The integration of digital technology in agriculture: smart farming adoption strategy in Indonesian farming communities

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Abstract. Data from the Central Statistics Agency (BPS) 28.64% of Indonesia's labor force was engaged in the agricultural sector in the first quarter of 2024, and this sector remains a primary source of livelihood for a large portion of the population. Despite its importance, the agricultural industry continues to face various challenges, including low productivity, limited access to modern technology, and the risk of ongoing food insecurity. Research attempts to analyze strategies for integrating digital technology into agricultural practices through the concept of smart farming. Adopting digital tools is viewed as a strategic effort to enhance operational efficiency, boost productivity, and ensure more sustainable management of natural resources. This research, conducted in West Java, employed a quantitative approach and involved 135 farmers from various agricultural groups. Structural Equation Modeling Partial Least Squares analyzed data. The research results indicated that farmers' characteristics, innovation attributes, external environmental support, and learning intensity significantly affect both the intention to adopt and the actual adoption of smart farming, thereby enhancing farm sustainability. It provided valuable insights for policymakers and stakeholders to develop technology-oriented training, extension services, and support programs aimed at boosting competitiveness and advancing digital transformation in Indonesia's agricultural sector.

1 Introduction

The agricultural sector remains a vital foundation of the Indonesian economy, as most rural communities depend on agriculture for their livelihoods. However, various challenges, such

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as productivity stagnation, limited access to technology, climate change, land degradation, and low supply chain efficiency, mean that this sector needs to transform. Amid global change and the Fifth Industrial Revolution, the integration of digital technologies has become an urgent imperative. Smart farming is considered an approach capable of overcoming structural challenges in Indonesian agriculture through the use of the Internet of Things (IoT), smart sensors, big data, artificial intelligence (AI), drones, and digitally based monitoring systems. Smart farming technologies, such as IoT sensors, drones, and AI-based analytics, play a vital role in improving decision-making accuracy, optimizing resource use, and increasing overall agricultural productivity [1]. According to Rogers' (2003) Diffusion of Innovations theory, the success of innovation adoption is heavily influenced by five innovation attributes: relative advantage, compatibility, complexity, trialability, and observability.

This theory has been the foundation for understanding how farmers evaluate and decide whether digital technology is worth adopting. In the context of digital agriculture, relative advantages such as increased yields, ease of land monitoring, and cost efficiency are important factors. Conversely, the level of technological complexity can hinder adoption, especially for farmers with low levels of digital literacy. Several international research studies have shown that digital technology can improve the effectiveness of production systems. For instance, research published in Computers and Electronics in Agriculture found that the use of IoT sensors and precision data analysis can increase water and fertilizer efficiency by more than 20%. Meanwhile, Agricultural Systems emphasizes that digital transformation in agriculture is not only about technology, but also requires institutional support, training, and the involvement of local actors for the adoption process to run effectively[2]. These findings are highly relevant in the Indonesian context, where the learning capacity of farmers and agricultural community institutions has played a crucial role in accelerating the diffusion of innovation.

Research also highlights the low level of adoption of digital agricultural technology in developing countries. The main barriers to the adoption of digital technology among smallholder farmers include limited infrastructure, investment costs, and low technological literacy. Another research published in Precision Agriculture states that risk perception and low trust in new technology. They also influence adoption decisions. It suggests that the successful integration of smart farming in Indonesia must account for the social, economic, and psychological factors of farmers. Research findings in Agricultural Economics also reinforce that group learning and field demonstrations increase farmers' chances of trying digital technologies due to social trust and tangible examples of success.

Besides internal community factors, external environments such as government policies, support from agricultural extension officers, availability of internet networks, and the agritech ecosystem also have significant impacts. According to research in the Journal of Rural Studies, the adoption of digital technology in the agricultural sector is strongly influenced by the presence of an innovation ecosystem involving collaboration between the government, universities, the private sector, and the local community. The Indonesian government itself has initiated various agricultural digitalization programs, such as the Agriculture War Room, a price information platform, and support for agritech startups. However, as with Sustainability, program availability is no guarantee of success; user readiness is a determining factor in implementation [3]. Therefore, technology-based training and demonstrations on the use of digital devices need to be strengthened at the village level.

Innovation attributes also have a significant influence on farmers' perceptions. Technologies that are considered too expensive or unsuitable for local conditions tend to be rejected. This aligns with research published in Food Policy, which suggests that the sustained adoption of digital technology in developing countries depends on its ability to adapt to the socio-economic context of end-users. Therefore, the development of smart farming in Indonesia must take into account local needs, commodity types, agroecological conditions, and farmers' ability to operate the technology [4]. Given the various challenges and opportunities, it is important to conduct comprehensive research on digital technology adoption strategies in Indonesian agricultural communities. In-depth analysis can identify how farmer characteristics, innovation attributes, external environmental support, and learning intensity influence the intention and level of smart farming adoption. Such research not only contributes to academic literature but also provides practical recommendations for governments, extension workers, and other stakeholders in designing more effective policies and programs.

This research was conducted due to the limited number of scientific reports on the influencing factors and adoption strategies of smart farming technologies among horticultural and rice farmers in Indonesia. Despite this gap in the literature, smart farming technologies have already been implemented by farmers in West Java. Horticultural farmers who use Smart Farming technology in the form of “Habibi Garden” technology have implemented it by farmers in the villages of Cibodas, Cipendawa, Panondaan, Ciherang, and Warna Sari. Smart Farming technology in the form of the Internet of Things has also been implemented by crop farmers in the villages of Cipacing, Warga Mekar, Cigantang, Mandalawangi, and Batu Sela. Haiwell Smart Farming tools are located in the villages of Kerta Jaya, Ciseureuh, Cijambe Girang, Alamendah, Lebak Muncang, Pangadegan, and Galungpit. Netafim Smart Farming tools are located in Cipendawa and Dago villages. Meanwhile, NSC Pro Smart Farming tools are located in Cibeureum, Pangalengan, Laksana, Mandalawangi, and Cikidang villages. Rice farmers who use Smart Farming technology in the form of Ritx Soil and Weather Sensors are located in Cikembulan.

Overall, the integration of digital technology is a strategic imperative to strengthen Indonesia's agricultural sector against global challenges such as climate change, rising food demand, and international market competition. Through evidence-based strategies, digital transformation can optimize efficiency, sustainability, and farmers' welfare. By addressing the factors that influence smart farming adoption, Indonesia can accelerate the transition toward a modern agricultural system that is both inclusive and highly competitive.

2 Research method

This research was conducted in West Java province. Horticultural farmers who use Smart Farming technology in the form of “Habibi Garden” technology have implemented it by farmers in the villages of Cibodas, Cipendawa, Panondaan, Ciherang, and Warna Sari. Smart Farming technology in the form of the Internet of Things Smart Farming has also been implemented by crop farmers in the villages of Cipacing, Warga Mekar, Cigantang, Mandalawangi, and Batu Sela. Haiwell Smart Farming tools are located in the villages of Kerta Jaya, Ciseureuh, Cijambe Girang, Alamendah, Lebak Muncang, Pangadegan, and Galungpit. Netafim Smart Farming tools are located in Cipendawa and Dago villages. Meanwhile, NSC Pro Smart Farming tools are located in Cibeureum, Pangalengan, Laksana, Mandalawangi, and Cikidang villages. Rice farmers who use Smart Farming technology in the form of Ritx Soil and Weather Sensors are located in Cikembulan.

This research used a positivist paradigm with a quantitative approach. Qualitative data support it. It was conducted using the survey method. The survey method is a research technique that involves selecting samples from a population and utilizing questionnaires as the primary data collection tool. The qualitative approach involved in-depth interviews with members of farmer groups, extension workers, and experts in Smart Farming. 48 farmers used the Habibi Garden tool, 11 farmers used the Ritx soil and weather sensor, 17 farmers used the Internet of Things, 11 farmers used Haiwell IoT, 16 farmers used Netafim, and 32 farmers used NSC Pro. The total number of farmers actively using Smart Farming tools is

135. The data were analyzed using Structural Equation Modeling (SEM) with a Partial Least Squares (SEM-PLS) approach to examine causal relationships among latent variables in the research model. The analysis included testing the measurement model to assess construct validity and reliability, and the structural model to evaluate relationships among variables and test research hypotheses, using bootstrapping techniques. This method was chosen because it is suitable for small samples and for data that are not normally distributed.

3 Results and discussion

3.1 Characteristics of farmers using smart farming technology

The initial stage of descriptive analysis was carried out by examining the frequency and percentage of respondents' answers to each statement in the questionnaires. This process aims to provide a general overview of the emerging response trends, allowing researchers to identify dominant patterns and the distribution of answers across various scale categories. after that, the data are summarized to show respondents' responses to each item. This research involved 135 respondents as the primary data source. To understand the characteristics of the participants were conducted by an identity analysis that based on demographic categories and other relevant aspects, so that the respondents' backgrounds could provide context in interpreting the research results.

Age is the length of time that a person, animal, or object has lived since birth, creation, or manufacture until a certain point in time (usually the present). It is usually measured in years, but can also be measured in months, days, or other units of time, depending on the context. Age is the period of an individual's life calculated from the time of birth to a certain point in time and is the basis for grouping individuals into specific stages of development. The majority of respondents fall into the middle adulthood category (30–50 years), accounting for 106 individuals (80.00%). Early adulthood (18–29 years) represented 12 respondents (8.89%), while 15 respondents (11.11%) were in the late adulthood group (over 50 years). The dominance of the 30–50 age bracket suggests that this productive group was the most active in Smart Farming–based agricultural activities, whereas younger (18–29 years) and older (over 50 years) groups represent only a small fraction of the total participants."

The highest level of formal education refers to the most advanced stage of schooling completed by an individual within a structured and government-recognized national education system. Pursuant to Law No. 20 of 2003 concerning the National Education System, formal education in Indonesia comprises primary, secondary, and higher education."The distribution of the education levels of 135 respondents divided into four categories: elementary school (32.59%), junior high school (9.63%), senior high school (48.89%), and higher education (8.89%). The majority of respondents had a senior high school education, namely 48.89% or 66 people. This condition reflects reasonably good access to secondary education, as well as relatively adequate literacy and numeracy skills within the community.

Farming experience refers to the length of time a person has been actively involved in agricultural activities, including land cultivation, planting, maintenance, harvesting, and marketing of produce. 135 respondents were divided into three categories of experience: less than 1 year, 1–5 years, and more than 5 years. The data shows a very large dominance in the intermediate experience category, namely 1–5 years. A total of 124 respondents (91.85%) had farming experience between 1 and 5 years. This dominance indicates that most farmers are still at the beginner-intermediate stage. This condition may reflect the development of farming activities in the last five years, the existence of new agricultural programs, or a generational shift among farmers in the region. The high concentration in a specific experience range may also indicate the expansion of the agricultural sector during a specific period. Only 7 respondents (5.19%) had less than 1 year of experience, indicating a low level of new farmer entry or a slow regeneration process. Meanwhile, only 4 people (2.96%) had more than 5 years of experience. This very small number may reflect a decline in senior farmers, possible career changes, or a lack of interest and support for long-term farming.

Land ownership refers to the area of agricultural land controlled or owned by farmers through various mechanisms, such as direct ownership, leases, crop-sharing, or loans, used to run their farming businesses. Land ownership encompasses all land that farmers can cultivate, whether owned individually or through collaboration with other parties. Land ownership is a crucial aspect because it determines production capacity and opportunities for farming development. Based on the table, the 135 respondents were divided into three land area categories: small land (<1,000 m²), medium land (>1,000–5,000 m²), and large land (>5,000 m²). This distribution demonstrates the inverted pyramid pattern common in Indonesia's agrarian structure, with the majority of farmers belonging to the small-land group.

Non-formal education is a form of education provided outside the formal education system, to meet the learning needs of the community, either for personal development, improving job skills, or strengthening social life. It is flexible in terms of time, place, and learning methods, and does not require a specific level of education. The level of respondent participation in non-formal education is dominated by the low category, with 104 participants (77.04%) receiving 1–2 training sessions. This indicates that most respondents received only basic training, likely due to limited access, cost, or opportunities for advanced training. Furthermore, minimal training is often a prerequisite before participating in certain activities. The medium category (3–4 training sessions) was attended by 12 participants (8.89%), while the high category (5–6 training sessions) was attended by 18 participants (13.33%). Only one person (0.74%) had never attended non-formal education but still acquired skills through direct mentoring from more experienced farmers. This finding suggests that, despite widespread participation, training intensity remains relatively low.

Land ownership refers to the total agricultural land area controlled and/or owned by a farmer or a farm household, whether through direct ownership, leasing, sharecropping, loans, or other forms of tenure that is utilized for agricultural activities. The table shows the distribution of land ownership among 135 respondents, divided into three categories: small land (<1000 m²), medium land (>1000-5000 m²), and large land (>5000 m²). The distribution shows an inverted pyramid pattern typical of Indonesia's agrarian structure. The majority of respondents owned land of <1000 m² (0.01-0.1 hectares), indicating the characteristics of smallholder farmers: by definition, land <0.5 ha is limited to commercial scale. This composition illustrates that most of the farmers who responded still face limited physical assets in the form of land, which is an important factor in the success of farming businesses.

Respondent characteristics included cosmopolitanism, farming motivation, Smart Farming knowledge, attitudes toward Smart Farming, and business capital ownership. Cosmopolitanism had a mean score of 3.45, categorized as high, with a standard deviation of 0.46. This low variation indicates that most farmers share a similar level of openness to the outside world, characterized by good access to information and fairly extensive connections beyond the village. Farming motivation had a mean score of 3.49, categorized as high, and was the aspect with the highest average score. The standard deviation of 0.51 indicates a relatively narrow distribution of scores, indicating that farmers' motivation to farm is relatively even and strong. This reflects strong mental readiness and internal drive to increase productivity.

Knowledge of Smart Farming yielded a mean score of 3.00, falling into the 'moderate' category, with a standard deviation of 0.75. The high variation in scores suggests a significant knowledge gap; while some farmers possess a solid grasp of Smart Farming concepts, others have minimal understanding. This finding underscores the necessity of enhancing digital literacy and technical proficiency in modern agriculture. Attitudes toward Smart Farming had a mean of 3.24 and were categorized as moderate, with a standard deviation of 0.55. Although knowledge is not yet high, relatively positive attitudes indicate significant potential for technology adoption with further training, mentoring, or outreach. Business capital ownership had a mean of 2.53 and was categorized as moderate, with a standard deviation of 0.77, indicating significant variation among farmers. A small percentage of farmers had adequate capital, but the majority still faced limitations.

Knowledge of Smart Farming includes an understanding of the application of digital technology in agriculture to improve efficiency, productivity, and sustainability. Smart Farming utilizes information and communication technologies, including the Internet of Things (IoT), big data, and artificial intelligence (AI), to support more accurate decision-making and reduce environmental impact. The results of the study show that farmers' level of knowledge about Smart Farming is at an average of 3.01, which is categorized as moderate. The mode of 3 reinforces that most of the respondents' answers are at a medium level of understanding. The standard deviation of 0.75 indicates that there is variation.

The results of the descriptive analysis of 135 respondents indicate that the majority of farmers are in middle adulthood (30–50 years) with formal education predominantly at the high school level, 1–5 years of farming experience, and small land ownership (<1,000 m^2), reflecting the characteristics of small-scale farmers who are still at the early–intermediate stage. Participation in non-formal education is relatively low, knowledge and attitudes toward Smart Farming are moderate, while farming motivation and openness to information (cosmopolitanism) are high; however, capital ownership varies and is mostly limited. This condition indicates significant potential to improve productivity and adopt modern agricultural technologies through training, mentoring, and capital support.

3.2 Factors influencing the adoption of smart farming technology

Statistical analysis Table 1 reveals that farmer characteristics have a positive and significant effect on the level of innovation adoption. These findings suggest that personal factors such as age, formal education, farming experience, farm size, and openness to information play a crucial role in determining a farmer's readiness to adopt new technologies. Farmers with higher education levels or extensive experience tend to possess superior cognitive and analytical skills, enabling them to better assess the benefits and risks of innovation and, consequently, make faster adoption decisions

These findings are consistent with various studies that indicate that individual characteristics are an important foundation in the process of innovation diffusion [5]. The relationship between variables and the level of adoption that has a significant effect shows that the better the characteristics of farmers (age, experience, education), the higher the level of innovation adoption. Positive perceptions of innovation encourage increased adoption, external support (policies, institutions, markets) increases adoption, and farmers who actively learn adopt innovations more quickly. Testing farmer characteristics against innovation adoption shows that farmer characteristics have a positive and significant effect on innovation adoption. Psychological and sociodemographic factors, such as education level and proactivity in obtaining information, significantly influence farmers' propensity to adopt innovations [6].

Farmers' perceptions of innovation characteristics are a major factor in the adoption of Smart Farming. Attributes such as ease of use (complexity), relative advantage, compatibility with local conditions, observability, and trialability determine the level of acceptance. If innovations are considered useful, easy to implement, and compatible with farmers' resources and land, adoption increases significantly. These findings support Rogers' theory of innovation diffusion, which emphasizes that perceptions of innovation attributes greatly determine adoption decisions. Previous studies have also shown the direct influence of these attributes on the adoption of agricultural technology. Each of these aspects determines how quickly and to what extent innovations are adopted. Specific innovation characteristics, such as relative advantage and compatibility, significantly increase the likelihood of sustainable innovation adoption among farmers.

External environmental support, encompassing market access, production facilities, government policies, and supporting institutions exert a positive influence on technology adoption. The conducive environment incentivizes farmers to embrace innovation; for instance, guaranteed market access motivates the adoption of technology to enhance both crop quality and yield. Furthermore, institutional infrastructure facilitates better access to inputs and information, thereby streamlining the adoption process. Empirical research in Shaanxi Province (China) found that institutional support and market access significantly influence farmers' adoption of environmentally friendly production technologies [7]. Institutional support helps farmers gain access to high-value markets, thereby increasing technology adoption. The data can be seen in Table 1.

Table 1. T-statistic test of SEM-PLS model

Relationships Between Variables	Coefficient Path	T Statistics	P Values	Description
Farmer characteristics →Adoption rate	0.295	2.345	0.019*	Significant positive
Farmers' perceptions of innovation characteristics→Adoption rate	0.372	2.402	0.017*	Significant positive
Extension support→Adoption rate	0.046	0.701	0.484	Not Significant
External environmental support→Adoption rate	0.135	2.215	0.027*	Significant positive
Farmer learning intensity level→Adoption level	0.159	2.137	0.033*	Significant positive
Media exposure→Adoption rate	-0.055	0.951	0.342	Not Significant

The level of learning intensity among farmers has a significant and positive effect on the adoption of Smart Farming. The more often farmers participate in learning activities such as field schools, farmer groups, comparative studies, or discussions with extension workers, the greater the knowledge and technical skills they acquire. This learning process reduces uncertainty and risk perception, increasing farmers' confidence to adopt innovations. These findings emphasize the importance of capacity building and facilitating conditions, such as training and technical support, as significant factors that drive farmers' intentions and acceptance of modern agricultural technologies [8]. In a recent study in South Korea on farmers' motivation to adopt smart-farm technology, the author shows that training programs and government programs, along with other support (e.g., financial assistance + education/digital training), play an important role in increasing technology adoption .

The results show that extension worker support and media exposure do not significantly influence the adoption of Smart Farming. The insignificance of extension worker support may be due to insufficient frequency of assistance, inappropriate extension methods, or irrelevant and inapplicable materials. Previous studies have also found that the interaction between extension services and social networks can have a negative impact if farmers trust social networks more than extension workers . A study in Zimbabwe found that structural weaknesses such as underfunding, limited resources, and extension worker mobility undermine the effectiveness of extension services, which ultimately reduces adoption rates among farmers.

Media exposure has no significant effect on the adoption of Smart Farming, indicating that the information received by farmers is not in-depth or contextual. Rural farmers need direct, visual, and demonstrative media, while public or digital media is often insufficient to change farming practices. These results confirm that the current type and delivery of information are ineffective at encouraging changes in farmer behavior. These findings reveal that although farmers are exposed to various media sources, the level of media exposure does not significantly influence their decision to adopt Smart Farming, possibly because the media used is not contextual or applicable.

3.3 Effective Smart Farming 4.0 adoption strategies to support farming sustainability

Strategies to enhance the adoption of Smart Farming innovations are based on the factors that influence the adoption process. The results of the Partial Least Squares (PLS) analysis indicate that the level of Smart Farming adoption is significantly affected by four key factors: farmer characteristics, farmer perceptions, external environmental support, and the intensity of farmer learning. Farmer characteristics include age, level of formal education, participation in non-formal education, land ownership, farming experience, level of cosmopolitanism, business motivation, knowledge of Smart Farming, attitudes toward Smart Farming, and capital ownership. Farmers' perceptions of innovation characteristics encompass relative advantage, complexity, compatibility, trialability, and ease of use. Meanwhile, external environmental support comprises government policies, farmer institutions, access to finance, market capacity, availability of information, agricultural production facilities, physical environmental conditions, and internet services.

Empirical research in Korea indicates that farmers' adoption of smart farms is strongly influenced by technological compatibility (the extent to which the technology fits existing agricultural systems), organizational costs, and changes in the surrounding digital environment (e.g., digital infrastructure, internet access) [9]. These factors are among the external and technological factors that have been statistically shown to significantly support the adoption of Smart Farming. Another study in the context of greenhouse farming in Kenya found that "farm factors" (e.g., land characteristics), farmers' perceptions of technology, product/technology factors, and environmental factors were positively and significantly associated with the adoption of agricultural IoT technology. This supports the notion that land characteristics and external conditions, such as access to facilities, infrastructure, and environmental conditions, influence farmers' decisions to adopt innovations. A recent literature review shows that the adoption of Smart Farming is influenced by farmers' dispositional and socio-demographic aspects: for example, land size, land ownership, and capital ownership. Farmers who own larger land areas and have adequate capital tend to find it easier to adopt Smart Farming technology. In addition, the literature mentions that incompatibility between innovations and local conditions (e.g., existing cultivation systems, social characteristics, customs) can hinder adoption. The level of farmer learning intensity includes: variety of learning methods, suitability of learning materials, frequency of learning, variety of information sources, intensity of interaction within groups, and intensity of interaction with learning resources. Meanwhile, factors that influence the sustainability of farming businesses include farmer perceptions, external environmental support, and farmer intensity levels.

Farmers are able to adopt actively and utilize Smart Farming innovations in their agricultural activities now. These adoptions are supported by increased competence, active learning, and support from the external environment, such as the government, related institutions, finance, and technology. As stated in the review study, the combination of technologies such as the Internet of Things (IoT), artificial intelligence (AI), drones, and data-based systems can transform agricultural practices to be more efficient and sustainable [10]. The implementation of Smart Farming by farmers is effective: farmers are not only familiar with the technology, but are also able to apply it in their daily activities. They can operate digital devices, sensors, applications, or automation systems that support cultivation.

This is in line with findings that IoT-based systems can improve efficiency in monitoring soil conditions, humidity, temperature, and other environmental factors, then recommend precise irrigation and fertilization times, which in turn reduceoperational costs and increase productivity [11]. More and more farmers are trying to implement this technology, indicating that the adoption of Smart Farming is increasing significantly, a sign that this technology is considered useful, easy to use, and relevant to their needs. Thus, the strategy offered is to improve farmer characteristics, farmer perceptions, external environmental support, and farmer learning intensity. The strategy for increasing the adoption of Smart Farming technology innovations was developed using a logic model consisting of inputs, processes, outputs, and outcomes. The inputs for a Smart Farming adoption strategy encompass various factors that influence farmers' readiness and their decisions to embrace new technologies. These include individual characteristics such as age, education, experience, motivation, attitude, and capital, which collectively determine their capacity to understand and implement innovations. Furthermore, farmers' perceptions regarding the benefits, ease of use, risk levels, and relevance of the technology to their specific needs significantly shape their interest in adoption. External factors, such as government policy, digital infrastructure, access to financing, extension support, and market conditions, also play a role in accelerating technology adoption. The intensity of learning through training, farmer groups, or access to digital information further strengthens farmers' ability to understand Smart Farming. These four aspects form a crucial foundation for designing effective and sustainable adoption strategies. Figure 1: Strategy adoption Smart Farming.

The characteristics of farmers themselves describe the personal, social, and economic conditions that influence their readiness to accept innovation. Formal and Non-formal education help farmers understand technical information, while age and farming experience can influence openness to change. Land area and capital determine the economic feasibility of implementing technology, while the level of cosmopolitanism reflects how connected farmers are to modern sources of information. Motivation, knowledge, and attitudes toward Smart Farming also influence their initial ability to assess the benefits and challenges of technology. In Generally, highly motivated farmers who have adequate knowledge and are technologically literate will be quicker to adopt digital agriculture.

Farmers' perceptions of the characteristics of Smart Farming innovations are also a key factor in adoption. Assessments of relative benefits, level of complexity, suitability to local conditions, opportunities for trial, and ease of observing the results of implementation will determine the likelihood of adoption. This technology enables real-time monitoring of land and crop conditions, allowing for more accurate, measurable, and data-driven decisions on when to plant, water, fertilize, control pests, and estimate harvests.

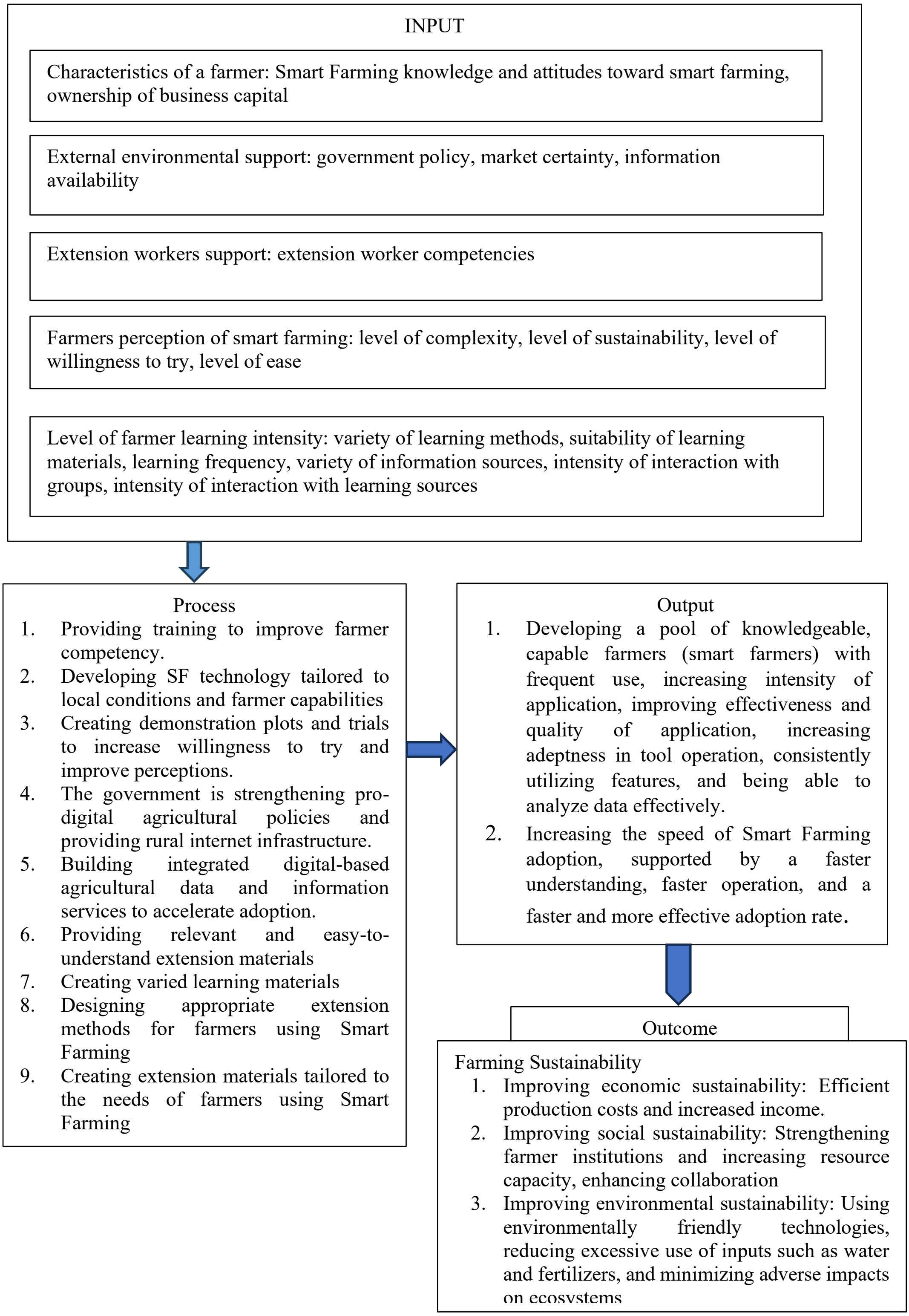

Fig. 1. Smart farming technology innovation adoption strategy

Research shows that the integration of IoT and data analytics can result in more efficient use of resources such as water and fertilizer, reduce waste, and lessen environmental impact while increasing crop yields and productivity. This provides tangible benefits: production costs are reduced, resources are used more efficiently and effectively, and agricultural productivity increases while maintaining environmental sustainability. The data can be seen in Table 2.

Table 2. Input components in the adoption of smart farming innovation

Input Components	Main Focus	Role in Smart Farming Adoption
Characteristics of Farmers	Personal & socio-economic profile	Determining the readiness and basic capacity of farmers
Perception of Innovation	Views and attitudes towards technology	Determining the level of acceptance and intention to adopt
External Environmental Support	Institutional, policy, and infrastructure factors	Providing a supporting ecosystem for SF implementation
Farmer Learning Intensity	Learning activities and interactions	Accelerating the understanding and diffusion of innovation

The process of developing the Smart Farming adoption strategy involves a series of interconnected steps designed to enhance farmer readiness, capability, and motivation while strengthening the supporting environment. Data can be seen in Figure 2. These efforts include capacity building through technical training, field mentoring, and digital workshops aimed at helping farmers master modern agricultural tools and applications. Furthermore, motivation is reinforced by showcasing success stories, granting awards, and providing empirical evidence of technological benefits to build farmers' confidence. Additionally, improving formal education such as through the 'Package C' equivalency program, is crucial for expanding literacy and analytical skills, thereby increasing farmers' receptiveness to innovation.

An empirical study in Smart Farming Revolution: Farmer's Perception and Adoption of Smart IoT Technologies for Crop Health Monitoring and Yield Prediction in Jizan, shows that factors such as access to information, training, and perceptions of government support are significantly and positively correlated with farmers' willingness to adopt agricultural IoT technology [12]. This supports the idea that technical training, knowledge provision, and motivational reinforcement through external information and support can encourage the adoption of Smart Farming..Another supporting aspect is ensuring farmers have access to capital and technical assistance. This is done through microcredit schemes, agricultural credit (KUR) financing, equipment subsidies, and assistance from extension workers and technical personnel.

This strategy enables farmers to overcome cost constraints and operational difficulties in implementing Smart Farming. Furthermore, technology development tailored to local conditions, such as simple, affordable tools, offline applications, and locally based sensors, is being undertaken to make the technology easier to understand and implement. Field trials and demonstration plots are also being established to provide concrete evidence of the technology's benefits, thereby increasing farmers' perceptions and willingness to try it. A meta-analysis in Ethiopia found that access to agricultural credit is significantly positively correlated with agricultural technology adoption, meaning access to capital helps farmers overcome financial barriers to adopting new technologies. However, results from a randomized trial among rice farmers in Tanzania indicate that access to micro-credit alone is not sufficient to guarantee the adoption of agricultural technology and increased productivity, suggesting that "technological capital" must be complemented by aspects of mentoring, training, and social and technical readiness.

In terms of policies and supporting ecosystems, the government plays a role by strengthening pro-digital agricultural regulations, providing rural internet infrastructure, and programs such as Digital Villages or Smart Villages. Furthermore, farmer institutions are being strengthened to become centers for the dissemination of innovation through the formation of digital farmer communities, organizational management training, and the revitalization of farmer groups (gapoktan) and cooperatives. The involvement of the financial and private sectors also encourages adoption by providing soft loans, public-private partnership investments, and data-driven agricultural insurance. At the same time, an integrated agricultural data system is being developed to provide fast, accurate, and easily accessible information services to farmers. To strengthen the learning process, extension services are structured in simple and contextual materials that are easy for farmers to understand, such as local-language modules, practical videos, and digital leaflets.

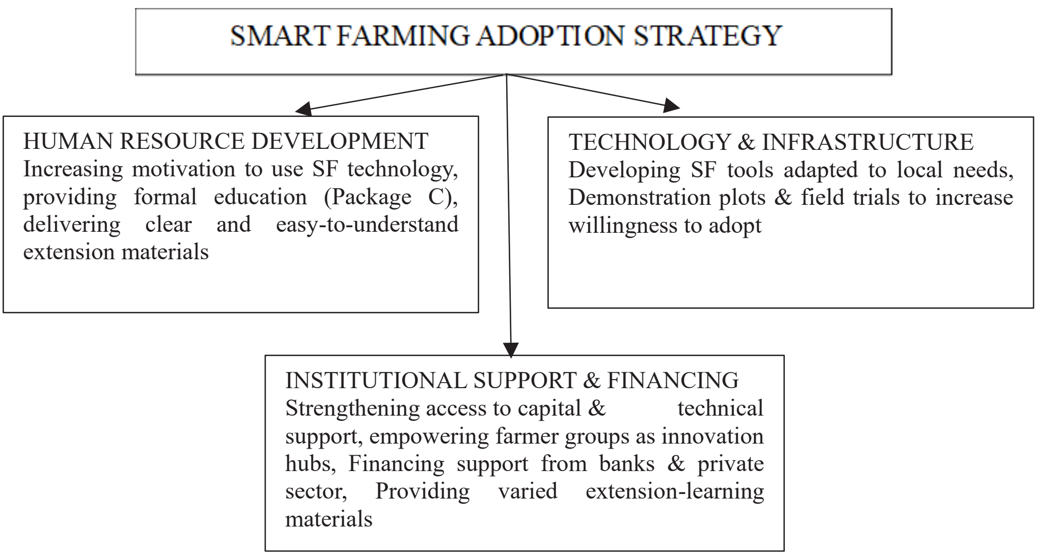

Fig. 2. Smart farming strategy process

Learning materials are developed using a diverse range of formats, including videos, infographics, simulations, and audio-visual media integrated into e-learning platforms to accommodate farmers' varying learning styles. Additionally, farmer groups serve as collaborative learning communities, facilitating regular discussions and field meetings. The involvement of young farmers is particularly vital, as they act as 'agents of change' to accelerate the adoption of new practices. AgTech (digital agricultural technology) adoption among smallholder farmers is heavily influenced by institutional and financial support, including access to financing, infrastructure, and digital training/literacy [13]. The study confirms that “public-private partnerships” and targeted training and mentoring programs emerge as “key enablers” or main drivers for smallholder farmers to overcome capital, technology, and infrastructure barriers, thereby increasing the chances of technology adoption [13]. These 13 components complement each other in the Smart Farming development model, where the first part focuses on empowering individual farmers, the second on technology and policy adaptation, the third on institutional ecosystems and digital infrastructure, and the final part on collective learning that accelerates the adoption of innovations sustainably. The expected output of the Smart Farming innovation adoption strategy is the development of farmers who are technologically proficient, highly knowledgeable, motivated, and adaptable.

This way, farmers can understand and utilize data, digital tools, and agricultural innovations to improve their yields and business efficiency. According to the study "Training Evaluation in a Smart Farm using the Kirkpatrick Model: A Case Study of Chiang Mai," after intensive training (mobile learning + smart farm lab), local farmers demonstrated increased knowledge and performance: the training improved the "knowledge and performance of local farmers" in using smart farm technology (sensors, IoT) for irrigation, fertilization, and farm management. Increasing the adoption of Smart Farming also depends heavily on active learning and adequate environmental support. Activities such as farmer groups, digital communities, varied and relevant extension services, and hands-on practice through training and field demonstrations are key factors. Furthermore, a conducive environmental support, including access to technology, pro-digitalization policies, incentives, and adequate digital infrastructure, ensures farmers have the opportunity and motivation to adopt technology effectively and sustainably. The formation of a sustainable digital agricultural ecosystem requires collaboration between the government, the private sector, academia, and the farming community.

The government provides policies, regulations, and infrastructure; the private sector plays a role in financing, technological innovation, and markets; academia supports through research and development of local technologies; and the farming community acts as an agent for innovation diffusion and institutional strengthening. This synergy drives increased productivity, efficiency, and farmer welfare, while creating an ecosystem that supports the transformation of traditional farmers into more productive, independent, and prosperous digital farmers. Table 3 Outcomes of Adoption of Smart Farming Innovation.

According to the research, 'Adoption of smart farm networks, a translational process to inform digital agricultural technologies,' the development of smart, connected farm networks, driven by the active participation of farming communities, enables the real-time exchange of data and knowledge. This process supports "community-led decisions" and strengthens shared land management. In a study on agricultural digitalization among smallholder farmers in Africa, it was found that agronomic training and capacity-building programs significantly increased the probability of adoption of digital agricultural solutions, indicating that "agrarian training and other capacity development programs" are the main drivers of ICT/agri-tech adoption [14]. A study in South Africa showed that the use of digital technologies by smallholder farmers, including mobile applications and ICT, helps democratize agricultural knowledge: farmers can access, share, and create knowledge collectively through digital platforms, reflecting the transformation from traditional agriculture to digital community-based agriculture and shared knowledge.

The evaluation of the smart farming (SF) program focuses on several key aspects: adoption rate, frequency of use, input efficiency, productivity, and farmers' attitudes and perceptions. The program is considered successful if at least 70% of the targeted farmers adopt SF technology and 80% of them consistently use it in every growing season. In terms of resource efficiency, the implementation of SF is expected to reduce the use of water, fertilizers, and pesticides by 20–30%, while increasing crop productivity by at least 25% compared to baseline conditions. In addition to technical and economic outcomes, farmers' attitudes are also critical, with success indicated when at least 85% of farmers perceive SF as useful and appropriate for their farming practices.

Farmers are empowered to actively utilize Smart Farming innovations now within their agricultural practices, underpinned by enhanced competencies, active learning, and robust support from external ecosystems, including government bodies, financial institutions, and technology providers. The anticipated outcome is the behavioural shift from traditional methods toward a data-driven approach. In this transition, farmers leverage digital tools for informed decision-making in irrigation, fertilization, harvesting, and marketing, ultimately bolstering their confidence and motivation to adopt these technologies sustainably. These implementations are very effective because farmers are not only familiar with the technology but also proficient in operating digital devices, sensors, applications, and automation systems. By integrating these tools into their daily routines, they ensure that cultivation activities become more controlled, precise, and easily manageable. The increasing number of farmers implementing Smart Farming demonstrates the high relevance of this technology to their needs, while also having a positive impact on the community and the agricultural sector as a whole.

Table 3. Outcomes of adoption of smart farming innovation

Aspect	Indicator	Target
Adoption rate	Percentage of farmers implementing SF technology	≥ 70% from the program targets
Frequency of use	Use of technology in each growing season	≥ 80% farmers consistently use
Input efficiency	Reduction in the use of water, fertilizers, and pesticides	20–30% savings
Productivity	Increased crop yields	≥ 25% compared to baseline
Attitudes and perceptions	Farmers feel SF is useful and appropriate	≥ 85% farmers stated positively

4 Conclusion

Although the agricultural sector still employs nearly a quarter of Indonesia's workforce, low productivity, limited access to technology, and food security risks underscore the need for innovative agricultural transformation. Quantitative research in West Java shows that integrating digital technology through smart farming effectively improves efficiency, productivity, and the sustainability of resource management.

Therefore, a smart farming adoption strategy needs to be designed in an integrated manner, taking into account farmer characteristics, perceptions of technology, external environmental support, and learning intensity. This approach involves farmer segmentation, increasing positive perceptions of technology through demonstrations and field trials, strengthening support from the government and relevant stakeholders, and enhancing farmers' learning capacity through participatory training and the use of digital media to ensure independent and sustainable technology adoption.

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