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The Extent and Patterns of Digitalization in Proactive Land Acquisition Strategy (PLAS) Farms in South Africa

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ABSTRACT

This study sought to develop an index for agricultural digitalization by applying composite confirmatory analysis (CCA). Another aim was to determine the factors that affect the development of digitalization in PLAS farms. Data on the indicators of the three dimensions of digitalization were collected from 300 Proactive Land Acquisition Strategy (PLAS) farms in South Africa using semi-structured questionnaires. Confirmatory composite analysis (CCA) was employed to reduce the items into three digitalization dimensions and ultimately to a digitalization index. Standardized digitalization index scores were extracted and fitted to a linear regression model to determine the factors affecting digitalization. The results revealed that the model shows practical validity and can be used to measure digitalization as measures of fit (geodesic distance, standardized root mean square residual, and squared Euclidean distance) were all below their respective 95%quantiles of bootstrap discrepancies (HI95 values). Therefore, digitalization is an emergent variable that can be measured using CCA. The average level of digitalization in PLAS farms was 0.02 and varied significantly across provinces. Although farmers have attempted to digitalise their farms, there are still minimal levels of digitalization in PLAS farms. The results further reveal different digitalization patterns. As judged by the estimated weights of various dimensions of digitalization, the use of digital technologies to collect, store, analyse, and disseminate (CSAD) farm-related data contributed more towards the digitalization index. The second most important component of digitalization was automation digitalization. In contrast, value chain digitalization was the least significant contributor. The factors that significantly influence digitalization were age, gender, farm type, network type, and cellular data type. Since PLAS farmers have not embraced much digitalization, it is important to focus on awareness and capacity building. A balanced approach to digitalization would benefit PLAS farms by ensuring that strategies to integrate digital solutions within the value chain are developed. To foster and support the digitalization in PLAS farms, policymakers and stakeholders should tailor their strategies to fit specific socioeconomic factors.

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Introduction

The integration of new technologies and digital tools within conventional agricultural methods is referred to as agricultural digitalization, sometimes known as digital agriculture or smart farming (Araújo, Peres, Barata, Lidon, & Ramalho, 2021; Kovács & Husti, 2018; Nambisan, Lyytinen, Majchrzak, & Song, 2017). It entails using information and communication technologies (ICT) to collect, analyse, and use data to improve many areas of agricultural operations (Kovács & Husti, 2018). Digitalization has received considerable attention from policymakers. The African Union commits to the transformation of African Societies and economies by harnessing digital technologies and innovation (African-Union, 2020). The South African government has supported the development of the digital economy through the enactment of various national policies and strategies. Some of the key national plans include the science, technology, and innovation (STI) policy, digital and future skills strategy policy, and the commission on the Fourth Industrial Revolution.

Agriculture is one of the key sectors that can benefit from these national policies and strategies. The digital and future skills policy can improve the digital literacy of farmers leading to adoption of digital tools and data-driven decision making (Albani, Anyfantaki, & Lazaretou, 2019). Digital literacy is crucial for changing the digital culture of people (Mazwane, Makhura, & Senyolo, 2022). The science, technology and innovation policy can foster research, and development leading to improved knowledge base and innovation of new digital technologies (Rotz et al., 2019). This will help improve agricultural productivity. The commission of 4IR prioritises technologies such as artificial intelligence, robotics, Internet of Things etc. and this revolutionise agricultural activities such as crop and livestock monitoring and supply chain management (Mazwane et al., 2022).

However, a major concern for academia and policymakers is whether farmers can reap the full benefits of the fourth industrial revolution. Moreover, questions about whether the land reform farmers can also take advantage of the opportunities provided by digitalization to improve the state of productivity these farms demand answers. The land reform program was instituted by the democratic government to reverse the land injustices of the past (Greyling, Vink, & Mabaya, 2015). It has three pillars – the land redistribution, land restitution and land tenure reform (Lahiff & Li, 2012). While the land redistribution aims to achieve balance in the holding of land and agricultural production by the previously disadvantaged population, land restitution aims to reclaim historical rights. The tenure reform seeks to secure land rights in the former homeland. The strategies for implementing the three pillars of the land reform program in South Africa have undergone several changes overtime.

Thus, the current strategy for implementing land redistribution is the proactive land acquisition strategy (PLAS). Although it still lags in terms of reaching the initial amount of land targeted for redistribution, a sizable amount of land has been transferred under this current land redistribution implementation strategy (Lahiff & Li, 2012). Thus, a large group of farms called PLAS farms have emerged from this strategy and are explored at length here. Land tenure reform and land restitution have faced several implementation challenges and are not investigated further in this study.

Digitalization has several implications for the land reform program, particularly if it can be incorporated within other forms of existing government support. The land reform program faces various implementation challenges (Lahiff & Li, 2012). The available budget not only limit the amount of land that can be acquired for distribution but also post settlement support which is critical for the success transferred land (Lahiff & Li, 2012).

The redistributive land reform and other government support programs have continued with little success (Greyling et al., 2015). The adoption and use of agricultural digital solutions can be beneficial for PLAS farmers. Agricultural digital solutions promote value chain optimisation, automation and improved precision and data collection, processing, and dissemination (Qin et al., 2022; Scuderi, La Via, Timpanaro, & Sturiale, 2022). Nevertheless, there are limited studies that have attempted to measure agricultural digitalization. The current literature offers disaggregated evidence on the use of various digital agricultural solutions (Bonke, Fecke, Michels, & Musshoff, 2018; Falentina, Resosudarmo, Darmawan, & Sulistyaningrum, 2020; Lio & Liu, 2006; Michels, Bonke, & Musshoff, 2020). Consequently, various agricultural digitalization dimensions have been studied separately, hindering efforts to measure and quantify the level of digitalization in agriculture.

A recent attempt to fill this gap by developing an index of the dairy industrial complex in Russia has been coupled with serious limitations (Mikhail, Olesya, & Maria, 2021). The index excludes important dimensions of digitalization and lacks assignment of weights on the dimensions that have been featured. This study proposes a composite index for the development of a digitalization index and attempts to feature all four dimensions of digitalization. Confirmatory Composite Analysis is a sub-type of composite based structural equation modelling (c-SEM) and will be used to compute and examine the digitalization index. Index computation techniques in previous studies have been based on the measurement theory (Schuberth, Henseler, & Dijkstra, 2018). Measurement theory is good when assuming that indicators are the consequences of an underlying construct.

Composited indices are based on composite models which are used to implement synthesis theory based on the hypothesis that a composite of observed variables is the only means of transmitting information between blocks of observed variables (Schuberth et al., 2018). As a result, composite models are the outer models that implement the relationship between the observed variables and the construct. Henseler (2020) argues that the outer model should be appropriate not only for the type of construct but also for the role of the observed variables. Thus, this study seeks to fill this gap in the literature by computing an index that measures digitalization development on farms based on a composite model that includes all the dimensions of digitalization.

The factors that influence patterns of digitalization in PLAS farms will also be assessed. The scientific contribution is through the application of novel techniques for computing an index – confirmatory composite analysis – on farm-level data. Specifically, the development of an agricultural digitalization index using a confirmatory composite model and testing its suitability on farm-level data of PLAS land reform farmers will provide a basis and direction for future studies owing to the lack of application of these methods to agricultural data. This study advances the relevance, specificity, and comprehensiveness of methods used to assess agricultural digital transformation. Developers will gain an understanding of the factors that influence digitalization development thereby aiding in the future alignment of new digital solutions with farmer needs. Policymakers will also benefit from the study's output on the progress of the agricultural sector toward digital transformation. Identifying the factors that affect digitalization will help policy makers and developers in assisting farmers to fully integrate into the entire value chain by developing a relevant agricultural digital policy and ensuring that land reform programmes emphasize the value chain approach.

Hypotheses

Hypothesis 1: There is no difference between the model-implied indicator covariance matrix and population indicator covariance matrix.

Hypothesis 2: Farmer and farm characteristics such as age, gender education level etc. have no influence on the digitalization level of PLAS farms.

Review of related literature

This section provides a concise summary of the existing empirical evidence on the factors that affect agricultural digitalization, and a framework for developing a digitalization index.

Empirical review of digitalization literature

Bukht and Heeks (2017) formulated a conceptual definition of the digital economy, which entails three distinct scopes: the Information Communication Technology (ICT/IT) sector, the digital economy, and the digitalised economy. The ICT/IT sector is the foundation of the digitalised economy, encompassing hardware manufacturing, software and IT consulting, telecommunications, and information services. The narrow scope is the digital economy, which includes the ICT/IT sector and digital services, platform economy, sharing economy, and gig economy. The broadest scope is the digitalised economy, which encompasses the ICT/IT sector, digital economy, and digitalised economy. The digitalised economy is characterised by the e-businesses, e-commerce, and algorithm economy (Bukht & Heeks, 2017). ICTs have brought about significant transformations in the agricultural sector.

There is evidence of the impact of information and communication technologies on agricultural productivity growth. In South Asian economies like India, the use of mobile phones in agricultural-related activities has significantly improved the productivity of smallholder farmers (Mittal & Tripathi, 2009). Katengeza, Okello, and Jambo (2011) outlined the role of mobile phones in connecting farmers to lucrative formal markets and further revealed factors such as literacy, distance to markets and land size to be significantly impacting on the adoption and use of mobile phones in agricultural marketing. There is also little but growing evidence of the benefits of digital agricultural solutions, such as mobile applications. For example, offering price information to Kenyan farmers through mobile applications such as M-Farm has yielded positive results, such as planning production processes leading to changes in cropping patterns and harvesting times (Baumüller, 2015). Efforts to digitalize agriculture have continued to spread across the sub-Saharan region.

While most studies have investigated the adoption of digitalization, the focus has been on specific ICTs such as cell phones and computers. (Lio & Liu, 2006; Matteucci, O'Mahony, Robinson, & Zwick, 2005; Mendonça, Freitas, & Souza, 2008; Salim, Mamun, & Hassan, 2016). Fragmented evidence also exists regarding the adoption of digital agricultural solutions. For example, mobile applications in Kenya have been studied by Baumüller (2015). In Germany, factors affecting adoption of drones by large scale farmers have been revealed (Michels, von Hobe, & Musshoff, 2020) and adoption of crop protection app (Bonke et al., 2018; Michels, Bonke, et al., 2020). While Molina-Maturano et al. (2021) have examined the adoption of mobile applications in Mexico, Sun et al. (2021) have looked at factors affecting the adoption of internet of things for pig farmers in China. These studies contribute to the literature on the adoption of digital agricultural solutions but say little about the degree of digitalization in these farms. Measuring farm-level digitalization remains a challenge.

The empirical literature on the drivers of the digitalization of agriculture takes many different directions. The first deals with the factors that predict the adoption of agricultural digital solutions. Performance expectancy, effort expectancy, social influence, and facilitating conditions are behavioural factors that are likely to predict the adoption of agricultural digital solutions, and exogenous variables such as age and gender are more likely to play a mediating role. Several empirical studies have shown a positive correlation between the intention to adopt digital agricultural solutions and performance expectancy (Michels, Bonke, et al., 2020; Molina-Maturano et al., 2021; Sun et al., 2021). There are mixed results on the role of facilitating conditions in predicting the intention to adopt. While Michels, Bonke, et al. (2020) argue that facilitating conditions are only relevant for determining actual adoption, Molina-Maturano et al. (2021) found the intention to adopt agricultural apps to be strongly associated with facilitating conditions in Mexico.

Although no significant relationship has been found between effort expectancy and intention to adopt an agricultural app in Mexico (Molina-Maturano et al., 2021), effort expectancy is considered a good indicator of the user-friendliness of a particular technology. It is therefore argued to be a strong predictor of the intention to adopt agricultural digital technologies. As both these studies are based on farmers' perceptions, Mexican farmers may perceive overcoming constraints associated with learning digital solutions as important as opposed to German and Chinese farmers, who may enjoy the dynamic capability associated with their advanced economies. Michels, Bonke, et al. (2020) reported a positive relationship between smartphone crop protection app adoption and social influence (i.e. the extent to which certain individuals influence the adoption belief of the farmer). Similarly, Sun et al. (2021) found that social influence significantly affects the adoption of the Internet of Things in China. Although Molina-Maturano et al. (2021) found no significant positive effect of social influence in Mexico, farmers' social networks are important for the adoption of new technologies. Digital solutions such as agricultural apps are still in development and pilot stage in Mexico (Molina-Maturano et al., 2021), which may explain the poor role played by farmer networks in predicting adoption.

There are also studies that have considered the role that farm and farmer characteristics, other than behavioural factors, play in determining adoption. These focus on factors influencing actual use. Michels, von Hobe, et al. (2020) revealed farm size, age, and literacy on PAT to be the factors that affect the actual adoption of drones by large-scale German farmers. Farmers' age, farm size, knowledge about specific crop protection apps, potential for crop protection, and potential for reducing negative environmental effects have been identified as significant predictors of willingness to pay for crop protection apps in Germany (Bonke et al., 2018). The evidence produced in these studies is inconclusive and varies with context. They show that while some factors are significant determinants of digitalization in some regions, they are not insignificant in others. Moreover, the evidence produced is only related to the adoption of one dimension of digitalization, namely, the adoption of agricultural digital solutions. Therefore, this justifies the need for further research on the level of digitalization and associated factors in South Africa.

Emerging studies on PLAS farms are limited to success factors and land size determination (Gandidzanwa, Verschoor, & Sacolo, 2021; Zantsi, Mack, & Vink, 2021). Moreover, a farm assessment toolkit for determining the potential viability of a farm compared to current performance has been proposed in Verschoor et al. (2023). The findings highlight the below par performance of PLAS farms compared to potential viability. Specifically, only 7% of 57% of potential commercially viable PLAS farms performed accordingly (Verschoor et al., 2023). This coincides with the findings of Kirsten, Machethe, Ndlovu, and Lubambo (2016) that the performance of land reform farms in the North West province has deteriorated overtime. The literature on digital technology adoption by PLS farms still scanty. Only Mazwane, Makhura, Senyolo, and Ginige (2023) evaluated the adoption intention of Eastern Cape PLAS farmers to adopt value chain digital technologies and found the significant role played by effort and performance expectancy in the adoption intentions of farmers.

The literature shows that farmers' efforts to digitalize farming activities have been accompanied by scientific evidence attempting to measure digitalization. However, methods used to measure digitalization have been limited in that they focus on specific agricultural technologies, resulting in the identification of only factors associated with the adoption of such agricultural digital solutions. While these studies advance a certain understanding of the factors that affect the adoption of agricultural digital solutions, they are limited to European, Central, South American, and South Asian regions. Thus, there is limited scientific evidence on the factors that could contribute to the adoption of digitalization by South African PLAS farmers. Digitalization literature in agriculture focuses on the adoption of specific agricultural digital technologies (Bahn et al., 2021; Michels, von Hobe, et al., 2020; Molina-Maturano et al., 2021; Prabhu & Joshi, 2018; Sun et al., 2021).

Conceptual framework

The proposed framework for the current investigation is depicted in Figure 1. The direction in which the arrow points indicate the relationship between variables, although it may not always indicate the nature of the relationship. Farm digitalization is considered an emergent second-order construct (Figure 1). Higher-order constructs are those with indicators that are not directly observable but can be described using constructs. The framework simplify the model and promote parsimony by requiring fewer paths to be estimated and the researchers' objective is to demonstrate that correlations between constructs can be ascribed to an underlying process (Henseler, 2020). Similarly, since digitalization cannot be directly observed, it is described using its dimensions as constructs: value chain digitalization, automation, data collection, storage, analysis, and dissemination. Thus, it is argued that the existent relationships between these constructs cause underlying digitalization.

Composite measurements will be used to investigate the abstract concept of digitalization. It is represented in the statistical model as an emergent variable rather than a latent variable (Benitez, Chen, Teo, & Ajamieh, 2018). Thus, Confirmatory Composite Analysis (CCA) was used to determine whether the constraints imposed by the composite model were consistent with the data, that is, whether the emergent variable fully conveyed the information between the constructs (Figure 1). The level of digitalization in PLAS farms is also believed to be influenced by a few other factors. As depicted in Figure 1, exogenous variables include farm and farm manager/owner characteristics as well as the geographic location of the farm. The observable variables AUT1 through AUT5 pertain to automation, the initial dimension of digitalization, whereas indicators CSAD1 through CSAD3 cover data collection, storage, analysis, and dissemination (Figure1).

VCO1–VCO4 are observable variables for the value chain digitalization dimension (Figure1). The dimensions of digitalization (first-order constructs) intended to be constructed based on the corresponding blocks of observable variables are also presented in Table 1. Moreover, Table 1 provides a list the dimensions' observable variables measured using five Likert scale responses and gives the wording of the respective questionnaire items that were adopted from Yu, Jiang, Zhang, and Du (2021) and adapted to measure farm digitalization.

Materials and Methods

This section presents the study's methods for model index computation, provides data and collection measures and a model for determining factors that affect agricultural digitalization.

Data and Sources

This study used a cross-sectional design. Heavy reliance was placed on farm variation and no attention was paid to time variation. The sample comprises 300 PLAS land reform farmers from three provinces: Mpumalanga, Gauteng, and Eastern Cape. PLAS farmers are spread throughout the country, and the implementation of a simple random sampling technique at provincial level would be costly and time-consuming (Spector, 2019). However, to ensure that a representative sample was obtained, the Eastern Cape, Mpumalanga, and Gauteng provinces were purposively sampled. Mpumalanga and Eastern Cape are rural provinces, with Mpumalanga having the highest number of PLAS farms (Gandidzanwa et al., 2021). Gauteng is an urban province and can be regarded as a locus of innovation. However, district municipalities, local municipalities, and farms were randomly sampled. A list of all active farmers in the selected local municipalities was obtained from the Department of Agriculture, Land Reform, and Rural Development (DALRRD) in all three provinces. Five enumerators in each local municipality were enlisted, and a semi-structured questionnaire was used for data collection.

Table 1. A summary of Digitalization dimensions and observable variables, and wording of the respective questionnaire items

DC	DD	VIN	Item wording on the questionnaire
Digitalization	Automation	AUT1	I have digital solutions that connect essential business activities with customers, suppliers, employees, and assets
		AUT3	I have centralized irrigation pumps that have set times and remote activation
		AUT4	I have automized fertiliser application using unmaimed aerial vehicles and GPS technologies
		AUT6	I have automated ploughing using digital robotic tractors
		AUT7	I have automated fattening, milking, and health monitoring livestock systems
	Collection, Storage, Analysis & Dissemination	CSAD1	I have sensors for collecting temperature and humidity of the soil, air and products and for monitoring agricultural machinery, staff, and cattle.
		CSAD2	I have livestock tracking devices that monitors livestock movement and performance.
		CSAD3	I have aerial imagery systems like UAVs and GIS for mapping and monitoring crops
	Value Chain optimisation	VCO1	I used digital procurement to obtain information/data and insight more easily into the input market
		VCO3	I use an intelligent equipment to improve the quality and efficiency of producing a product
		VCO4	I use digital technology for marketing services
		VCO6	I use an intelligent customer service to transmit the after-sales information and user feedback in real time

DC: Digitalization construct (Second-order emergent variable); DD: Digitalization Dimensions (First order constructs); VIN: Variable Indicator name

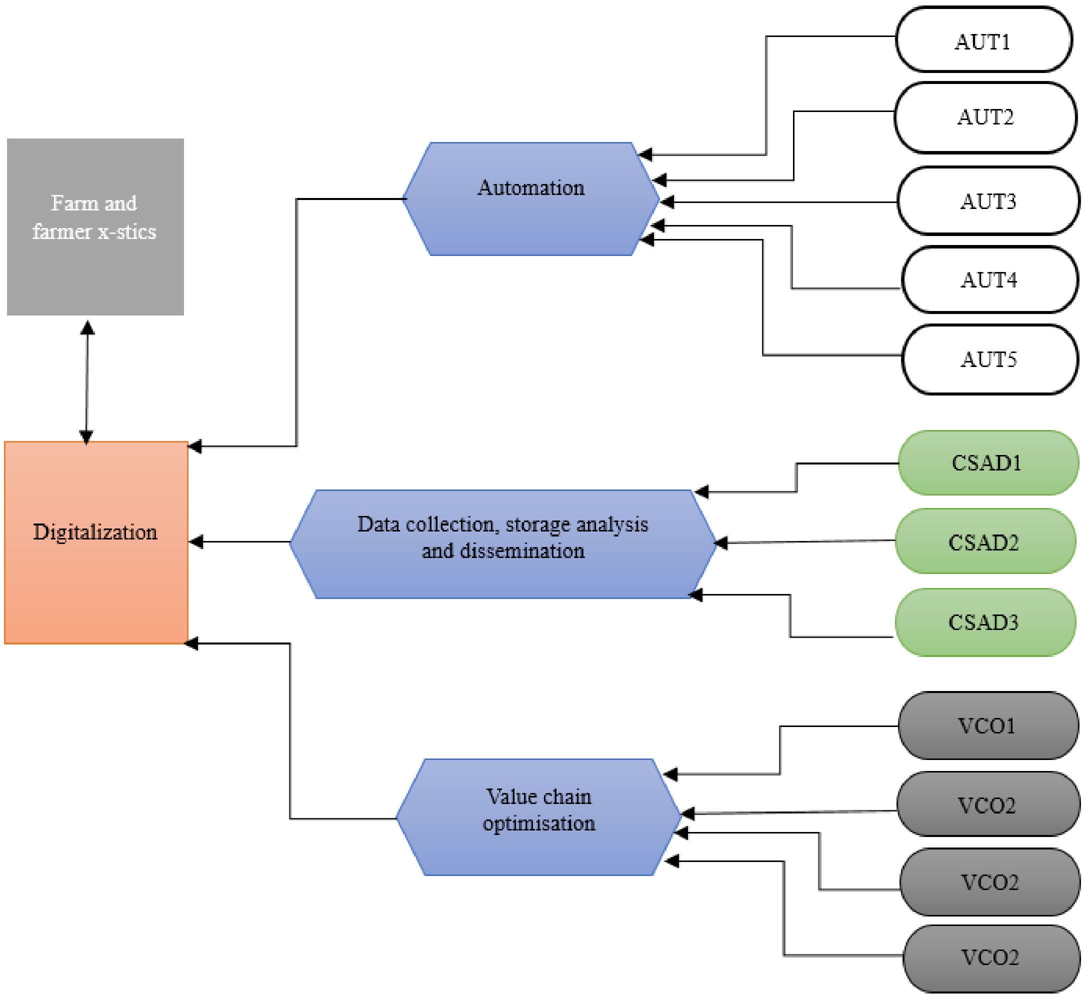


Figure 1. Digitalization measurement framework Source: Author’s computation

Table 2. Summary of factors considered for digitalization model and a-priori expectations.

Dependent variable	Measure/type	Description	ES
Digitalization	Continuous	Scores of digitalization index extracted from the digitization model	
Independent variables	Measure/ type		ES
Farm manager characteristics			
Age	Continuous	The number of years from birth.	-
Gender	Dummy	A two-level unordered categorical variable representing the sex of the farmer: 0 Represents female and 1 represents male.	+/-
Level of education	Continuous	Number of years of completed formal education.	+
Family size	Continuous	Number of people in the family.	+
Farm characteristics			
Land size	Continuous	Size of farming land owned in hectares	+
Type of farm activity	Dummy	A categorical variable with four levels: 0 indicates farming cereal or field crops, 1 indicates horticultural crops, 2 denotes livestock keeping, 3 indicates mixed farming (livestock and crops), and 4 denotes other types of farming (e.g., trees)	+/-
Cooperative membership	Dummy	A categorical variable with two levels: 1 if yes and 0 otherwise	+
Cellular signal strength	Continuous	Number of bars that are reflected on the phone	+
Network type	Dummy	A categorical variable with three levels four levels 0 if Vodacom, 1 MTN, 2 Telkom and 3 other types of networks (Cell C, Eita etc.)	+/-
Cellular data type	Dummy	0 if no signal, 1= 2G up to 5 = 5G	+
Extension visits	Continuous	Number of visits/ extensions contact per month	+

ES: Expected sign

Data collection took place in three phases, between January and April 2023 and lasted for about 3 weeks in each province. The first phase included collecting data from Eastern Cape farmers, followed by Gauteng and Mpumalanga farmers. The University of Pretoria approved the ethical application with the number NAS005/2022. Ethical consideration governed the data collection and results reporting process. Thus, ethical aspects, such as informed consent, respect for dignity, voluntary participation, and confidentiality, were adhered to**.**

Data Analysis

Digitalization index specification and estimation

An index of digitalization was developed by modelling digitalization as a type four second-order construct (i.e., an emergent variable made up of emergent variables). According to Schuberth et al. (2018), type-IV second-order constructs can be specified, estimated, and tested using both covariance-based and variance-based SEM. As a type-four second-order construct, digitalization was modelled as a second-order emergent variable that is made up of three first-order emergent variables. The definitional role of the components was assumed, and each digitalization dimension was regarded as a linear combination of weighted w_{jk} components y_{jk}:

$$\eta_j = \sum_{k=1}^{K} w_{jk} \times y_{jk} \quad (1)$$

w_{jk} is the weight of component k, y_{jk} is the component k of farmer j, and η_j is the digitalization dimension level for farmer j. The components of the index were regarded as defining. The composite model considers the emergent variable η_j as a linear combination of its components y_{jk}, each component is weighted by a weight w_{jk}. The weights were estimated using mode B in partial least squares path Modelling (PLS-PM). This method has an advantage over other weight determination methods such as sum of scores since the relative contribution of indicators to the construct is expected to differ (Benitez et al., 2018; Henseler, 2020).

Confirmatory composite analysis (CCA) was conducted in two-stages in R statistical package to examine whether the specified model was consistent with the collected data (Schuberth et al., 2018). Figure 1 presents the 2-stage estimation procedure for a type 4 second order emergent variable. The first stage involved reducing the dimensions of the observed indicators of the first-order constructs (the three dimensions of digitalization – value chain optimisation, automation, and data collection storage and analysis) in three steps. In the first step, the model was estimated without a second-order construct.

The hypothesis tested was that digitalization is a composite concept. Specifically, there is no difference between the model-implied indicator covariance matrix and population indicator covariance matrix. The automation digitalization dimension was assumed to be composed of five observable variables, and the value chain optimization dimension was assumed to be composed of four observable variables. Moreover, the data collection, storage, and analysis digitalization dimensions were assumed to be composed of three observable variables. Correlations between the three dimensions were allowed and assessed. After the estimation without the second-order constructs, a model assessment was conducted in the second step. The third step involved extracting the standardised scores of the digitalization dimensions that were used in the second stage (i.e., reducing the dimensions of digitalization into the digitalization index). The second stage was conducted in three steps (model estimation, assessment, and construct score extraction).

Empirical model for determining factors that affect digitalization.

The digitalization model was specified and estimated after digitalization index scores extracted from the second stage of CCA. This was done to identify some of the factors that significantly influence digitalization in PLAS farms. Several farm and farmer characteristics, as listed in Table 2, were considered. Due to the lack of knowledge about the factors that significantly influence digitalization prior to the estimation of the model, an explicit model was not specified. Consequently, a minimal adequate model was selected after the estimation of the model. Digitalization was modelled as a function of basic farm and farmer characteristics identified in previous studies (Falentina et al., 2020; Mikhail et al., 2021; Sun et al., 2021) such as age, education, gender etc. An implicit model was specified as follows:

$$Dig_{ij} = \mathrm{F}(\alpha, \mathrm{x}\beta, \mathrm{z}\delta, \varepsilon) \qquad (2)$$

where Dig is the continuous dependent variable which represents the digitalization level of farmer i in location j; x and z are the vectors of farmer and farm characteristics, respectively. Table 2 presents a summary of farm and farmer characteristics that are considered in the model, measurement type, description, and expected sign. α, β and δ are the parameters to be estimated. ε is the error term. A minimal and adequate model was selected after considering variable interactions as well also the presence of quadratic terms. A linear regression output was performed using the R statistical package to determine the factors that affect digitalization in PLAS land reform farms. A backward approach to regression estimation was employed, whereby a full model was estimated using the ordinary least squares estimation technique with all factors hypothesised to affect digitalization. Variables that were not statistically significant were then removed from the model step-by-step. Normality and homoscedasticity tests on the residuals using the Shapiro-Wilkson and Breusch-Pagan tests were performed at each step to ensure model adherence to standard normal regression assumptions.

Results and Discussion

The aim was to determine the level of digitalization PLAS farms by computing an agricultural digitalization index and shed light on the determinants of digitalization development in PLAS farms. The section presents the demographics of PLAS farmers, composite confirmatory analysis results and regression model results of the factors that affect digitalization in PLAS farms.

Demographics of PLAS Farmers

The demographic characteristics of farmers with respect to gender, age, and education status as well their distribution across the provinces are presented in Table 2.

The characteristics of the PLAS farmers according to gender reveals interesting patterns. The data indicates that the sample consists predominantly of respondents who are male farmers, accounting for 71% of the total sample, while female respondents represent 29%. This indicates that commercial agriculture is male dominated, and that South African land re-distribution may be biased.

The average age and age distribution of farmers among the three provinces are also provided (Table 3). The farmers are generally middle aged with an overall sample mean of 56 years. However, the female farmers were slightly younger compared to male farmers with an average age of 54 years and 57 years, respectively. The analysis provides valuable information regarding the sample's average age profiles, with males having a slightly older average age than females. This may be due to the application requirements, which typically require active and promising African farmers with some agricultural assets. Young farmers who often lack such assets may be discouraged, limiting their active participation on productive economic activities.

The data shed light on the average number of years of completed schooling for the entire sample. The average number of years spent in school for the entire sample is twelve. This indicates that, on average, the respondent farmers in the sample possessed a matric/ matric equivalent qualification or completed secondary/high school.

Table 3. Demographic characteristics of PLAS farmers from three South African provinces

Variable	Province			All provinces
	Eastern Cape	Gauteng	Mpumalanga	
Gender				
Females (%)	7	9	13	29
Males (%)	28	14	31	71
Average age				
Female (years)	53	53	54	54
Male(years)	56	57	58	57
Education status				
Female (years)	12	13	11	12
Males (years)	12	12	10	11

Source: Own compilation from survey data

Table 4. Weight and loading estimates of first-order constructs with confidence intervals.

Digitalization Dimension	Variable indicator	Weights	95% CI L	95% CI U	Loadings	95% CI L	95% CI U
Automation	AUT1	0.34***	0.17	0.49	0.85***	0.72	0.91
	AUT3	0.40***	0.20	0.59	0.89***	0.83	0.94
	AUT4	0.08*	0.07	0.27	0.83***	0.71	0.90
	AUT6	0.21**	0.02	0.42	0.83***	0.71	0.91
	AUT7	0.15**	-0.01	0.32	0.75***	0.59	0.84
Collection, Storage, Analysis & Dissemination	CSAD1	0.57***	0.37	0.76	0.91***	0.82	0.96
	CSAD2	0.09**	0.07	0.25	0.64***	0.43	0.78
	CSAD3	0.48***	0.29	0.67	0.88***	0.75	0.96
Value Chain optimisation	VCO1	0.56***	0.33	0.72	0.91***	0.82	0.95
	VCO3	0.29**	0.08	0.47	0.81***	0.69	0.90
	VCO4	0.17*8	0.12	0.15	0.63***	0.35	0.84
	VCO6	0.43***	0.19	0.61	0.86***	0.75	0.93

Source: Own compilation from survey data

Table 5. Model fit assessment measures of discrepancy for the first order constructs

Distance measure	Test statistics	Critical Value
dG	0.046	0.065
SRMR	0.026	0.030
dL	0.053	0.072
dML	0.240	0.320

Source: Own compilation from survey data

Composite Structural Equation Modeling Results

The first stage of the digitalization index computation involved reducing the observed variable indicators into three digitalization dimensions. Table 4 presents the weights estimates and correlations (i.e., loadings) between the observed variables and various dimensions of digitalization constructs. The PLS parameter estimates are associated with standard errors as no closed form solutions are possible. The bootstrapped methods were used for inference. Thus the 95% confidence intervals based on 999 bootstrap runs were obtained. Construct correlations ranged from 0.27 to 0.68 and none of their confidence intervals covered 0. According to Benitez et al. (2018), the composite model assessment is done in two steps. With regards to the overall model fit assessment, the values of the discrepancy measures used are the geodesic distance (dG), standardised root mean square residual (SRMR) and squared Euclidean distance (dL). Thus, the dG, SRMR and dL were above the corresponding critical values (Table 5).

The model that was specified in the first stage fits the obtained data well, i.e., the proposed model appropriately reflects the available information in the data. In the second step of model evaluation, each emergent variable is analysed separately, i.e., the model is evaluated locally. According to Benitez et al.'s (2018) assumptions and as shown in Table 4, all observable variables strongly contribute to their emergent variable, i.e., the computed weights' 95% percentile confidence intervals do not cover zero.

Similarly, all correlations between observable variables and their constructs, as well as correlations between emergent variables, are positive and significantly different from zero, indicating that the 95% percentile confidence intervals do not cover zero. There was no empirical evidence against the specified model based on the model evaluation results, and hence the proposed model cannot be rejected. Therefore, the first order emergent variables demonstrate practical validity. The scores of the value chain optimisation, automation and data collection, storage, analysis, and dissemination dimensions of digitalization were extracted and introduced to the data set for use in the second stage of analysis.

The second stage of analysis involved specifying the model for computation of the digitalization index from the scores of digitalization dimensions extracted in the first stage of analysis. Table 6 presents the weight estimates and correlations (i.e., loadings) between digitalization and its dimensions. The disparity between the empirical and model-implied variance-covariance matrix of observed variables was assessed. The SRMR, dL, and dG were all less than the respective HI95 values (Table 7).

The evaluation of the model locally revealed significant contribution from all the dimensions of digitalization to the emergent variable (i.e., digitalization) as the 95% percentile confidence intervals do not contain zero. This indicates that there is no significant misfit, and a failure to reject the model. Thus, digitalization is as an emergent variable. This is consistent with the findings of Henseler and Schuberth (2020) that information technology is a type four second emergent variable that is formed by modularity, IT compatibility, IT connectivity and IT personnel skills flexibility. The results corroborate that of Braojos, Benitez, and Llorens (2019) who also found good measurement properties for the model proposed for social-commerce IT capabilities. Hence, Hair Jr, Howard, and Nitzl (2020) argue the usefulness of CCA in developing new measures and the advantage it that it offers over other measures in confirming measurement models that comprise linear composites. Notably, the absence of disconfirmation does not necessarily indicate that the hypothesis is true. Like many empirical investigations, the study is worth replication to boost confidence in the model.

Table 6. Weight and loading estimates of second-order construct with confidence intervals.

Name	VI	Weights	95%CI L	95%CI U	Loadings	95%CI L	95%CI U
csad_ease	csad_ease1	0.26***	0.23	0.30	0.87***	0.75	0.99
csad_ease	csad_ease2	0.27***	0.24	0.31	0.90***	0.81	1.00
csad_ease	csad_ease3	0.28***	0.25	0.31	0.91***	0.80	1.00
csad_ease	csad_ease4	0.27***	0.24	0.31	0.90***	0.79	1.00
Digitalization	VCO	0.02***	0.01	0.07	0.01***	-0.32	0.33
Digitalization	AUT	0.68***	0.29	1.09	0.56***	0.24	0.80
Digitalization	CSAD	0.89***	0.48	1.16	0.71***	0.49	0.87

Source: Own compilation from survey data; VI: Variable indicator

Table 7. Model fit assessment measures of discrepancy

Distance measure	Test statistics	Critical Value
dG	0.0124918	0.12466413
SRMR	0.0142121	0.04055049
dL	0.0056556	0.04604168
dML	0.0656075	0.82785549

Source: Own compilation from survey data

Patterns in the evolution of digitalization were apparent through the weights assigned to their dimensions (Table 6). The digitalization dimension, which pertains to the implementation of digital solutions within farming for the purposes of collecting, storing, analysing, and distributing (CSAD) farm data, is a greater contributor to the digitalization index. Next is automation digitalization (AUT). The digitalization of the value chain (VCO) contributes the least to the digitalization index. This indicates that PLAS farmers place greater emphasis on automating their farming activities rather than integrating them within the value chain. The CSAD, the highest contributor, underscores the significance of digital solutions in the processes of data collection, storage, analysis, and dissemination.

Overall, the findings indicate that the integration of automation and CSAD digitalization, facilitated by current digital technologies and precision technology, plays a substantial role in the digital revolution of PLAS farms, particularly in activities linked to crop production. This is consistent with McFadden, Casalini, Griffin and Antón (2022) findings on the wide application of digital technologies on row crop farms than livestock and specialty crops in OECD countries. There is a synergy in the dimensions of digitalization to promote the advancement of digitalization in PLAS farms. Nevertheless, the competing needs of PLAS farmers may result in the allocation of resources to the most favourable aspects of digitalization, such as CSAD and automating farm activities.

The standardised average level of digitalization in PLAS farms was 0.020 with a standard deviation of 1. The minimum level of digitalization was -4.58 and a maximum of 3.72. Caution should be exercised in the interpretation of the level of digitalization as it is without units and was derived from Likert scale measurement items. Thus, although farmers have attempted to digitalise their farms, there are still low levels of digitalization in PLAS farms. The low levels of digitalization on PLAS farms may be due the slow pace of development of markets for agricultural digital solutions in South Africa. Most Agricultural digital solutions that available are in the African continent are still donor funded and the focus has been on providing advisory services (Baumüller, 2016). It may be necessary for South African policy makers to enact policy that promote full development of markets for a full spectrum of agricultural digital solutions. Drones are still very expensive for many farmers (Tsan, Totapally, Hailu, & Addom, 2019). Development of value chains for farmers products may also be required to boost demand for agricultural digital solutions.

Determinants of digitalization in PLAS farms

A multiple linear regression output was performed to determine the factors that affect digitalization in PLAS farms. Table 8 presents the final regression model results (The full regression model results are presented in the Table 12). The Shapiro-Wilk test showed that the residuals ware normally distributed. Moreover, the residual variability was stable when plotted against fitted values. Thus, the assumption of homoscedasticity was confirmed using the Breush-Pagan test (i.e., $p > 0.05$). See Table 9, 10 and 11 for the for the residuals plot against the fitted values and normality plot.

Digitalization in PLAS farms is influenced by age, sex, farm type, network type, and cellular data type (Table 8). Age had a statistically significant effect on digitalization development in PLAS land reform farms ($p < 0.05$). This meant that an increase in farmer age negatively affects digitalization. This finding is consistent with that of Michels, von Hobe, et al. (2020) who found that age decreased the odds of adopting drones in large scale crop farmers in Germany. Old farmers tend to adopt new technologies slower compared to younger farmers. Old farmers are inexperienced in using digital tools and this prevent them from adopting new agricultural digital solutions (Rose et al., 2016). However, younger farmers rely heavily on digital technologies because they lack farming experience (Tamirat et al., 2018). Interventions that foster collaboration between young and old farmers could be beneficial.

Table 8. Determinants of digitalization on PLAS farms in three RSA provinces: EC, GP, and MP

	Dependent variable: Digitalization	Standard error
Age	-0.010**	0.005
Gender1	0.253**	0.112
Farm_type1	-0.798**	0.377
Farm_type2	-0.389***	0.138
Farm_type3	-0.239	0.153
Farm_type4	-0.201	0.454
Network_type1	-0.336***	0.115
Network_type2	-0.187	.0226
Network_type3	-0.189	.0616
Cellular_data_type1	-0.271	0.218
Cellular_data_type2	-0.245	0.170
Cellular_data_type3	-0.079	0.154
Cellular_data_type4	-0.438**	0.207
Constant	0.953***	0.323
Observations	300	
R^2	0.113	
Adjusted R^2	0.072	
Residual Std. Error	0.854 (df = 286)	
F Statistic	2.794*** (df = 13; 286)	

Source: Own compilation from survey data; Note: * indicates p<0.1; **p<0.05; ***p<0.01

There were also substantial differences between male and female farmers in terms of digitalization. Table 7 shows that gender had a statistically significant influence on digitalization in PLAS farms ($p < 0.05$). This meant that male PLAS farmers are developing their farms digitally faster than female farmers. Male farmers tend to have access to financial resources and knowledge which may increase opportunities for adopting new technologies (Abdulai, Tetteh Quarshie, Duncan, & Fraser, 2023). This may be an indication of an onset of digital divide in PLAS farms. Gender based agricultural productivity gaps are already one of the challenges of sustainable agricultural development and a major contributor of regional differences in agricultural productivity gaps in Africa (Ali, Bowen, Deininger, & Duponchel, 2016; Slavchevska, 2015). Thus, government intervention that target farmers may be necessary to prevent gender based digital divide in agriculture and promote sustainable uptake of agricultural digital solutions.

Another factor that affected digitalization was the type of farm activity. Table 7 shows that the type of farm activity significantly affected digitalization in PLAS land reform farms ($p < 0.01$). Thus, there were significant differences in digitalization between farms that focus on field crops and those that mainly rear livestock, with farms that reared livestock with lower levels of digitalization. Moreover, farms engaged in mixed farming (rearing livestock and growing crops) were also developing slower than farms that focused only on crops. However, there was no difference in terms of digitalization between farms that focus on growing crops and those that are in the other category (i.e., those that plant trees). According to Araújo et al. (2021), most agricultural digital applications are related to crop production. This may be due to the high relevancy of advanced precision agriculture technologies to crop production and the fact that recent digital technologies build on some existing precision technologies (Michels, von Hobe, et al., 2020). This might explain the skewness in digitalization development on PLAS farms. Thus, it may be necessary to support markets for development of agricultural digital solutions that focus on other types of farm activities including livestock.

The type of network used by a farmer affects digitalization. However, statistically significant differences in digitalization were observed between Vodacom and MTN network users ($p < 0.01$). This meant that PLAS farmers who use the MTN network had lower levels of digitalization than farmers who use Vodacom network. There were no significant differences between farmers who use Vodacom and those that use other types of networks such as Telkom and Cell C. Although MTN, Vodacom and CellC dominate the mobile telecommunication market in South Africa, Vodacom network users may be more digitalised due to its extensive and strong network coverage.

The differences in the average digitalization with respect to cellular data type were statistically significant. Specifically, Table 7 shows that farmers who own 5G cellular data types were below farmers who possess basic cellular phones by 0.438 in terms of digitalization ($p < 0.05$). Thus, the cellular data type significantly influenced the average digitalization development. Nevertheless, there was no significant difference between farmers who owned basic phones and other cellular phones that allowed 2G, 3G, and 4G data types. Cellular data network provides internet connectivity to mobile devices and the 5^{th} generation (5G) provides faster data speeds. However, this latest advancement in mobile technology is not yet available for the rural community, including farms. It has been met with negativity (with towers being destroyed) in some semi-urban areas of South Africa where it has been introduced due to myth about its association with the spread of Covid-19 (Ovenseri-Ogbomo et al., 2020). The lack of 5G infrastructure might have limited internet connectivity for 5G enabled mobile phones reducing the digitalization level for farmers who owned them.

Table 9. Correlation matrix for the first-order indicators/items of digitalization dimensions

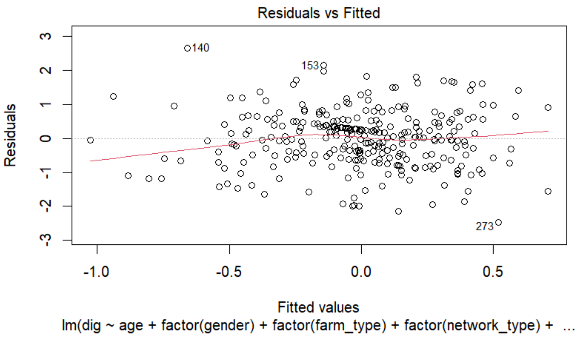
	aut1	aut3	aut4	aut6	aut7	csad1	csad2	csad3	vco1	vco2	vco3	vco4
aut1	1	0.61	0.67	0.60	0.55	0.49	0.38	0.49	0.56	0.51	0.37	0.53
aut2	0.61	1	0.71	0.67	0.58	0.60	0.40	0.52	0.54	0.52	0.41	0.53
aut4	0.67	0.71	1	0.71	0.60	0.47	0.42	0.51	0.53	0.49	0.40	0.54
aut6	0.60	0.67	0.71	1	0.62	0.52	0.37	0.53	0.52	0.51	0.37	0.46
aut7	0.55	0.58	0.60	0.62	1	0.41	0.36	0.50	0.46	0.36	0.28	0.51
csad1	0.49	0.60	0.47	0.52	0.41	1	0.49	0.62	0.55	0.48	0.39	0.47
csad2	0.38	0.40	0.42	0.37	0.36	0.49	1	0.56	0.35	0.23	0.21	0.35
csad3	0.49	0.52	0.51	0.53	0.50	0.62	0.56	1	0.50	0.40	0.29	0.48
vco1	0.56	0.54	0.53	0.52	0.46	0.55	0.35	0.50	1	0.64	0.63	0.64
vco2	0.51	0.52	0.49	0.51	0.36	0.48	0.23	0.40	0.64	1	0.62	0.65
vco3	0.37	0.41	0.40	0.37	0.28	0.39	0.21	0.29	0.63	0.62	1	0.63
vco4	0.53	0.53	0.54	0.46	0.51	0.47	0.35	0.48	0.64	0.65	0.63	1

Table 10. Digitalization dimensions correlation matrix

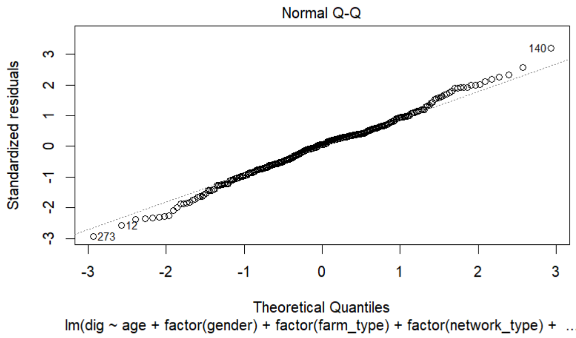
aut	Csad	val
1	0.68	0.70
0.68	1	0.62
0.70	0.62	1

Table 11. Indicators of digitalization dimensions correlation matrix

	csad_ease1	csad_ease2	csad_ease3	csad_ease4	VCO	AUT	CSAD
csad_ease1	1	0.82	0.81	0.78	0.02	0.21	0.24
csad_ease2	0.82	1	0.83	0.77	0.00	0.18	0.25
csad_ease3	0.81	0.83	1	0.80	0.01	0.20	0.25
csad_ease4	0.78	0.77	0.80	1	-0.02	0.18	0.23
VCO	0.02	0.00	0.01	-0.02	1	0.70	0.62
AUT	0.21	0.18	0.20	0.18	0.70	1	0.68
CSAD	0.24	0.25	0.25	0.23	0.62	0.68	1



Appendix E. Residuals vs fitted values for heteroskedasticity



Appendix F: Normality of residuals

Conclusion and Recommendations

An index for agricultural digitalization was developed by applying composite-based structural equation modelling on farm level data of Proactive Land Acquisition Strategy (PLAS) farms in South Africa. The 2-stage estimation approach to computing a digitalization index was adopted, whereby the first stage involved reducing the observable variable to three dimensions of digitalization and extracting construct scores, while the second stage involved reducing the three dimensions of digitalization into a composite index. Moreover, the factors that influence digitalization development were determined using a multiple linear regression model.

Therefore, the model for indexing digitalization demonstrates practical validity. All observable variables strongly contributed to the emergent variables. All correlations between observable variables and their constructs, as well as correlations between emergent variables, were positive and significantly different from zero, indicating that the 95% percentile confidence intervals do not cover zero. There is no empirical evidence against the specified model based on the model evaluation results; hence, the proposed theory for digitalization cannot be rejected.

Table 12. Full model results

Dependent variable: dig	
Independent variable	Coefficient
age	-0.011** (0.005)
educ	0.003 (0.012)
factor(gender)1	0.241** (0.115)
factor(farm_type)1	-0.800** (0.381)
factor(farm_type)2	-0.378*** (0.144)
factor(farm_type)3	-0.236 (0.158)
factor(farm_type)4	-0.157 (0.461)
signal_strength	-0.008 (0.044)
factor(network_type)1	-0.487* (0.272)
factor(network_type)2	-1.046 (0.983)
factor(network_type)3	0.285 (1.378)
factor(cellular_data_type)1	-0.272 (0.224)
factor(cellular_data_type)2	-0.254 (0.178)
factor(cellular_data_type)3	-0.092 (0.164)
factor(cellular_data_type)4	-0.476** (0.220)
signal_strength:factor(network_type)1	0.052 (0.086)
signal_strength:factor(network_type)2	0.266 (0.295)
signal_strength:factor(network_type)3	-0.238 (0.614)
Constant	0.966** (0.395)

Observations = 300; R^2 = 0.117; Adjusted R^2 = 0.060; Residual Std. Error = 0.860 (df = 281); F Statistic = 2.068*** (df = 18; 281); Note: *p<0.1; **p<0.05; ***p<0.01; Standard errors are in the parentheses.

The study provides evidence that PLAS farmers have embraced little digitalization. Extension officials and practitioners should continue to educate farmers on the various digital solutions available in the market. The government should also prioritise the reallocation of resources, such as subsidies and training, for the use of digital solutions in farms. The findings point to an environment in which CSAD, and automation digitalization have a substantial impact on the digital transformation of agriculture, particularly crop-related operations. Additionally, the importance of data-driven approaches demonstrated by CSAD technologies underscores the role played by digitalization in optimising farming practices. Therefore, the adoption patterns of digital solutions on PLAS farms vary. Digital transformation efforts of PLAS farmers have disproportionately emphasised primary production processes and overshadowing critical value chain activities. Policymakers should also provide incentives to develop digital solutions that can enhance the automation of specific farm activities. The conclusions of this study also offer valuable insights for initiatives to balance approaches aimed at promoting digitalization in PLAS farms to include value chain digitalization.

Digitalization in PLAS farms is influenced by age, sex, farm type, network type, and cellular data type. Age has a negative effect on digitalization. Interventions aimed at promoting and speeding up digitalization in PLAS farms should consider collaborations that comprise a mix of young, middle-aged, and older generations of farmers. There is a digital divide between PLAS farms owned or leased to male farmers and those owned or leased to female farmers, indicating the onset of a digital divide between the two groups of farmers. Female farmers and their representation in farmer support groups should be prioritized in government intervention and training programs for digital agricultural solutions. Network and cellular data types also prove to be important factors for digitalization. Therefore, age, gender, farm type, network, and cellular data types should be considered in any agenda that attempts to influence digitalization in PLAS farms. It is important to give consideration and prioritise these factors to ensure that resources are allocated accordingly when designing and implementing agricultural policies. This will help speed up the process of digitalising PLAS farms. Aligning strategies and support with these factors will improve the effectiveness and efficiency of digitalization initiatives.

Limitations and Directions for Future Research

The measurement items for digitalization indicators were Likert scales, which do not have units of measurement. This constraint on the dependent variable's interpretation. Future research may monitor investment amounts on digitalization indicators to guarantee a standardised measurement unit for each item, thereby facilitating interpretation. In addition, sources and techniques for monitoring investments on various digitalization indicators should be developed in order to ensure future studies measure digitalization effectively.

Future research should also consider exploring the preferred attributes of specific agricultural digital solutions within each dimension of digitalization. Moreover, factors that influence farmers' preferences for certain attributes should be examined. The influence and involvement of farmers in the design of agricultural digital solutions also require investigation in future studies. There is a need to investigate the economic returns of specific agricultural digital solutions to yield more empirical evidence of the benefits of digitalization. This will increase the confidence of farmers, as their allocation of resources is supported by evidence.

Declarations

Submission Declaration and Verification

The manuscript has not been published previously and is not under consideration for publication elsewhere. The submission of the manuscript and its publication has been approved by all authors and tacitly or explicitly by the responsible authorities where the work was carried out, and that, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright-holder.

CRediT Author Statement

Sukoluhle Mazwane: Conceptualization, Methodology, Data curation, Formal analysis, Visualization, Writing- Original Draft. Moraka N Makhura: Conceptualization, Supervision, Writing- Reviewing and Editing. Athula Ginige: Conceptualization, Supervision

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