 2023, doi: 10.5194/isprs-annals-X-1-W1-2023-1143-2023.

[4] S. N. Dlamini *et al.*, "Food insecurity and coping strategies and their association with anxiety and depression: a nationally representative South African survey," *Public Health Nutr.*, vol. 26, no. 4, pp. 705–715, Apr. 2023, doi: 10.1017/S1368980023000186.

[5] L. Baiyegunhi and M. Chasomeris, "Examining the Determinants of Agricultural Innovation Activities: A Case Study of Emerging Sugarcane Farmers in South Africa," *SSRN Electronic Journal*, 2022, doi: 10.2139/ssrn.4109336.

[6] C. de Villiers, C. Munghemezulu, Z. Mashaba-Munghemezulu, G. J. Chirima, and S. G. Tesfamichael, "Weed Detection in Rainfed Maize Crops Using UAV and PlanetScope Imagery," *Sustainability*, vol. 15, no. 18, p. 13416, Sep. 2023, doi: 10.3390/su151813416.

[7] Q. Mokoena, I. Daniyan, K. Mpofu, and O. Abisuga, "TOWARDS STRATEGIC MANAGEMENT OF DRONE APPLICATION PROCESS AND REGULATION IN SOUTH AFRICA," *South African Journal of Industrial Engineering*, vol. 33, no. 4, 2022, doi: 10.7166/33-4-2691.

[8] K. Dixit, K. Aashish, and A. Kumar Dwivedi, "Antecedents of smart farming adoption to mitigate the digital divide – extended innovation diffusion model," *Technol. Soc.*, vol. 75, p. 102348, Nov. 2023, doi: 10.1016/j.techsoc.2023.102348.

[9] S. P. Singh, A. Sharma, and A. Adhikari, "Investigating the barriers to drone implementation in sustainable agriculture: A hybrid fuzzy-DEMATEL-MMDE-ISM-based approach," *J. Environ. Manage.*, vol. 371, p. 123299, Dec. 2024, doi: 10.1016/j.jenvman.2024.123299.

[10] K. T. Thinda, A. A. Ogundeji, J. A. Belle, and T. O. Ojo, "Understanding the adoption of climate change adaptation strategies among smallholder farmers: Evidence from land reform beneficiaries in South Africa," *Land use policy*, vol. 99, p. 104858, Dec. 2020, doi: 10.1016/j.landusepol.2020.104858.

[11] V. Mathinya, A. Franke, G. Van De Ven, and K. Giller, "Productivity and constraints of small-scale crop farming in the summer rainfall region of South Africa," *Outlook Agric.*, vol. 51, no. 2, pp. 139–154, Jun. 2022, doi: 10.1177/00307270221091839.

[12] N. Islam, M. M. Rashid, F. Pasandideh, B. Ray, S. Moore, and R. Kadel, "A Review of Applications and Communication Technologies for Internet of Things (IoT) and Unmanned Aerial Vehicle (UAV) Based Sustainable Smart Farming," *Sustainability*, vol. 13, no. 4, p. 1821, Feb. 2021, doi: 10.3390/su13041821.

[13] A. D. Boursianis *et al.*, "Internet of Things (IoT) and Agricultural Unmanned Aerial Vehicles (UAVs) in smart farming: A comprehensive review," *Internet of Things*, vol. 18, p. 100187, May 2022, doi: 10.1016/j.iot.2020.100187.

[14] M. McCaig, R. Dara, and D. Rezania, "Farmer-centric design thinking principles for smart farming technologies," *Internet of Things*, vol. 23, p. 100898, Oct. 2023, doi: 10.1016/j.iot.2023.100898.

[15] C. Giua, V. C. Materia, and L. Camanzi, "Smart farming technologies adoption: Which factors play a role in the digital transition?," *Technol. Soc.*, vol. 68, p. 101869, Feb. 2022, doi: 10.1016/j.techsoc.2022.101869.

[16] M. Javaid, A. Haleem, R. P. Singh, and R. Suman, "Enhancing smart farming through the applications of Agriculture 4.0 technologies," *International Journal of Intelligent Networks*, vol. 3, pp. 150–164, 2022, doi: 10.1016/j.ijin.2022.09.004.

[17] A. Milella *et al.*, "Robot-as-a-Service as a New Paradigm in Precision Farming," *IEEE Access*, vol. 12, pp. 47942–47949, 2024, doi: 10.1109/ACCESS.2024.3381511.

[18] A. T. Balafoutis, F. K. Van Evert, and S. Fountas, "Smart Farming Technology Trends: Economic and Environmental Effects, Labor Impact, and Adoption Readiness," *Agronomy*, vol. 10, no. 5, p. 743, May 2020, doi: 10.3390/agronomy10050743.

[19] M. Kernecker, A. Knierim, A. Wurbs, T. Kraus, and F. Borges, "Experience versus expectation: farmers' perceptions of smart farming technologies for cropping systems across Europe," *Precis. Agric.*, vol. 21, no. 1, pp. 34–50, Feb. 2020, doi: 10.1007/s11119-019-09651-z.

[20] J. Kim, S. Kim, C. Ju, and H. Il Son, "Unmanned Aerial Vehicles in Agriculture: A Review of Perspective of Platform, Control, and Applications," *IEEE Access*, vol. 7, pp. 105100–105115, 2019, doi: 10.1109/ACCESS.2019.2932119.

[21] S. K. Phang, T. H. A. Chiang, A. Happonen, and M. M. L. Chang, "From Satellite to UAV-Based Remote Sensing: A Review on Precision Agriculture," *IEEE Access*, vol. 11, pp. 127057–127076, 2023, doi: 10.1109/ACCESS.2023.3330886.

[22] A. Jabbari, A. Humayed, F. A. Reegu, M. Uddin, Y. Gulzar, and M. Majid, "Smart Farming Revolution: Farmer's Perception and Adoption of Smart IoT Technologies for Crop Health Monitoring and Yield Prediction in Jizan, Saudi Arabia," *Sustainability*, vol. 15, no. 19, p. 14541, Oct. 2023, doi: 10.3390/su151914541.

[23] S. M. Farhan, J. Yin, Z. Chen, and M. S. Memon, "A Comprehensive Review of LiDAR Applications in Crop Management for Precision Agriculture," *Sensors*, vol. 24, no. 16, p. 5409, Aug. 2024, doi: 10.3390/s24165409.

[24] R. Kumar, R. Mishra, H. P. Gupta, and T. Dutta, "Smart Sensing for Agriculture: Applications, Advancements, and Challenges," *IEEE Consumer Electronics Magazine*, vol. 10, no. 4, pp. 51–56, Jul. 2021, doi: 10.1109/MCE.2021.3049623.

[25] Y. Inoue, "Satellite- and drone-based remote sensing of crops and soils for smart farming – a review," *Soil Sci. Plant Nutr.*, vol. 66, no. 6, pp. 798–810, Nov. 2020, doi: 10.1080/00380768.2020.1738899.

[26] C. McCarthy *et al.*, "Can Drones Help Smallholder Farmers Improve Agriculture Efficiencies and Reduce Food Insecurity in Sub-Saharan Africa? Local Perceptions from Malawi," *Agriculture*, vol. 13, no. 5, p. 1075, May 2023, doi: 10.3390/agriculture13051075.

[27] A. Shazwan Azizul, D. El Pebrian, S. Mustaffha, S. Mariam Shamsi, Mohd. Khairy Zahari, and N. Aziera Ruslan, "The use of drone for rice cultivation in Malaysia: Identification of factors influencing its farmers' acceptance," *Journal of the Saudi Society of Agricultural Sciences*, vol. 22, no. 7, pp. 461–468, Oct. 2023, doi: 10.1016/j.jssas.2023.04.005.

[28] K. O. Akpeji, A. O. Olasoji, C. Gaunt, D. T. O. Oyedokun, K. O. Awodele, and K. A. Folly, "Economic impact of electricity supply interruptions in South Africa," *SAIEE Africa Research Journal*, vol. 111, no. 2, pp. 73–87, Jun. 2020, doi: 10.23919/SAIEE.2020.9099495.

[29] Y. N. Saravanakumar *et al.*, "Power Sources for Unmanned Aerial Vehicles: A State-of-the Art," *Applied Sciences*, vol. 13, no. 21, p. 11932, Oct. 2023, doi: 10.3390/app132111932.

[30] R. Ming, R. Jiang, H. Luo, T. Lai, E. Guo, and Z. Zhou, "Comparative Analysis of Different UAV Swarm Control Methods on Unmanned Farms," *Agronomy*, vol. 13, no. 10, p. 2499, Sep. 2023, doi: 10.3390/agronomy13102499.

[31] Y. Huang, R. Srivastava, C. Ngo, J. Gao, J. Wu, and S. Chiao, "Data-Driven Soil Analysis and Evaluation for Smart Farming Using Machine Learning Approaches," *Agriculture*, vol. 13, no. 9, p. 1777, Sep. 2023, doi: 10.3390/agriculture13091777.

[32] M. N. K. Saunders, P. Lewis, and A. Thornhill, *Research Methods for Business Students*, 9th ed. Pearson, 2023.

[33] B. Smit, "Introduction to ATLAS. ti for Mixed Analysis," in *The Routledge Reviewer's Guide to Mixed Methods Analysis*, Routledge, 2021, pp. 331–342.

[34] M. Michels, C.-F. von Hobe, P. J. Weller von Ahlefeld, and O. Musshoff, "The adoption of drones in German agriculture: a structural equation model," *Precis. Agric.*, vol. 22, no. 6, pp. 1728–1748, Dec. 2021, doi: 10.1007/s11119-021-09809-8.

[35] H. Puppala, P. R. T. Peddinti, J. P. Tamvada, J. Ahuja, and B. Kim, "Barriers to the adoption of new technologies in rural areas: The case of unmanned aerial vehicles for precision agriculture in India," *Technol. Soc.*, vol. 74, p. 102335, Aug. 2023, doi: 10.1016/j.techsoc.2023.102335.

[36] D. Pivoto *et al.*, "Factors influencing the adoption of smart farming by Brazilian grain farmers," *International Food and Agribusiness Management Review*, vol. 22, no. 4, pp. 571–588, Jun. 2019, doi: 10.22434/IFAMR2018.0086.

[37] M. Savari, H. E. Damaneh, H. E. Damaneh, and M. Cotton, "Integrating the norm activation model and theory of planned behaviour to investigate farmer pro-environmental behavioural intention," *Sci. Rep.*, vol. 13, no. 1, p. 5584, Apr. 2023, doi: 10.1038/s41598-023-32831-x.

[38] I. Ajzen, "The theory of planned behavior," *Organ. Behav. Hum. Decis. Process.*, vol. 50, no. 2, pp. 179–211, 1991.

[39] G. Dilleen, E. Claffey, A. Foley, and K. Doolin, "Investigating knowledge dissemination and social media use in the farming network to build trust in smart farming technology adoption," *Journal of Business & Industrial Marketing*, vol. 38, no. 8, pp. 1754–1765, Jun. 2023, doi: 10.1108/JBIM-01-2022-0060.

[40] F. Toscano *et al.*, "Unmanned Aerial Vehicle for Precision Agriculture: A Review," *IEEE Access*, vol. 12, pp. 69188–69205, 2024, doi: 10.1109/ACCESS.2024.3401018.

[41] S. Gokool *et al.*, "Crop Monitoring in Smallholder Farms Using Unmanned Aerial Vehicles to Facilitate Precision Agriculture Practices: A Scoping Review and Bibliometric Analysis," *Sustainability*, vol. 15, no. 4, p. 3557, Feb. 2023, doi: 10.3390/su15043557.

[42] J. Das V., S. Sharma, and A. Kaushik, "Views of Irish Farmers on Smart Farming Technologies: An Observational Study," *AgriEngineering*, vol. 1, no. 2, pp. 164–187, Apr. 2019, doi: 10.3390/agriengineering1020013.

[43] P. Gerli, J. Clement, G. Esposito, L. Mora, and N. Crutzen, "The hidden power of emotions: How psychological factors influence skill development in smart technology adoption," *Technol. Forecast. Soc. Change*, vol. 180, p. 121721, Jul. 2022, doi: 10.1016/j.techfore.2022.121721.

[44] G. GRAINSA, "Maize Production Report - Grain SA," https://www.grainsa.co.za/upload/report_files/NOK-Wit-geelmielies-white-and-yellow-maize-per-provinsie.xlsx.

[45] S. Skyfarmers, "Agriculture Drone Product Pricing," https://www.skyfarmers.co.za/pages/products.

[46] J. Agrawal and M. Y. Arafat, "Transforming Farming: A Review of AI-Powered UAV Technologies in Precision Agriculture," *Drones*, vol. 8, no. 11, p. 664, Nov. 2024, doi: 10.3390/drones8110664.

[47] A. Rejeb, A. Abdollahi, K. Rejeb, and H. Treiblmaier, "Drones in agriculture: A review and bibliometric analysis," *Comput. Electron. Agric.*, vol. 198, p. 107017, Jul. 2022, doi: 10.1016/j.compag.2022.107017.

[48] M. Bahari, I. Arpaci, O. Der, F. Akkoyun, and A. Ercetin, "Driving Agricultural Transformation: Unraveling Key Factors Shaping IoT Adoption in Smart Farming with Empirical Insights," *Sustainability*, vol. 16, no. 5, p. 2129, Mar. 2024, doi: 10.3390/su16052129.

[49] I. U. W. and W. FAO, *The State of Food Security and Nutrition in the World 2024*. FAO; IFAD; UNICEF; WFP; WHO;, 2024. doi: 10.4060/cd1254en.