Evaluating the intention to use Industry 5.0 (I5.0) drones for cleaner production in sustainable food supply chains: an emerging economy context

Abstract

Purpose – The purpose of this study is to evaluate food supply chain stakeholders' intention to use Industry 5.0 (I5.0) drones for cleaner production in food supply chains.

Design/methodology/approach – We used a quantitative research design and collected data using an online survey administered to a sample of 264 food supply chain stakeholders in Nigeria. The partial least square structural equation model (PLS-SEM) was conducted to assess the research's hypothesised relationships.

Findings – We provide empirical evidence to support the contributions of I5.0 drones for cleaner production. Our findings showed that food supply chain stakeholders are more concerned with the use of I5.0 drones in specific operations such as reducing plant diseases which invariably enhances cleaner production. However, there is less inclination to drones adoption if the aim was pollution reduction, predicting seasonal output and addressing workers health and safety challenges. Our findings outline the need for awareness to promote the use of drones for addressing workers hazard challenges and knowledge transfer on the potentials of I5.0 in emerging economies.

Originality – This is the first study to address I5.0 drones' adoption using a sustainability model. We contribute to existing literature by extending the sustainability model to identify the contributions of drones use in promoting cleaner production through addressing specific system operations. This study addresses the gap by augmenting a sustainability model, suggesting that technology adoption for sustainability is motivated by curbing challenges categorised as drivers and mediators.

Keywords: Industry 5.0 drones, agricultural operations, emerging economy, Nigeria, sustainability

Paper Type Research Paper

1.0 Introduction

The contributions of agriculture to economic growth in emerging economies are well documented. For instance, a report by the World Bank (2022) showed that in 2018, agriculture's contribution to the gross domestic product (GDP) in emerging economies was over 25%. The notion is that the accurate development and dissemination of agricultural products would reduce poverty, raise incomes, and facilitate economic growth (Zeng et al., 2015). However, the global population explosion, agriculture security and safety (Ge et al., 2016; UN 2022), and environmental concerns have threatened agriculture operations (Adams et al., 2021). Moreover, the recent pandemic further highlighted the vulnerabilities of the agricultural sector, evident through disruptions in what are predominantly human-oriented production processes (Choudhury et al., 2020). Also, transportation issues and labour shortages, which meant overreliance on inexperienced workers', often under informal or casual arrangements has affected food production (Ahmed et al., 2021).

Emerging digital technologies have transformed the way in which organiations operate and manage their supply chains (Frederico et al. 2019), thus it is unsurprising that research on technology use is considered pertinent within the agricultural domain (Liu et al., 2020). Hence there are renewed calls on innovative solutions in tackling challenges faced in the agricultural sector, including the use of technology for cleaner production. It is particularly relevant since emerging technologies have the potential to respond to disasters and societal challenges effectively and efficiently (Dennehy et al. 2021). Industry 4.0 (I4.0) and more notably the advent of Industry 5.0 (I5.0) applications, including smart farming, blockchain, cloud computing, drones, precision agriculture, connected applications and real-time virtualisation, have been suggested to increase production efficiencies by tackling food supply operation challenges (Saiz-Rubio and Rovira-Más 2020; Panetto et al. 2020).

Despite the pivotal role the food sector plays on the global scale, and the apparent benefits I5.0 related techniques can have, the uptake has been predominantly slower across food supply chains when compared with other manufacturing industries (Duong et al. 2020). In order to achieve this, focus must shift from the technology and process to people. Preuss and Fearne (2022) highlight the importance of studying supply chain stakeholders, given their role within supply chain in achieving sustainability goals. Hence, there is a need to understand human related factors, which impede the uptake of such technologies within food supply chains.

While Michels et al. (2020) examined the adoption of drones by farmers, their study is based in Germany, which is a developed economy. Other studies have focused on understanding the adoption of technology in agricultural supply chains, such as their attitudes towards electronic identification (Lima et al. 2018), agricultural technology extension modes (Gao et al. 2020) and photovoltaic agriculture (Li et al., 2021). Yet, a criticism of I4.0 literature is that it has largely focused on technical perspectives, largely overlooked human factors (Grabowska et al. 2022) and focused more on profit-maximisation (Oláh et al, 2020), at the expense of sustainability. It can be argued that I5.0 are ideal lenses to explore the interplay between innovation, sustainability and food supply chains, as it shifts the focus solely on technology, as is the case for I4.0 (Erboz et al. 2022), towards a more encompassing approach, in which it attempts to consolidate resilience, sustainability, and human-centricity with advanced technologies (Ivanov 2023). Moreover, Maddikunta et al. (2022) highlight the potential of I5.0 in overcoming challenges posed by the pandemic, such as optimising supply chains. Thus, there is a need for more studies exploring the potential of I5.0, drones in food supply chains across emerging economies, such as Nigeria, given majority of the world's top ten countries that grow food are emerging economies (World Bank, 2022).

For example, Rejeb et. al (2023) concludes that drones contribute significantly positively to the logistical issues by reducing delivery time and cost, as well as increasing flexibility and sustainability. The research also highlight a salient feature of the drone in resulting into a net-positive environment by a reduced carbon emission, compared to the utilisation of fossil-fuel machineries in agricultural activities, resulting into environmental sustainability. The investigation also suggests that looking through the lens of social sustainability, the adoption of drone technology has the potential to decrease the vulnerability and intricacy of various tasks. For instance, by employing drones, critical safety issues tied to hazardous agricultural-field terrain inspections, such as steep-sloped and tall structure in vertical farming activity, and pesticide application, can be effectively mitigated. These views are shared by Damoah et al (2021) who investigated the potential benefits of the use of AI-drones against the backdrop of healthcare supply chain (HSC), in Ghana. The investigation unveils that the AI-drones use impacted positively on the climate sustainability. This has been made possible through a reduced carbon emission a s the result of deployment of carbon and noise-free drones in the delivery of emergency medical products to healthcare centres. Further to that, the adoption of medical drones in the healthcare system improves societal and economic conditions by lowering mortality rates contributed by timely delivery of supply better coordination of healthcare supplies, and potentially leading to enhanced social and economic well-being for the population. Additionally, the implementation of medical drones contributes to the long-term corporate sustainability of the organization involved in the initiative.

A host of studies carried out in the realm of healthcare sustainability agree that the use of AI-drone in HSC, or medical drone brought numerous social and environmental benefits, leading to sustainability. Regardless, its use in rural HSC is still at infancy, mainly due to lack of government regulations, which then leading to the lack of commitment in the drone adoption (Koshta et al, 2022). As such, the research suggest a future work to understand and assess the challenges to drone technology adoption, particularly in the context where small AI drones are used to perform tasks such as spraying, temperature sensing and transporting small deliveries.

In recent times, overcoming the adverse impact of excessive, unrestricted pesticide use has received growing attention, particularly within an emerging economy context (Owusu and Abdulai 2019). Agritech companies are increasingly growing, creating reliable data-based systems that connect farmers across the country. However, more needs to be done because the minimal adoption of farming technology, ineffective agricultural-service delivery culture, and low incentives for start-ups derails progressive, competitive farming and agribusiness. Agriculture in emerging economies, such as Nigeria, is highly affected by low skills, and it is supported largely by humans rather than machinery. Agricultural processing is deprived of value-adding content, which leads to excessive post-harvest losses annually (Ekiyor et al., 2019). Other constraints include a poor infrastructural base, inadequate stakeholders' long-term financing structure, and a poor market base (Adebiyi et al., 2020).

Focusing on emerging economies is important as there is a dearth of research and development in agriculture supply chains, especially across African nations (Swinnen and Kuijpers, 2019). Such emerging economies also face other challenges, such as lacking infrastructure; higher social inequalities and informality; as well as greater degree of corruption (Pereira et al. 2021). Given these challenges, including that of poverty and food security faced by these economies, it is pertinent to understand how technological infrastructure can facilitate the growth of agriculture in emerging economies (Fuglie et al., 2019). Similarly, the literature examining the contributions of innovative solutions in enhancing food supply chains in emerging economies is evasive (Mohamed et al., 2021), where existing studies have primarily focused on technological factors (Moshref-Javadi et al., 2020).

This study engages in the debate for the potential of drones in agricultural supply chains including its capacity for cleaner production (Mubarik et al., 2021; Mahroof et al., 2021). For instance, the use of drones has been suggested as a realistic solution to global food challenges and shortages (Spanaki et al., 2021). Similarly, Strandhagen et al., (2020) showed that I4.0 sustainability in supply chains through optimised automation, enhanced collaboration, efficient knowledge sharing and enhanced working conditions. Yet, more research is needed to understand the potential of I5.0 drones with agricultural supply chain contexts. In support of this, Panagou et al. (2023), outlines the need for more empirical research which places focus on human-centricity with I5.0 research. Accordingly, this research focuses on the following research questions:

RQ1. What factors influence food supply chain stakeholders to adopt I5.0 drones for cleaner production?

RQ2. Does the application of I5.0 drone solve food supply chain challenges?

We approached our research objective by adopting a parsimonious sustainability model developed by Mahroof et al., (2021) which measured specific activities in agricultural operations whilst incorporating sustainability. The model was considered appropriate as it captured precise aspects of agricultural production that could influence stakeholders' uptake of I5.0 drones which have not been considered in other models (Featherman et al., 2021). As such, we combined existing literature to measure a broad selection of variables including pesticide hazards, prediction accuracy, plant disease eradication, workers hazard and planting accuracy. Our research therefore aims to understand the determinants of drone use among stakeholders in a food supply chain from an emerging economy context.

This article is structured as follows. Following details relating to the context of this research, section two presents a literature review, which expands on research and development in agriculture supply chain, followed by hypotheses development and the adopted conceptual model. Section three presents the methodology used, followed by the result and analysis in section four. The discussion of results and conclusion are presented in sections five and six, highlighting the research limitations and future research agenda.

1.1 Emerging economy context: Nigeria

Agricultural technologies can lead to financial freedom for emerging economies (Odularu, 2020), thus raising awareness regarding technological advancements within food production is necessary for contexts such as Nigeria, where farmers are heavily reliant on traditional methods. Within such contexts, food production is contingent on seasonal rains; sparsely available irrigations systems, and limited pest control mechanisms (Muzari et al., 2012). With it rising Nigerian populace, expected to reach 400 million by 2050 (FAO, 2021) and its aspiring export portfolio, it is pertinent to explore the benefits of enhanced technologies such as I5.0 to ensure its agricultural sector can remain both competitive and sustainable.

Thus, the Nigeria context for this research is relevant as it may signposts lessons to other emerging economy contexts. More importantly, the agriculture sector plays a highly significant role in Nigeria's economic development and progression, serving as the primary source of livelihood for up to 30% of 250 million Nigerians (FAO, 2022). It also accounts for 22.35% of its GDP (FAO, 2022). Notwithstanding the contribution of agriculture to Nigeria's economy, the sector is saddled with several challenges. These include climate change, low technology utilisation, harvest losses, and poor market access, affecting farming operations and productivity (Ayittey, 2016).

Nigeria's agricultural practice is diversely represented through its multi-indigenous and multi-cultural setup. It functions with every clan having specific methods, which present an exciting platform to explore (Ayittey, 2016). Despite the enormous prospects that exceed farming to include animal husbandry and fishing, there is a struggle for the Nigerian government to provide the required infrastructure. This is significant, as environmental factors, such as government policies and investment are shown to play a key role in the adoption of technology (Ali et al. 2022). The sector suffers losses in earnings attributed mainly to ineffective leadership resulting in poor technological adoption (Agbachom et al., 2019; Osabohien et al., 2019). Meaning the diffusion of technology in farming is at its lowest (Baiyegunhi et al., 2019). The proposed research will offer further insights into factors which impede and support adoption of technology within Nigeria's supply chain stakeholders.

2.0 Literature Review: Research and development in agriculture supply chain

2.1 Technology adoption in agriculture supply chain

There remains limited research exploring agricultural stakeholders' intentions towards adopting I5.0 drones, particularly from an emerging context. Extant literature suggests institutional, economic and technological factors (Takahashi et al., 2020). However, technological adoption within agricultural settings, constitutes complex interactions of interconnected factors, including workers' health and safety, pesticide hazards reduction, pollution reduction, and seeding accuracy, which are often overlooked (Mahroof et al., 2021; Adebiyi and Olabisi, 2022). Hence, utilising a conceptual model that precisely captures key agricultural challenges is essential for this research, as overcoming these challenges may determine and influence stakeholders' uptake of I5.0 drones. Moreover, previous research (Alamgir Hossain and Quaddus 2011) found that farmers adoption of RFID technology was influenced by the industry readiness of the technology, thus indicating that the adoption of technology in agriculture is also contingent on its wider adoption across the sector.

Introducing technology to agricultural practices presents numerous opportunities for change, innovations and economic development. However, stakeholders' intention to these technologies are encumbered by several factors. Traditionally, the adoption of technology within agriculture is associated with personal endowments, uncertainty, availability of inputs and infrastructures (Uaiene, 2009). More recently, an aspect of literature has focused on learning & social network as factors that determine technology adoption. Other research classed these elements into distinctive categories. For instance, Akudugu et al. (2012) organised the determining aspects of agricultural technology adoption into three (3) social, institutional, & economic elements.

Features of the technology are crucial requirements, influencing stakeholders' perception of adopted technology. For instance, in a study exploring the determinants to consider adopting Climate-Smart Agriculture (CSA), it was found that age, sex, and education amongst other factors influences the adoption of CSA technologies (Sisay et al. 2023). The findings reveal that stakeholders' intention to technology adoption were influenced when they perceived it to suit their needs. Jiang et al. (2023) also outlines the adoption of low-carbon agricultural technologies was contingent on targeted incentives and purchasing subsidies, technical guidance, and agricultural cooperative services. Yet, more studies are needed to understand adoption of I5.0 drones amongst food supply chain stakeholders.

2.2 Industry 5.0 and Agriculture Sector

Despite the advancements of I4.0, with studies outlining its potential to achieve higher sustainable supply chain performance (Belhadi et al. 2022), over the time, the application of I4.0 has mainly been for profit maximisation, thus leading to the depletion of natural resources, negative consequences on the environment, and inappropriate work conditions - all of which subsequently caused unsustainable consumption pattern environmentally, economically, and even socially (Bonilla et al., 2018). Therefore, it is argued that I4.0 still entails a huge cost to the environment (Oláh et al, 2020). Such concerns have triggered the evolution of I4.0 to I5.0, a terminology first coined by the European Commission (EC, 2021). Complementing the paradigm of the existing I4.0, I5.0 emphasises on the research and innovation as the elements driving the economy transition to a more sustainable economy, prioritising on delivering value to the stakeholders rather than solely to the shareholders.

The trajectory witnesses higher commitment on safeguarding the environment as well as the wellbeing of the workers (Ivanov, 2021). Ivanov (2023:1688) recently characterised I5.0 as a technological-organisational framework, by proposing that I5.0 is underpinned by the major technological principles of "*collaboration, coordination, communication, automation, data analytics processing, and identification*" covering four areas of organisation, management, technology, and performance assessment across societal, network and plant (field) levels, framing a new triple bottom line as resilient value creation, human well-being, and sustainable society, which spans the dimensions of planet, people, and profit (see framework of I5.0 in figure 1). The framework conceptualises that in the context of society, I5.0 constructs networks that enable the provision of products and services during crisis periods, a perspective which is complemented by the human-centric contextualisation of ecosystems such as food and agriculture, for sustainable production and usage of resources. Meanwhile, at the network level, supply chain capabilities are designed to stay resilience and sustainable through lean management, such as redundancy avoidance and risk mitigation, calling for the network resilience to be considered from a value-creation perspective (Aldrighetti et al. 2021, Ivanov, 2021).

In food supply chains, variations in production, prices, weather, and workers health are huge risks that threaten the supply chain network integrity (Mahroof et al., 2021). Thus, agile, flexible, and reconfigurable supply chains are required as they are sustainable and resilient (Shekarian et al., 2020). For instance, drainage water management or water gates systems are efficient in protecting farms against flood, but the benefit of investing in them can only be gained if the flood happens. Therefore, from a value creation perspective, these interventions are inefficient. Instead, the use of drones that connect to cloud computing to collect and analyse weather data and send alert to farmers if risks are detected is more valuable. At the plant (field) level, a human-centric perspective is adopted for the creation of an inclusive work environment, which is done through integrating AI into operation and creating health protection protocols (Shen et al. 2021, Sodhi et al. 2021).

Echoing the European Commission's (2021) vision of making workplaces more inclusive, building more resilient supply chains, and adopting more sustainable ways of production, Choi et al. (2022) suggest that I5.0 advocates the concept of 'sustainable social welfare' through human-machine interactions. This contributes towards sustainability of each plant (field) in the supply chain network, which eventually fortifies such network into a more resilient and sustainable network. To conclude, while a technology-centred approach drove the I4.0 (Ivanov et al. 2021, Zheng et al. 2021), I5.0 focuses on value creation through technology use with resilience, sustainability, and human-centricity as its key components (Ivanov, 2023).

Industry 5.0

	Resilience	Sustainability	Human-Centricity
Society Level	*Viability of intertwined supply networks*	*Sustainable usage of resources and energy on the earth*	*Viability of human-centric ecosystems*
Network Level	*Supply chain resilience* *Reconfigurable supply chain*	*Supply chain sustainability* *Life cycle assessment of value-adding chains*	*Cyber-physical supply chains* *Digital supply chains*
Plant Level	*Resilience of manufactur-ing and logistics facilities* *Reconfigurable plants*	*Reduction of CO2 emissions* *Energy-efficient manufacturing and logistics*	*Human-machine collaboration* *Health protection standards and layouts*
Organisation: Resilient Value Creation and Usage - Human's Well-being – Sustainable Manufacturing and Society			
Management: Viability as Integrative Perspective of Resilience, Sustainability and Human-Centricity			
Technology: Collaboration – Coordination – Communication – Automation – Identification – Data Analytics			
Performance: Efficiency – Productivity – Resilience – Viability			

Figure 1: Industry 5.0 framework (Source: Ivanov, 2023)

In the context of agriculture and food supply chain, precision agriculture principles that underpinned agriculture 4.0 in the era of I4.0 helps farmers to enhance strategic and operational decisions making. The technology helps to tackle the counterproductive activities such as excessive use of pesticides and seasonal seedings. The technology provides a systematic tool to detect unforeseen problems hard to notice by visual inspection on occasional checks, or those that can only being detected through accumulation of experience. Nonetheless, some challenges remain. These include a cleaner production and value optimisation towards the triple bottom line. On top of these, people and processes such as lack of awareness on the use of technology and sustainability, high cost of technology acquisition, economic of scales and digital divide have widened the challenge gaps.

The recent pandemic further inflicts labour shortage. I5.0 presents solutions to this issue, especially through I5.0 drones. The use of I5.0 drones, that distinguished by the interaction between human and technology for value creation, allows farmers to collect data and/or map their lands for problem detection, where solutions can be applied immediately to avoid problem escalation that may be more costly to manage. Thus, more focus should be placed on understanding the human-centricity of I5.0 within the context of sustainable supply chains.

2.2.1 Transitioning from I4.0 to I5.0

In the context of agriculture, I4.0 focuses on the integration of advanced technologies such as robotics, AI, and IoT to improve the efficiency and effectiveness of the entire agricultural value chain (Liu et al. 2020). These technologies have great potential in helping agricultural stakeholders make more informed decisions based on real-time data. A plethora of research has focused on precision agriculture (Liu et al, 2020; Meshram et al. 2022; Condran et al. 2022), where I4.0 technology is deployed for data collection on soil conditions, crop health, and weather patterns using sensors, drones, and satellite imaging. This information is then analysed to optimise irrigation, fertilisation, and pesticide application, resulting in better resource utilisation and crop yields. Another popular focus is the "smart agricultural systems", where the I4.0 technology is advocated for farming process automation, such as planting, harvesting, and monitoring. The proponents of this suggest that farmers may streamline operations, reduce labour requirements, and enhance production by combining robotics and automation technologies with modern data analytics (Abbasi et al. 2022; Zhai et al. 2020).

Research has also focused on addressing supply chain disruptions with I4.0, through real-time monitoring and tracking technologies (Helo and Shamsuzzoha, 2020), data analytics (Seyedan and Mafakheri, 2020), traceability and transparency tools (Centobelli, 2022), assuring quality control (Tsang et al, 20219), eliminating waste (Dzhuguryan and Deja, 2021), and enabling more effective logistics (Sharma et al. 2022). “Data-driven decision making” has also received significant attention from researchers, from the use of machine learning algorithms to assist farmers in better understanding patterns (Gardezi et al. 2022), to predicting crop diseases (Chin et al. 2023), through to optimising resource allocation and managing risks (Sharma et al. 2020).

Nonetheless, there are various challenges that I4.0 agricultural-related research left unaddressed, particularly in terms of understanding human factors and their adoption intentions. With the emergence and rise of I5.0 technology, there is a shift in focus towards human-machine interaction for sustainability, ethical ways of working and value creation. The current state of I5.0 has resulted in a paucity of research pertaining to its application in the agricultural domain and to enhance supply-chain value.

Moreover. Ferreira et al (2022) suggested that majority of studies do not explicitly address the paradigm of I5.0 and there has not been much analysis on the application of I5.0 in the extant literature. Although focus was placed on addressing innovation and environmental sustainability challenges related to farming practices, discussions on factors facilitating the adoption of I5.0 technologies have hardly surfaced (e.g. Pallagst et al. 2019; Sodano 2019; Holroyd 2022).

Given that I5.0 shifts the attention from shareholder to stakeholder value (Nahavandi, 2019), researchers (e.g. Chin 2021, Colla et al., 2021) have highlighted the significance of understanding the value of human intelligence before placing the cognitive, and technical capabilities in manufacturing operations. Despite these calls, there are a paucity of I5.0 research which has empirically addressed human-technology interaction as a system, thus demonstrating the need for more research (Panagou et al. 2023).

2.2.2 I5.0 and Human-Centricity

Despite drones being one of the most intensively studied technologies in logistics in recent years (Kirschstein, 2020) the focus has largely been from technical perspectives, in terms of precision agricultural applications (Condran et al. 2022), 3D-mapping approaches (Jimenez-Brenes et al. 2017) thermal imaging (Khaliq et al 2021) and remote phenotyping (Han et al. 2021) as well as crop management. While studies have explored it from applied perspectives, such as its potential for last-mile deliveries (Kirschstein 2020), less studies have focused on the application of drones from within the emerging paradigm of I5.0 and its adoption by operational workers. With the advent and proliferation of I5.0 and given the focus has previously been from technical lenses, there is a gap in addressing and understanding the adoption of such technologies from a human perspective.

Through examining the role of I5.0 for better food security, Guruswamy et al. (2022) outline that agriculture is set to become the second-largest user sector of I5.0 drones in the coming years. Thus, highlighting the significance of understanding the adoption and intention to use such innovative solutions by agricultural stakeholders. Zizic et al. (2022) argue that whist I4.0 was based on the concept of smart factory and cyber-physical production systems, I5.0 has extended the social and environmental dimensions by focusing on the workers’ skills, knowledge, and abilities to cooperate with machines and robots, hence making it imperative that research is tailored towards understanding the intention to use I5.0 tools by workers.

Researchers (e.g., Grabowska et al., 2022; Longo et al., 2020; Ivanov, 2023) have called for better humanization and sustainability of I4.0 and argue the need to redress the balance between human and machines, by placing the role of humans central to discussions of future industrial development, such as I5.0. For instance, Grabowska et al. (2022) outline a drawback of the extant I4.0 literature is that the role of current workers is very rarely mentioned and given that I5.0 involves returning the human factor to industry, through a combination of automaton alongside humans' cognitive skills and critical thinking (Longo et al., 2020), it makes it even more critical to look at human factors. Ivanov (2023) also argues that I5.0 cuts across a multitude of key concepts, namely sustainability, human-centricity, and resilience and that the contextualisation of the human-oriented and society-oriented aspects within I5.0 is a nascent area, worthy of academic attention and focus.

A review of the extant I5.0 literature indicates the importance of integrating I5.0 technologies within organisations supply chains (see Cillo et al., 2021; Xu et al., 2021). Contrary to I4.0, the significance of human involvement within the I5.0 paradigm should be appreciated and further explored in academic research (Maddikunta et al., 2022). According, the research addresses this void, by drawing attention to the role of humans within I5.0 advancements. The proposed research also responds to Karmaker et al. (2023) call to conduct research into the adoption of I5.0 tools within emerging economy contexts. The authors argue implementing I5.0 applications to manage supply chain sustainability is easier for developed countries than emerging economies, therefore outlining the opportunities and barriers to its adoption within emerging economies is important.

2.3 Theoretical background and conceptual model

While a plethora of studies have explored the role of innovative solutions in driving sustainable supply chains, limited focus has been placed on the role of drones in achieving this, through cleaner agricultural production. However, through taking an Interpretive Structural Modelling (ISM) approach, Mahroof et al. (2021) offer a robust model which uncovers 12 challenges which impede sustainable supply chains. Their study reveals the potential role of drones in overcoming these challenges, which in turn may assist organisations in transitioning towards sustainable supply chains. Given that the Mahroof et al. (2021) sustainability model outlines specific barriers and potential solutions to attaining sustainable supply chains, makes it a highly appropriate model for the purposes of the current study.

While their exploratory study derives insights through a Circular Economy and Agritech literature, as well as expert opinions, the authors called for researchers to validate their parsimonious model in the future, as it is yet to be tested through empirical research. As such, this study aims to respond to this call by validating the model, while investigating the propositions put forward in their research.

Extending research by empirically validating ISM analysis is a robust and appropriate approach. As highlighted by Singh and Rathi (2021), who state that a hybrid approach consisting of ISM-SEM analysis offers significant insights, through firstly the ability to conceptualise and classify barriers according to their degree of influence and secondly by allowing for the validation of a relational structural model. In the context of this research, the ISM findings from Mahroof et al. (2021) will be used as a basis to further explore and validate the role of I5.0 drones in achieving sustainability in supply chains, whilst also validating factors which influence its uptake amongst agricultural stakeholders.

Moreover, unproductive workers and pesticide hazards are identified as key drivers of agricultural challenges by Mahroof et al. (2021). Accordingly, this study adapts the sustainability model and aims to validate the model through further empirical research. The framework (Figure 2) is an adaption of unvalidated Mahroof et al. (2021) model, which is adjusted for the context of our paper, in which the aim is to evaluate the determinants of I5.0

drones' adoption among food supply chain stakeholders in Nigeria. The augmented conceptual model is presented in Figure 2, and we discuss the relationship between these variables in the sections below. As the research model proposed by Mahroof et al. (2021) is based on the data collected from the experts largely from the agriculture and technology domains for drone as a service for promoting cleaner agricultural production and circular economy for ethical sustainable supply chain, it makes sense to validate the proposed model and its related propositions to explore and validate this further with the primary data collected to evaluate food supply chain stakeholders' intention to use Industry 5.0 (I5.0) drones for cleaner production in food supply chains. By using the research model suggested by Mahroof et al. (2021), we are not only testing the strength of the model performing in the similar context but also enriching that model with the context specific constructs such as seeding accuracy and drone application.

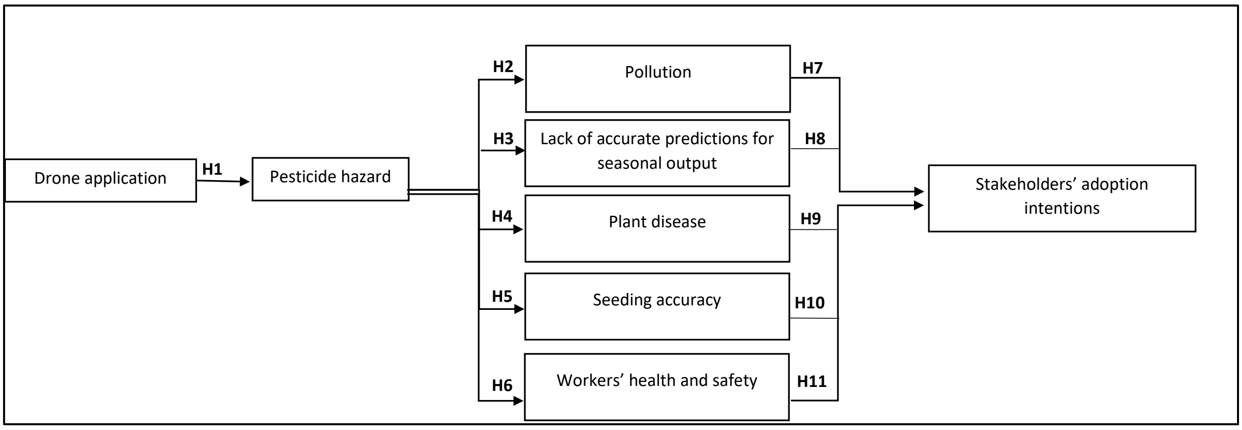

Figure 2: Drone adoption model (Adapted from Mahroof et al., 2021)

2.4. Hypotheses Development

The sustainability model by Mahroof et al. (2021) argues for a hierarchical process to the adoption of a human-machine collaborative technology. Within this framework, pesticide hazard is considered an underlying challenge in farming operations. Thus, if adequately tackled could increase cleaner production in agricultural supply chain. We adopt this framework in this study and identify the key driver for human-machine collaboration as pesticide hazard reduction, mediated by five variables: pollution reduction, plant diseases alleviation, seeding accuracy, workers' health and safety and prediction accuracy. These variables will be discussed, and related hypotheses presented.

2.4.1 The link between I5.0 drones and pesticide hazard reduction

One of the major challenges of agricultural production is pesticide usage (Vasseghian et al. 2022). Several solutions have been developed to facilitate its application, such as using real-time detection systems, precise real-time treatment and unmanned drones to minimise hazards caused by pesticide use (onzalez-de-Santos et al. 2017). Researchers have argued for the use of emerging technologies such as AI, IoT, blockchain and digital twin to enhance automation and precise production systems (Rajput and Singh, 2020; Mubarik et al., 2021; Bag et al., 2021). As such, the agricultural sector is extensively utilising drones within its operations for aerial observations, sensing purposes, as well as, spraying pesticides (Ayamga et al. 2021). Moreover, Liu et al. (2023) recently found that large scale agricultural producers in China preferred drone services for pesticide reduction. From an agricultural supply chain perspective, most emerging technology applications are still at the nascent stage and require further exploration.

While human expertise has been touted as pertinent in enhancing technological models, there are however limited studies on human-machine collaborative dynamics in enhancing precise application of pesticide. The study places emphases on these dynamics for cleaner production, pesticide hazards reduction and increased agricultural efficiency. As such, if human expertise is used in conjunction with efficient and accurate drones, pesticide application would be enhanced thus reducing hazards. It is therefore argued that I5.0 drones offers user-preferred manufacturing solutions, hence the following hypothesis is put forward:

Hypothesis 1. The use of I5.0 drones will significantly reduce pesticide hazards.

2.4.2 The mediating links between pesticide hazards and stakeholders' intention to use I5.0 drones

Agriculture production is negatively impacted by several issues, including plant pests and using pesticides is one of the most promising ways to tackle this issue (Rojas et al., 2022). The frequency and mode of employing chemical pesticides has raised concerns for individuals and governments (Vasseghian et al. 2021). Although pesticides are frequently employed to safeguard agricultural production and fulfil global food demand, they are also pervasive environmental pollutants (Alshemmari et al. 2021; Tang et al. 2021). As such precise or reduced pesticide application may positively impact the environment. Diendéré et al. (2018) studied the interactions between stakeholders' beliefs relating to water pollution and pesticide use, revealing that they were less inclined to use pesticides when they understood the impact on water degradation. A recent study has shown that drone-assisted deliveries can reduces carbon emissions and overall costs (Meng et al. 2023). The sustainability model by Mahroof et al. (2021) suggests that addressing pesticide hazards will address the underlying agricultural supply chain issues and thus stakeholders may be inclined to use I5.0 drones. It implies that collaborative efforts of human expertise and machine accuracy if used to mitigate hazards caused by using pesticides, may reduce pollution. This entails understanding when and how to precisely use drones for pesticide applications. As such we propose that:

Hypothesis 2. Pesticide hazard reduction using I5.0 drones significantly influences pollution reduction for cleaner production.

Davidson et al. (2022) outline that precision agriculture has provided greater access of data to farmers and that aerial crop imagery can assist in estimating vegetation indices and boosting efficiency. Perz and Wronowski (2019) relate how aerial measurements can assist in increasing yields and improving the condition and efficiency of farms. Similarly, Mendoza et al. (2021) posit how data collected through drones allows farmers to optimize their use of water or chemicals to boost yield, which ultimately will help increase their net profit. Jensen et al. (2021) also reveal the predictive power of regression models trained on drone imagery, used within fields to predict infestations of annual grass weeds in the late growth stages of cereals. In addition, Herrmann et al. (2019) highlight how drones allow farmers to accurately predict yield. Spectral models can also differentiate between development stages and irrigation treatments, thus emphasising the predictive abilities to utilise drones in agricultural settings. Thus, the following hypothesis is put forward:

Hypothesis 3. The application of pesticides through precision I5.0 drones will increase prediction accuracy.

The relationship between pesticide hazard reduction and plant diseases has been established in the literature. It depicts that plant disease will be eliminated if pesticide hazards are curbed and that by automating the plant disease detection process, losses in yield can be prevented (Chin et al. 2023). Many studies have examined the potential of I4.0 applications in minimising plant diseases or their earlier detection (Khattab et al., 2019). Similarly, Stella et al. (2017) highlights the importance of such applications to optimise pesticides, particularly for the future of farming practices. Khanal et al. (2017) used hyperspectral sensing to monitor crop stresses, diseases, and irrigation stress. Although studies have examined how diseases and crop health can be monitored through sensory techniques (Spalević et al., 2018), drones have unlocked even more opportunities for plant disease management (Mahroof et al., 2021). A thorough understanding of the plant, the surrounding conditions, and the common illnesses or other issues that the plant is prone to is pertinent in plant disease management. A false diagnosis might result in the overuse of pesticides, a waste of resources in terms of time and money, and a plant's ongoing deterioration if such information is not provided. Therefore, it is argued that collaborative human-machine expertise in plant disease management would contribute to precise application of pesticide hazard which in turn mitigate plant disease. As such it is proposed that:

Hypothesis 4. The effective and precise application of pesticides using I5.0 drones will significantly impact plant disease.

According to Huang et al. (2021) having a higher awareness of the harms of pesticides to the ecological environment lowers the possibility of its overuse. Thus, when guiding farmers to use new agricultural technologies, disseminating information to those who have adopted such technologies is imperative (Gao et al. 2020). The application of pesticides not only assists in eradicating harmful microorganisms, but it can also be counter-productive, killing beneficial microorganisms and vertebrates, thus disrupting the seeding process (Liu et al. 2023). As well as causing ecological damage, pesticides have been shown to negatively impact sales and quality of yields (Xie et al., 2019). Hence, the utilisation of precision treatment to overcome the disease of plants, thus impacting revenues raised through the cultivation of plants and crops, may influence stakeholders' intention to use precision technologies. Moreover, the spraying capabilities of drones can offer precision agricultural solutions, from precision use of pesticides through to accurate aerial seeding (Liu et al. 2023). Therefore, the following hypothesis is put forward:

Hypothesis 5. The application of pesticides through precision I5.0 drones will increase seeding accuracy.

Although pesticides contribute to food security, they are considered detrimental to workers health and are to blame for acute illnesses in populations (Ngwoi et al., 2016). Pesticide issues on workers are generally due to incorrect and poor application of pesticides (Kumar et al. 2014). Xu et al. (2021) discusses the potential of I5.0 through augmenting human values and approach in building resilient manufacturing systems and supply chains. The emphasis is on human-robot collaboration where human and machines can work together to optimise systems operations (Leng et al., 2021). It extends beyond programming the drones for pesticides use on farmlands to understand areas where health and safety may be breached. It requires the intervention of human expertise. Moreover, studies highlight the role of drones in reducing health and safety challenges. For instance, Roldán-Gómez et al. (2021) found that drone swarms can be used to improve firefighters' efficiency and their safety. Conversely, in the context of farming operations, if workers use I5.0 drones to enhance precision application of pesticides, their health and safety challenges may also be minimised. Therefore, the use of I5.0 drones may reduce pesticide hazards and in turn mitigate workers health and safety challenges. Accordingly, the following hypothesis is put forward:

Hypothesis 6. The precise application of pesticides hazards using I5.0 drones will reduce workers' health and safety challenges.

It is reported that farmers exposed to a large quantity of information on agriculture safety and agricultural pollution can induce emotional resonance and crisis awareness, stimulate their sense of responsibility, and form awareness of green production (Kansiime et al., 2019). Moreover, studies have shown that pesticide application and fertiliser technologies affect stakeholders' production and investment behaviours. According to Zhao et al. (2020), stakeholders' awareness of food safety and agricultural pollution can ultimately impact and change their agricultural practices. In adopting the framework set out by Mahroof et al. (2021) it can be argued that pesticide hazard reduction may act as a mediator between pollution reduction and stakeholders' intention to use I5.0 drones. It demonstrates that if precision pesticide application can accurately reduce pollution, then stakeholders in the agricultural supply chain would be more inclined to use I5.0 drones. Thus, the following hypothesis is put forward:

> ***Hypothesis 7. Pollution reduction through increased precise pesticide application increase stakeholders' intention to use I5.0.***

Research reported that the motivation to adopt new technology is heavily influenced by it perceive usefulness and perceived ease of use (Ali et al, 2021). Agricultural stakeholders who lack an understanding of I5.0 technology will be less likely to adopt the technology, despite its usefulness. Tang et al. (2021) outlines the use of pesticides conflicts with UN Sustainable Development Goals (e.g. SD3, good health, SDG 6, clean water, SDG 15, protection of life on land) and contributes to the loss of biodiversity (Singh et al, 2023). In spite of these negative connotations, Strange et al. (2022) argue that pesticide use is expected to increase to help attain food security (SDG 2), in response to the global food crisis. Drone precision in agriculture is not only able to reduce the use of pesticides, but has the potential to increase yields, through healthier crops and cost optimisation (Mahroof et al. 2021). A lack of accurate yield forecasts can lead to inefficient allocation of resources, such as labour, tools as well as transportation. However, machine learning through I5.0 drones equipped with RGB (red, green, blue) cameras can assist in offering more precise yield predictions (Chen et al. 2019). Ali et al. (2021) also highlight the ability of drones to expedite agricultural processes, while being accurate and cost efficient, can garner interest in its adoption. Therefore, we argue that:

> ***Hypothesis 8. The significant increase in prediction accuracy through efficient and precise pesticide application will increase stakeholders' intention to use I5.0.***

Plant diseases have adverse effects on both the quantity and quality of agricultural products, posing a threat to food safety (Hofmann et al., 2023). These harmful impacts lead to financial losses in crucial production sectors that are especially consequential for emerging economies, as the manual examination by specialised experts is not only time-consuming but also costly (Chin et al. 2023). Consequently, automating plant disease detection such as blight and fungus using Color-infrared (CIR) images, and applying treatment based on machine learning algorithms through the use of drones appears as a viable method to mitigate yield loss risks effectively (Devi and Priya, 2021; Sinha, 2020). Moreover, Liu et al (2018) also found that agricultural actors are likely to adopt new practices if it leads to increased profits. The precise treatment of plant diseases, leads to increased and healthier yield, thus leading to profitability. Therefore, we therefore propose that:

> ***Hypothesis 9. Precision treatment of plant disease using I5.0 drones facilitates stakeholders' intention to adopt the new technology.***

Zuo et al. (2021) found that tangible benefits can assist with the uptake of drones in farming operations. Mohan et al. (2021) reveal spraying mechanisms on drones can offer practical and tangible benefits to yield, by helping initial vegetation growth periods. Moreover, Yawson and Frimpong-Wiafe (2018) highlighted how aerial data captured from drones can assist crop inventories conduction and yield estimates. A plethora of studies have also outlined the role of drones in accurately facilitating seeding processes within agricultural settings. For instance, Wang et al (2022) posit how drones can successfully and stably plant seeds into the soil through sow seed capsules, whilst Liu et al (2023), outline how modern drones have the capability to fire seeds into the soil for plantation purposes. Therefore, drones, along with image processing, can optimise management and assist with breeding purposes (Gnädinger and Schmidhalter 2017). Accordingly, the following hypothesis is put forward:

> ***Hypothesis 10. Seeding accuracy facilitated by precise drone application increases stakeholders' intention to use I5.0 drones.***

The agricultural sustainability model by Mahroof et al. (2021) also highlights the link between workers' health and safety challenges and stakeholders' intention to use I5.0 drones as hierarchical. The debate here is that if the challenges workers face whilst executing farming operations is adequately addressed using I5.0 drones, then the intention to use this technology may increase. It stems from the role of drones being perceptive and informed about workers desires and aiding in the decision-making process to addressing them (Nahavandi, 2019). Several studies have examined the role of I4.0 in tackling workers health and safety challenges (Trivelli et al., 2019; Bernhardt et al., 2021). However, these studies consider combining manual and automotive processes in addressing challenges. It depicts the absence of trust when using autonomous technology. In this study we argue that the collaborative relationship between humans and machines through I5.0 drones would increase farming operations efficiency including tackling workers challenges especially pesticide hazards. It in turn will motivate stakeholders in their intention to use I5.0 drones. Hence, the following hypothesis is put forward:

> ***Hypothesis 11. Workers' health and safety increases agricultural stakeholders' intention to use I5.0 drone.***

3.0 Research methods

Dora et al. (2020) outlines the need for more studies to evaluate the interaction between different stakeholders in the food chain including upstream stakeholders, such as farmers. As such, this study aimed to examine the determinants of I5.0 drones' adoption in the food supply chain in Nigeria using a sustainability model for cleaner production. Data was gathered using survey questionnaires administered in English to achieve the research objectives. All items of the constructs were measured using a 7- point Likert scale with "1" indicating "strongly disagree" and "7" indicating "strongly agree." The questionnaire was divided into two parts.

3.1. Developing constructs

The constructs used in this study were generated from existing literature and in line with the Mahroof et al. (2021) framework. Eight constructs were adopted from Silva et al. (2011), Tey et al. (2012) and Barnes et al., (2019) to measure precision agricultural techniques (PAT), in this case, drone application. The responses included '*Drones will lead to lower environmental impact' 'Drones will lead to a higher yield'*. Constructs were adapted from Lithourgidis et al. (2016) to measure precise and effective pesticide application on a 3-item scale. Sample items included '*I believe pesticides affect the environment'* and *I use the product with the frequency indicated on the label'.*

Items taken from Bagheri et al (2019), were used to measure plant disease reduction. Sample items included '*I use chemical as well as non-chemical methods to reverse crop disease and 'The current methods used are effective in protecting crops.* Workers' health and safety challenges were also a construct used to measure stakeholders' intention towards adopting I5.0 drones. Thus, lower workers' health and safety challenges through drones' application compatibility increased stakeholders' intention. A 5–item scale adapted from Román-Muñiz et al. (2006) and Lunner-Kolstrup and Ssali (2016) measured workers' health and safety. The cross loadings and Cronbach item values suggested the elimination of variables. As such in this study, a two-item scale was used. The sample items included '*I have experienced skin-related problems (such as rash, itching, discolouration) from work during the past 12 months* and '*I have experienced skin-related problems (such as rash, itching, discolouration) from work during the past 12 months.*

Precision and effective pesticide application has also been suggested to increase predictions accuracy. A 4-item scale from Liu and Huang (2013) was employed to measure the predictions accuracy construct. The items included '*if I spray less, my income will be reduced*', '*if I use pesticides, this leads me to a favourable result, i.e., increased production'* and '*if I use pesticide spraying, my farm revenue will sustain'.*

Pollution reduction was also a defining construct in measuring drone compatibility and stakeholders' intention to use. A five-item scale adapted from Pan et al. (2016) was used to measure pollution reduction. Three of these items were dropped due to failure to meet the required Cronbach and AVE 0.60 thresholds. The sample items were '*My farming methods will not harm the environment'* and *'I am willing to treat pollution.* Thus, the effective use of drones through efficient pesticide application will reduce pollution. To measure stakeholders' intention to use I5.0 drones, an eight-item scale was adopted Yamano et al., (2015) and Bagheri et al. (2019). The items were measured on a five-point Likert scale, where one indicated 'strongly disagree' and five 'strongly agree'. A summary of our constructs' development is presented in Appendix A.

3.2. Data Collection

The empirical context of this study is Nigeria's food supply chain due to the prominent level of agricultural activities in the country and its classification as a developing economy (World Bank, 2022). Our unit of analysis were focal firms where each participant represented a single firm in the supply chain. It was essential that the participants were knowledgeable on the decision-making processes of their firms and as such the views provided were representative of their focal firms. A questionnaire administered through a web-link survey was used to collected data from participant. We piloted the questionnaire with fifteen (15) food supply chain experts and 7 academics to ensure the clarity of all measurement items. All identified issues including ambiguity, wording and formatting were addressed before administering the questionnaire (Saunders et al. 2019). For instance, I5.0 drones was used instead of Unmanned Aerial Vehicle (UAV) and pollution reduction replaced sustainable practices.

3.2.1. Population, sampling techniques and response rate

Since the aim of our study was to evaluate the intention to use Industry 5.0 drones for sustainable farming operations, it was pertinent that respondents in charge of the decision making process and who understood the phenonmenon under study completed the questionnaire. As such, we considered the non-probability sampling technique (snowballing and purposive) as suitable (Saunders, 2019). It implied that anybody identified as knowledgeable about the researched phenomena was approached to complete the survey.

We approached 950 stakeholders of managerial positions involved in various activities in the food supply chain around Nigeria with particular emphasis in the decision-making processes. The questionnaire was circulated via a Web survey link in an email. A detailed information on purpose of the study, confidentiality information and a consent form was attached to the questionnaire sent through their emails. To facilitate in recruitment, a multi-channel strategy was used through industry connections and professional groups. Emails were sent fortnightly as reminders to prompt questionnaire completion.

The data were collected between January and March 2021. A total of 270 responses were completed and returned. However, 264 were considered valid, indicating a response rate of 27.7%. A response rate between 6-16% is considered valid (Dillman, 2011). Similarly,the total number of valid responses is appropriate for the partial least squares structural equation modelling (PLS-SEM). Since each respondent represented single firms, the possibility of common method biased (CMB) may occur (Podsakoff et al. 2003). We used the VIF and Harman's test to check (Harman, 1976; Kock 2017). The results demonstrate the absence of CMB as the VIF values are below 5 and the CMB had a cumulative average variance of 26.3%.

3.3. Sample characteristics

We used a sample of 264 stakeholders in the food supply chain in Nigeria to achieve our research objectives. A summary is presented in Table 1. The summary shows that most of the stakeholders in our sample were male with over ten years of experience in perishable food supply chain farming. A cross-tabulation between age and type of supply chain showed that most respondents above 35 years engaged in perishable foods and grains supply chain more than any other age group. Also, stakeholders above the age of 36 had more positive toward towards the use of I5.0 drones in agricultural operations.

Table 1 Demography characteristics of respondents

Variable	**Characteristic**	**Frequency**	**Percentage (%)**
Gender	Male	261	98.9
	Female	3	1.1
Education	None	2	0.8
	Primary School	102	38.6
	High School	129	48.9
	College	21	8.0
	University	9	3.4
	Others	1	0.4
Experience (in Years)	Less than five years	4	1.5
	6-10 years	63	23.9
	11 or more	197	74.6
Age (in Years)	Younger than 26	65	24.6
	26-35	56	21.2
	36 and over	143	54.2
Supply Chain Type	Animal Husbandry	1	0.4
	Grains	33	12.5
	Mixed Farming	6	2.3
	Seasonal Farming	30	11.4
	Vegetables	192	72.7
	All of the Above	2	0.8

3.4. Data Analysis

3.4.1. Model measurement assessment

We examined the constructs of our measurement model using (i) item loadings and composite reliability, (ii) discriminant validity (AVE) and (iii) convergent validity. As presented in Table 2, the findings establish construct reliability as all the outer loadings, the overall Cronbach alpha score, and composite reliability stood above the recommended 0.60 (Bland and Altman, 1997; Hair et al., 2017; Vaske et al., 2017). The values for the convergent validity were also above the recommended 0.50 threshold, which suggests that the model used in this study to measure was a good fit.

Table 2 Assessing measurement model.

Construct/Items	Outer loadings	Cronbach's Alpha	Average Variance Extract	Composite Reliability
Drone Applications		0.985	0.904	0.987
DA1	0.937			
DA2	0.861			
DA3	0.955			
DA4	0.967			
DA5	0.971			
DA6	0.976			
DA7	0.972			
DA8	0.964			
Stakeholders' Intention to use	0.770	0.944	0.720	0.953
SHA1	0.704			
SHA10	0.804			
SHA2	0.898			
SHA3	0.868			
SHA4	0.929			
SHA5	0.895			
SHA6	0.895			
SHA7				
Seeding Accuracy		0.866	0.689	0.917
SA1	0.853			
SA2	0.853			
SA3	0.893			
SA4	0.754			
SA5	0.788			
Predictions Accuracy		0.950	0.870	0.964
PA2	0.908			
PA3	0.939			
PA4	0.940			
PA5	0.943			
Plant Disease		0.839	0.609	0.886
PD1	0.782			
PD2	0.789			
PD3	0.807			
PD4	0.804			
PD5	0.717			
Pesticide Hazard		0.720	0.600	0.818
PH1	0.768			
PH2	0.774			
PH4	0.781			
Pollution Reduction		0.982	0.982	0.991
PR3	0.991			
PR4	0.991			

Workers' Health and Safety WHS2 WHS5	 0.978 0.977	0.953	0.955	0.977

1. The output of SmartPLS3 (PLS-SEM) is based on a research sample.
2. AVE = average variance extracted.

3.4.2. Discriminant validity tests

The discriminant validity was considered using the Fornell-Larcker criterion (1972) to assess the model parameters. To measure this, the square root of a construct's AVE should be lower than its highest correlation. The findings are presented in Table 3.

Table 3 Discriminant validity

Variables	PA	DA	FA	PH	PD	PR	SA	WHS
Predictions Accuracy (PA)	**0.933**							
Drones' Applications (DA)	0.235	**0.951**						
Stakeholders' Intention to Use (SHA)	0.178	0.170	**0.849**					
Pesticide Hazard (PH)	0.328	0.329	0.301	**0.774**				
Plant Diseases (PD)	0.416	0.241	0.189	0.585	**0.781**			
Pollution Reduction (PR)	0.313	0.467	0.106	0.658	0.374	**0.991**		
Seeding Accuracy (SA)	0.425	0.755	0.126	0.486	0.348	0.607	**0.830**	
Workers' Health and Safety (WHS)	0.435	0.472	0.110	0.446	0.404	0.615	0.576	**0.977**

[Note: Values across the diagonal in bold font are the square root of AVE]

3.4.3 Quality of model

The structural model quality was examined using the R^2 and the Q^2 by Geisser (1974) model measurements as presented in Table 4. Pollution reduction (PR) was measured by two constructs and had significant R^2 and Q^2 (0.436 and 0.418). Plant disease (PD) was measured using five constructs with R^2 and Q^2 (0.324 and 0.206).

Table 4 Model quality

Constructs	R^2	Q^2
Predictions accuracy	0.157	0.092
Stakeholders' intention	0.049	0.031
Pesticide hazard	0.108	0.038
Plant disease	0.343	0.206
Pollution reduction	0.436	0.418
Seeding accuracy	0.304	0.158
Workers' health and safety	0.99	0.209

4.0 Findings

We analysed the data using partial least square based structural equation models (PLS-SEM). The PLS-SEM was used to provide a predictive approach to handle complex models where no prior assumptions have been considered (Hair et al., 2019; Sarstedt et al., 2020; Dash and

Paul, 2021). In this case, our complex model involves six drivers and challenges of sustainability technology adoption. Presented in Figure 3 are the standardised estimates from the SEM. The results of the hypotheses are presented in Table 5. First, our findings confirmed that the use of I5.0 drones increased the effectiveness and precision application of pesticides supporting H1 (β = 0.302, p>0.000). We found that effective pesticide application using I5.0 drones had positive and significant effect on PA (β = 0.327, p>0.000), SA (β = 0.459, p>0.000), PD (β = 0.590, p>0.000) and PR (β = 0.238, p>0.000) The findings also indicated positive and statistically significant relationship between PH and WHS(β = 0.301; p>0.000), denoting the support for H2-H6. We found statistically insignificant relationships between SHA and PR, PA, SA and WHS. Hence H7, H8, H10 and H11 were not supported. A positive and statistically significant link between PD and SHA (β = 0.127, p>0.005, supports H9. The findings indicate that although reduced pesticide hazards mitigated sustainability challenges, they did not influence stakeholders' intention to adopt I5.0 drones. A summary of the hypothesis tested is presented in Table 5. A summary of the structural path analysis is presented in Appendix B.

The indirect effect of I5.0 drones and sustainability challenges indicate positive and statistically significant relationships as presented in Table 6. It implies that I5.0 drones have the capacity to also directly address sustainability issues of farming operations.

Table 5 Structural path for identified constructs.

Path coefficients	**Direct effect**	**T value**	**Total effect**	**T value**
Drones' applications → Pesticide hazard	0.302	5.759**	0.329	6.430***
Pesticide hazard → Pollution	0.238	4.292**	0.658	16.091***
Pesticide hazard → Prediction accuracy	0.327	6.10**	0.328	5.980***
Pesticide hazard → Plant diseases	0.590	13.301**	0.585	12.605****
Pesticide hazard → Seeding accuracy	0.459	10.878**	0.486	12.083***
Pesticide hazard → Workers' health and safety	0.301	5.435***	0.300	5.435***
Pollution → Stakeholders' intention	0.120	2.053*	0.011	0.123
Prediction accuracy → Stakeholders' intention	0.069	0.819	0.113	1.528
Plant diseases → Stakeholders' intention	0.127	2.021**	0.133	2.300**
Seeding accuracy → Stakeholders' intention	0.106	1.358	0.037	0.353
Workers' health and safety → Stakeholders' intention	0.038	0.351	-0.022	0.209

1. Significance **p < .01, *p < .05.
2. Results of bootstrapping 500 replications PLS-SEM based on N=264

Table 6 Indirect effects of drone application

Structural Path	**Indirect effect**	**T statistics**
Drones Application -> Plant diseases	0.193	5.583***
Drones Application -> Pollution reduction	0.218	5.306***
Drones Application -> Prediction accuracy	0.108	3.837***
Drones Application -> Seeding accuracy	0.182	4.76***
Drones Application -> Stakeholders' intention	0.043	2.339**
Drones Application -> Workers' health and safety	0.148	4.223***
Pesticide Hazard -> Stakeholders' intention	0.130	2.67**

The specific structural path to increase stakeholders' intention toward the I5.0 application was analysed. We found the path for *Drones' applications Pesticide hazard → Plant diseases → Stakeholders' intention to use* statistically significant ($\beta = 0.021$, $p<0.10$). Thus, Stakeholders' intention towards I5.0 drones is largely influenced by efficient and precise pesticide application and plant disease reduction. We also found the DA→ PH →WHS path statistically significant ($\beta = 0.091$, $p< 0.01$) 0.005). It implies that drone applications will reduce workers' health and safety through pesticide hazard reduction.

Table 7 Hypothesis testing

No	Hypothesis	Findings
H1	The use of I5.0 drones will significantly reduce pesticide hazards	Supported
H2	Pesticide hazard reduction using I5.0 drones significantly influences pollution reduction for cleaner production	Supported
H3	The application of pesticides through precision I5.0 drones will increase prediction accuracy	Supported
H4	The effective and precise application of pesticides using I5.0 drones will significantly impact plant disease.	Supported
H5	The application of pesticides through precision I5.0 drones will increase seeding accuracy.	Supported
H6	The precise application of pesticides hazards using I5.0 drones will reduce workers' health and safety challenges.	Supported
H7	Pollution reduction through increased precise pesticide application increase stakeholders' intention to use I5.0	Not Supported
H8	The significant increase in prediction accuracy through efficient and precise pesticide application will increase stakeholders' intention to use I5.0.	Not supported
H9	Precision treatment of plant disease using I5.0 drones facilitates stakeholders' intention to adopt the new technology	Supported
H10	Seeding accuracy facilitated by precise drone application increases stakeholders' intention to use I5.0 drones.	Not supported
H11	Workers' health and safety increases agricultural stakeholders' intention to use I5.0 drone.	Not supported

PLS-SEM, a variance-based structural equation modelling, was used to test the model. Analysis was calculated using complete Bootstrapping with 5000 replications.

Figure 3: Structural path model

In Table 7, we present the results of the performance map analysis. This analysis aims to rank factors that influence Stakeholders' adoption of I5.0 drones. Our findings rank predictions accuracy as the most critical factor, followed by drone application, pesticide hazard, and plant diseases. We find pollution, seed accuracy, and workers' health and safety the least factors influencing stakeholders' adoption of I5.0 drones. These are in line with our hypothesis testing.

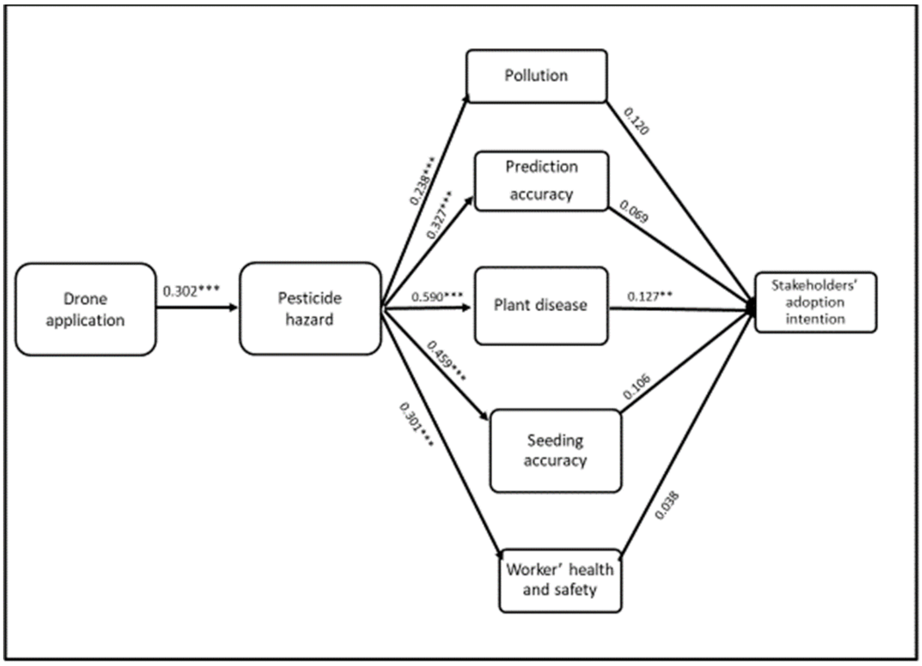

Table 8 Latent Variable Ranking

Latent Variables	LV Performance
Predictions Accuracy	74.325

Drone’s applications	86.481
Stakeholders’ intention to use	89.379
Pesticide hazard	54.389
Plant diseases	59.878
Pollution	69.367
Seeding accuracy	78.607
Workers’ Health and Safety	68.034

5.0 Discussions on the adoption of I5.0 drones for cleaner food production

Our findings advocate for the use of I5.0 in increasing agricultural operational performance and environmental sustainability by reducing plant diseases. However, we found that while I5.0 does reduce health and safety challenges, this was not an influencing factor for the uptake of I5.0 by supply chain stakeholders. The logical explanation suggests that emerging technologies such as I5.0 are squarely focused on improving operations processes with less focus on people in operations.

RQ1. What factors influence food supply chain stakeholders to adopt I5.0 drones for cleaner production?

In this study, we were concerned with the factors that propelled food supply chain stakeholders to use I5.0 drones for cleaner production. With the use of an augmented parsimonious model developed by Mahroof et al., (2021), our findings highlight factors that influence I5.0 adoption and their implications. First, the analysed data showed a positive and statistically significant relationship between pesticide hazard reduction and the use of I5.0 drones. A reduction in pesticide hazards in turn reduced plant diseases and increased prediction and seeding accuracy. It therefore suggests a hierarchical link between I5.0 drones and food production operations where stakeholders’ intention to adopt I5.0 technology begins with the contribution of drone use to pesticide hazard reduction.

We also found that stakeholders were not necessarily concerned with pollution reduction and, as such, may not be motivated to adopt I5.0 technologies to address these issues. It highlights stakeholders' environmental behaviour and the poor understanding of factors capable of mitigating pollution in an emerging economy like Nigeria. However, some studies have suggested that understanding identities, behavioural beliefs; agency; networks and relationships; and social norms may propel farmers' intention to pollution reduction through the precise application (Wang et al., 2019). Notwithstanding, policies need to be in place to educate farmers on environmental behaviours. Therefore, our analysis reveals pollution reduction through increased precise pesticide application does not increase farmers' intention to use I5.0.

However, although food supply chain stakeholders are more concerned about the precise application (pesticide hazard reduction, seeding accuracy) of drones in agricultural operations, these activities invariable enhances cleaner production. As such, we provide empirical evidence to support the contributions of I5.0 in cleaner production. It is particularly relevant as over 16% of climate change issues have been attributed to land degradation caused by pesticide application (Pinguet, 2020). Through precise application the land is preserved without excesses encroaching on the environment and plant diseases are curbed (Khattab et al., 2019). Thus, a reduction of pesticide hazards through precise application positively impacts the environment (Balafoutis et al. 2017). These findings are in consonance with the study of Sharma and Arya (2022), who found that the use of I5.0 UAV contributed to improving air quality.

Further, the findings also indicated that the absence of a relationship between stakeholders’ intention to adopting I5.0 drones and workers' health and safety challenges. It implied that although stakeholders considered I5.0 drones beneficial to farm operations, they were less inclined to adopt drone use if the specific purpose were to address workers health and safety challenges. It supports existing literature of stakeholders' concern about workers' health and safety challenges. For instance, Lotfi et al. (2021) found that workers' safety is often neglected in supply efficiency. Alsamawi et al. (2017) also provided evidence of hidden workers' challenges along supply chains that have been overlooked. However, I5.0 use tackles this challenge as it emphasises collaborative operations between robots and human (Ivanov, 2023). Due to the increased small footprint and adaptability of drones, I5.0 drones can be used to make working environments safe thus addressing workers' health and safety challenges (Grobbelaar et al., 2021).

RQ2. Does the adoption of I5.0 drones tackle food supply chain challenges?

Several challenges to production in the food supply chain have been identified to include pesticide hazard, pollution reduction, seeding accuracy, plant diseases, accurate prediction and workers health and safety (Mahroof et al., 2021). Our findings indicated I5.0 drones has the capacity to tackle these challenges and in turn support sustainable supply chain operations. For instance, we found that the use of I5.0 drones contributed to reducing pesticide hazards and plant diseases. It in turn enhances agriculture operations and food production. It implies that the use of I5.0 drones enhances agricultural production, facilitates the flow of produce in the supply chain by reducing hazards caused by pesticides and promotes cleaner production. The findings also indicate that I5.0 has the potential to reduce worker's health and safety, an issue which is extensively highlighted within agricultural research.

Thus, the precise application of pesticides reduces associated hazards such as pollution and plant diseases, which invariably has a ripple effect on other aspects of agricultural production. Our findings are in line with existing literature which argues that I5.0 enhances production systems (Bag et al., 2021). In this case food production, which could help alleviate issues with food shortages. For instance, Liaghat and Balasundram (2010) and Wang et al. (2018) showed that the use of drones improved crop yield through precise application of pesticides. Similarly, Guruswamy et al., (2022) showed that the vulnerability of food systems can be mitigated using I5.0 drones.

5.1 Theoretical implications

For researchers interested in gaining valuable insights into the understanding of I5.0 drones use for cleaner agricultural production, this study and its findings offer several theoretical implications. The first substantial contribution is that it is one of the first studies to adapt and test the proposed sustainability model by Mahroof et al (2021). It does this by demonstrating the various stages influencing stakeholders' intention to use I5.0 drones. Previous research (Bag et al. 2021; Kumar et al. 2022) have not focused on the capacity of the human dimension in facilitating sustainable practices in farming operations.

In this regard, we showed that the intention to use industry I5.0 drones began from the collaborative ability to ensure precise application of pesticide for hazard reduction which in turn ensures seeding accuracy, pollution reduction, workers health and safety challenges and prediction accuracy. The research thus extends the human-AI discourse by validating the Mahroof et al. (2021) sustainability model and demonstrating the importance of drones in facilitating sustainable agriculture for food security. Hence, the study helps to provide insights into human factors within the paradigm of I5.0. Previous literature within the paradigm of I4.0 focused largely on the automation and technical aspects and overlooked human factors and those who were tasked with adopting the technology.

Industry experts and I5.0 drone operators have always believed that drones' ability to overcome a host of long-standing agricultural challenges naturally influences the stakeholders' intention towards drones, increasing the uptake of I5.0 drones in agriculture. This study tests whether I5.0 drone-led solutions to the existing, overarching agricultural challenges previously identified in a study by Mahroof et al. (2021) could influence the uptake of I5.0 drones by farmers in the context of an emerging economy. The novel contribution of this model is underpinned by its discovery that these solutions do not necessarily influence the stakeholders. Hence, not all solutions to agricultural challenges that can be solved by I5.0 drones directly influence the stakeholder's intention or motivation to adopt drones in their farming activities. This study reveals a statistically significant influence of factors determining the stakeholders' intention towards using I5.0 drones.

Unlike what was suggested in many studies, the only drone led solutions to agricultural challenges that will increase the stakeholders' drone adoption are linked to factors that affect yield generation. Stakeholders are prone to adopt drones in a situation where drone usage helps to enhance plant health, which in turn, results in economical use of resources and increased crop production. The findings reveal that the ability to minimise plant disease is a critical factor in the adoption of I5.0 drones by agricultural stakeholders in this context, given severe constraints in production outputs resulting from poor crop quality, thus ultimately harming their yield.

Plant diseases have always been a tough challenge for agricultural stakeholders, especially when the extreme climate has already challenged the yield. These factors, their inter-relationship and criticality are mapped in Figure 3. The model suggests that environmental sustainability (i.e. environmental pollution), workers' health, prediction accuracy and safety are the stakeholders' most minor concerns, signposting the lack of awareness of those realms within this economic region, also alluding to the lack of planning undertaken by agricultural stakeholders. It is proposed that the same situation applies to the agricultural stakeholders in similar contexts of emerging economy nations, where monetary incentives primarily drive actions – hence healthy crops, translating to increased yields take priority over other outcomes regarding drone usage in agricultural activities.

The second main contribution of our findings is the negative link between pollution control and stakeholders' intention to use I5.0 drones. It contradicts existing studies which suggests that demonstrating the ability of a technology to reduce pollution in farming operations increases stakeholders' intention to use it (Wang et al. 2019). It thus highlights that in developing economies, the intention to use a human centric technology such as I5.0 drones is more focused on treating plant diseases though precise application of pesticides. Further studies should be carried out to provide possible explanations.

In addition, our model highlights that in developing economies the study helps to provide insights into human factors within the paradigm of I5.0. Previous literature within the paradigm of I4.0 focused largely on the automation and technical aspects and overlooked human factors and those who were tasked with adopting the technology. Therefore, this research provides empirical insights into the human centric perspective and contributes to a growing body of I5.0 literature and responds to the calls of Chin (2021), Colla et al. (2021) and Panagou et al. (2023), by placing focus on human-centricity and empirically exploring adoption of I5.0 through its human counterparts. Thus, I5.0 drones can improve sustainable agriculture through the practice of precision agriculture generated from real-time data of crop and soil moisture conditions. From the findings we can infer that the data generated by I5.0 drones can inform decision-making such as planting schedules, precision pesticide application and pollution reduction. This can provide valuable guidance for sustainable farming practices and more resilient Agri-Supply chains.

Further, the empirical testing the sustainability model demonstrates an approach to understanding how I5.0 drones can be used in ensuring sustainable operations in agricultural supply chain. However, the unsupported hypothesised relationships (Pollution reduction, seeding accuracy, prediction accuracy and workers health and safety challenges may indicate the need to address other factors including financial and cultural approach. As such adapting the model to accommodate different economies may be beneficial.

5.2 Practical implications

This research explored supply chain stakeholders' intention to adopt I5.0 drones based on a sample of 264 farmers. A questionnaire developed from the extant literature was distributed across farms in Nigeria, with a majority of stakeholders highlighting their willingness to adopt the drones to minimise plant disease. However, to maximise the benefits of I5.0 drones, there is a need for more research and awareness of the benefits of such technologies whilst also educating farmers on health and safety, how it can assist in proactive planning and better prediction accuracy and in particular on the benefits of using I5.0 for precision pesticides, which can minimise pollution and other associated adverse effects resulting from its excessive use. These key factors were not seen as influencing factors for the stakeholders. Accordingly, the following recommendations are proposed:

Firstly, there is a need for the Federal Ministry of Agriculture and Rural Development to commission further research about the economic and societal benefits for Nigeria associated with plant diseases across agricultural settings. This factor was seen to influence adoption intention. Yet, limited research has been conducted on the economic and ecological benefits resulting from reduced pollution (pesticides) and plant disease for Nigeria's agriculture production. Moreover, further evidence on the broader benefits of increased seeding accuracy and the impact of having better yield predictions would provide further impetus for adopting I5.0 drones among supply chain stakeholders. As this research has indicated these as influencing factors towards adopting I5.0 drones, more effort should be placed to understand how this can be operationalised within the farms.

Secondly, this research revealed that farmers were not interested in adopting I5.0 drones, despite acknowledging it may assist with health and safety-related challenges. Based on the findings, this can be attributed to the fact that the farmers fail to see the importance of health and safety and see economic benefits as priority. Moreover, the findings also indicated that despite acknowledging the role of I5.0 drones in offering more precise and accurate pesticides application, farmers failed to acknowledge the connection between the precision application and personal health and safety. Thus, it is proposed that the Federal Ministry of Agriculture & Rural Development and other agricultural agencies disseminate factual evidence regarding the adverse health effects of pesticide exposure. The findings also suggest that the stakeholders appreciate the role of I5.0 drones in reducing pollution, yet this was insufficient in influencing their uptake of drones. Therefore, more information needs to be shared with farmers to be aware of the practical economic and societal benefits of reducing pollution.

Thirdly, many farmers in developing and emerging countries face technology and credit market inadequacies, leading to financial constraints when adopting new forms of technology. Hence, the government should bolster research and development spending across agriculture to offer training and make the uptake of I5.0 drones accessible and affordable to farmers. Handheld sprayers are one of the most common methods of applying pesticides and are considerably cheaper and require little to no training. In other words, without government support schemes and financial support, the uptake of such innovative solutions in the form of I5.0 will always be impractical and too costly to implement.

6.0 Conclusion, limitations, and future research

Mendoza et al. (2021) have previously highlighted that the contradicting views and perspectives surrounding drones has slowed the rate of adoption and integration within public, governmental and commercial settings. Accordingly, this research set out to explore factors that influence the adoption of I5.0 drones among supply chain stakeholders from an emerging economy. In doing so, this research reveals the significance of utilising I5.0 drones for the precision treatment of plant disease as a critical factor in influencing the uptake of I5.0 drones among Nigerian supply chain stakeholders. Moreover, the research revealed how health and safety, and pollution reduction were not influencing factors. These findings offer a potentially vital precedent for agricultural stakeholders, such as farmers, policymakers, and food producers in emerging economies pursuing smart farming and intelligent systems for agricultural operations. The findings from this research can inform food producers and policymakers of the opportunities and challenges of implementing I5.0 drones.

In conclusion, the agricultural practice requires technological advancement in all spheres of its operations. However, human capital remains crucial in introducing and adopting technology in this context. Nigeria remains Africa's most populous country, with 30% of its population engaged in agricultural-related activities (UNICEF 2018). As mentioned earlier, there may be issues with technology adoption if the aspects of human capital development are neglected. Human capital has enormous potential in Nigeria; a careful integration of technology with due consideration of the human factor will be necessary for its advancement within this context.

Despite the valuable contributions resulting from this research, we must also acknowledge the limitations. Firstly, the sample size for this research was 264; thus, to validate the robustness of the results even further, this research should be replicated with a more significant and more representative sample.

In designing the sustainability model used in this study, we did not consider various variables including perceived usefulness, perceived ease of use, trust, compatibility, and other behavioural factors. As such, future studies should augment the model to include these variables. Moreover, while the purpose of the study was to explore drone adoption in Nigeria, many supply chain stakeholders in developing and emerging countries have limited exposure and awareness of drone technologies. It may have influenced their responses to the survey questions. Additionally, drone applications in agriculture are in their infancy, regardless of the economic status of countries. Therefore, to further validate the findings of this research, it is suggested that this research be conducted across other emerging economies and developed economies.

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Appendix A: Defining constructs

Items	Description	Source
Drones' application DA1 DA2 DA3 DA4 DA5 DA6 DA7 DA8	 I5.0 drones will lead to lower environmental impacts. I5.0 drones will lead to significant management changes. I5.0 drones will lead to improvements in crop quality. I5.0 drones will lead to a higher yield. I5.0 drones will lead to lower production costs. I5.0 drones will lead to a higher market share for the company. I5.0 drones will lead to compliance with regulations related to the domestic market. I5.0 drones will lead to compliance with regulations related to the international market	Silva et al. (2011); Tey et al., (2012); Barnes et al., (2019)
Stakeholder's intention to use FA1 FA2 FA3 FA4 FA5 FA6 FA7 FA10	 I consider myself a progressive farmer. I like to try new agricultural technologies or practices. I actively seek new information from others. I like new ideas in general. Other stakeholders think I am a progressive farmer Other stakeholders ask my opinions about agricultural technologies. Other stakeholders will not object to how I produce rice on my fields I can adopt new agricultural technologies which are profitable.	Yamano et al. 2015
Seeding accuracy SA1 SA2 SA3 SA4 SA5	 Aerial seeding can accelerate seeding process. Using a helicopter or plane for aerial seeding is expensive. Using a plane or helicopter for aerial seeding requires large amount of seeds Seeding is labour intensive. Seeding process needs special skills	Elliot (2016). Diwate et al. (2018)
Predictions Accuracy PA2 PA3 PA4 PA5	 If my plants have become pest resistant, I still continue to use excessive amounts of pesticides If I spray less, my income will be reduced. If I use pesticides, this leads me to a favourable result, i.e., increased production If I use pesticide spraying, my farm revenue will sustain	Liu and Huang (2013)
Plant disease PD1 PD2 PD3 PD4 PD5	 I believe pesticides are harmful to healthy crops (non-infested by pests) I believe pesticides residues contaminate crops. I can recognise the most common plant disease in my farm I use chemical as well as non-chemical methods to reverse crop disease	Bagheri et al (2019)

	The current methods used are effective in protecting crops	
Pesticide hazard PH1 PH2 PH4	 I apply the rates indicated on the product label. I use the product with the frequency indicated on the label I believe pesticides affect the environment	Lithourgidis et al. (2016)
Pollution reduction PR1 PR2	 My farming methods will not harm the environment. I am willing to treat pollution	Pan et al. (2016)
Workers' health and safety WHS2 WHS5	I have experienced skin-related problems (such as rash, itching, discoloration) from work during the past 12 months. After pesticides and agrochemicals, I experience either one or more of the following symptoms; dizziness, vomiting, pain and a burning feeling in the face and eyes after spraying	Román-Muñiz et al. 2006 Lunner-Kolstrup and Ssali (2016)

Appendix B: Structural Path Analysis

Path constructs	Effects	T value
Pesticide hazard → Plant diseases → Stakeholders' intention	0.071	1.924
Drones' applications → Pesticide hazard →Workers' Health and Safety→Stakeholders' intention	-0.002	0.168
Drones' applications → Pesticide hazard → Predictions Accuracy →Stakeholders' intention	0.007	0.737
Pesticide hazard → Predictions Accuracy →Stakeholders' intention	0.023	0.777
Drones' applications → Pesticide hazard → Seeding accuracy →Stakeholders' intention	0.005	0.309
Drones' applications → Pesticide hazard →Workers' Health and Safety	0.091	3.805**
Drones' applications → Pesticide hazard → Seeding accuracy	0.139	3.992**
Drones' applications → Pesticide hazard → Pollution →Stakeholders' intention	0.008	1.084
Drones' applications → Pesticide hazard → Pollution	0.072	3.237*
Drones' applications →Workers' Health and Safety →Stakeholders' intention	-0.007	0.184
Pesticide hazard →Workers' Health and Safety →Stakeholders' intention	-0.005	0.179
Pesticide hazard → Pollution →Stakeholders' intention	0.025	1.163
Pesticide hazard → Seeding accuracy →Stakeholders' intention	0.018	0.339
Drones' applications → Pesticide hazard → Plant diseases	0.178	5.208**
Drones' applications → Pesticide hazard → Plant diseases →Stakeholders' intention	0.021	1.739*
Drones' applications → Pesticide hazard → Predictions Accuracy	0.099	3.779**

[Note: Significance: ***p<0.01, **p<0.05, *p<0.10]