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Descriptive analysis of South African livestock Farmers Towards the Adoption of Smart Farming Technologies

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Abstract
This study investigates the factors influencing the adoption of smart farming technologies (SFTs) among South African livestock farmers, recognizing that their technology adoption behaviour differs from crop farmers. Using a quantitative descriptive research design, data were collected from 110 livestock farmers through a structured questionnaire. Structural Equation Modelling (SEM) was employed to test hypothesised relationships between technological, behavioural, institutional, and perceptual factors. The results show that Perceived Usefulness and Technical Infrastructure are significant predictors of adoption, while Farmers' Knowledge and Skills, External Support, and Regulatory Environment have weak or non-significant effects. These findings highlight the critical role of infrastructure and perceived benefits over institutional support in shaping adoption decisions. The study contributes to understanding livestock-specific adoption dynamics in a South African context, where infrastructural challenges and behavioural factors intersect. It recommends prioritizing infrastructure investment, emphasizing practical benefits in training programmes, and exploring context-specific business models for smallholder farmers. This research provides empirical evidence to guide policymakers, technology developers, and extension services in fostering digital transformation in the livestock sector.

Keywords
smart farming technologies, livestock farmers, technology adoption, structural equation modelling, digital agriculture

INTRODUCTION

The adoption of smart farming technologies (SFTs) has significant potential to transform the livestock sector in South Africa by improving farm management, enhancing productivity, and promoting climate resilience. Technologies such as the Internet of Things (IoT), drones, artificial intelligence (AI), and precision livestock farming tools are increasingly being used to optimize feeding systems, monitor animal health, and improve farm decision-making. IoT-enabled sensors can track vital signs, detect disease symptoms early, and provide real-time information on animal behaviour and environmental conditions, enabling timely interventions. AI-powered analytics can process large volumes of data to generate actionable insights on disease prevention, feed optimization, and breeding strategies, thereby improving livestock welfare and production efficiency. Drones and other automated systems can assist in pasture management, surveillance of remote grazing areas, and efficient resource utilization. Together, these technologies offer pathways to address long-standing challenges in the livestock sector, including disease outbreaks, high feed costs, labour shortages, and the growing impacts of climate variability (Molieleng et al., 2021; Mkhonto & Zuva, 2024).

Livestock farming plays a crucial role in South Africa's agricultural economy, supporting millions of livelihoods and contributing substantially to food security. Cattle, sheep, goats, pigs, and poultry form the backbone of rural and commercial farming systems. However, communal and smallholder farmers often operate under resource constraints, facing challenges related to limited access to technology, weak infrastructure, and insufficient advisory services. Research by Slayi et al. (2023) shows that smallholder livestock farmers are increasingly adopting communal feedlots to build climate change resilience, indicating a willingness to embrace innovative solutions. Similarly, Bontsa et al. (2023) highlight the growing interest in digital technologies among smallholder farmers in the Eastern Cape, though adoption remains constrained by socio-economic and infrastructural barriers. Bodiba and Legodu (2025) emphasize the critical role of agricultural advisors in facilitating knowledge transfer to smallholder farmers, suggesting that institutional support can accelerate digital transformation in livestock systems.

Despite these developments, most studies in South Africa and globally have focused predominantly on crop farmers, often generalizing technology adoption behaviours across the agricultural sector. However, livestock farmers have distinct operational systems, risk perceptions, and technological needs compared to crop farmers (Mbeche et al., 2025; Kgopa and Monchusi, 2025; Dippenaar, 2022). This lack of differentiation creates a critical research gap. The current study addresses this gap by investigating the perceptions and factors influencing the adoption of smart farming technologies among South African livestock farmers**.** It aims to develop a Structural Equation Model (SEM) to understand the relationships between behavioural, socio-economic, institutional, and technological factors, providing a more nuanced understanding of livestock-specific technology adoption patterns.

Aim of the Study

The aim of the study is to investigate the factors influencing the adoption of smart farming technologies by South African livestock farmers and to develop a Structural Equation Model (SEM) to explain the relationships between these factors.

Sub-Objectives

1. To examine the effects of technical, behavioural, institutional, and perceptual factors on livestock farmers' adoption of smart farming technologies.
2. To validate the measurement model and assess the reliability and validity of the identified constructs influencing adoption.
3. To develop and test a Structural Equation Model (SEM) that explains the interrelationships between the validated factors and livestock farmers' adoption behaviour.

RELATED LITERATURE REVIEW

Smart farming technologies (SFTs) are increasingly viewed as critical for enhancing productivity, sustainability, and climate resilience in the livestock sector. However, adoption remains uneven, particularly in developing contexts such as South Africa, where livestock farmers face unique structural, behavioural, and technological constraints. Existing studies conducted outside South Africa reveal that technology adoption behaviour differs significantly between crop and livestock farmers, emphasizing the need for livestock-specific analyses rather than generalized approaches.

Research in Kenya by Mbeche et al. (2025) shows that behavioural factors such as attitudes, subjective norms, and perceived behavioural control which are strongly influencing livestock farmers' intentions to adopt climate-smart agricultural practices. Similarly, Schukat and Heise (2021) found that German livestock farmers' attitudes towards smart products are shaped by perceived usefulness, ease of use, trust, and data privacy concerns. In South Africa, Bodiba and Legodu (2025) highlight the role of agricultural advisors in influencing technology transfer to smallholder farmers, underscoring the importance of institutional and informational support.

International evidence further enriches this understanding. Tikasz et al. (2023) identified varying levels of readiness and attitudes among pig and poultry farmers, while Kopler et al. (2023) emphasized that perceived benefits (e.g., productivity gains) often coexist with perceived risks (e.g., job displacement, data misuse) in the EU livestock sector. In Brazil, Silvi et al. (2021) showed that dairy farmers' perceptions of precision technologies are influenced by farm size, education, and expected economic returns. Consumer perspectives also matter, as Krampe et al. (2021) found that social acceptance shapes farmers' innovation decisions.

Marescotti et al. (2021) explored technophobia and technophilia among mountain livestock farmers, revealing psychological factors that affect adoption willingness. Makinde et al. (2022) documented similar patterns in the Canadian beef industry, were perceptions of complexity and cost influence adoption decisions.

Overall, the literature underscores the multi-dimensional nature of livestock farmers' perceptions spanning behavioural, socio-economic, institutional, and technological factors necessitating a tailored analytical approach. This study addresses this gap by applying Structural Equation Modelling (SEM) to examine South African livestock farmers' adoption of SFTs, recognizing their distinct technological adoption behaviour compared to crop farmers.

Underpinned theoretical models and hypothesis

The development of the Structural Equation Model (SEM) is underpinned by well-established technology adoption frameworks, particularly the Technology Acceptance Model (TAM) and Computer Self-Efficacy Theory.

TAM, introduced by Davis (1989), theorizes the two key beliefs such as Perceived Usefulness (PU) and Perceived Ease of Use (PEOU) which determine individuals' behavioural intention to adopt technology, which subsequently influences actual usage. Davis, Bagozzi, and Warshaw (1989) further compared TAM with other theoretical models and confirmed its robustness across different technological contexts. In this SEM, PU is represented as a latent construct influencing the Adoption of Smart Farming Technologies (ASFT), illustrating farmers' belief that smart technologies can enhance livestock management productivity and efficiency.

Additionally, Computer Self-Efficacy Theory (Compeau & Higgins, 1995) informs constructs such as Farmers' Knowledge and Skills (FKS) and Technical Infrastructure (TI), which capture farmers' confidence and ability to use technology, as well as the enabling infrastructure required for adoption. High self-efficacy correlates with increased willingness to experiment with and adopt new technologies. External Support (ES) and Regulatory Environment (RE) reflect facilitating conditions and external influences, aligning with Chau and Hu's (2001) emphasis on integrating external factors into technology adoption models for professional contexts.

This combination of TAM and self-efficacy perspectives has been widely applied in agricultural and digital technology adoption studies (e.g., Mbeche et al., 2025; Bodiba & Legodu, 2025), supporting its relevance for modelling livestock farmers' adoption behaviour. By integrating behavioural beliefs, facilitating conditions, and external influences, the SEM provides a comprehensive framework to explain livestock farmers' perceptions and adoption of smart farming technologies in South Africa.

HYPOTHESIS DEVELOPMENT

The hypotheses were formulated based on established technology adoption frameworks particularly the Technology Acceptance Model (TAM) (Davis, 1989; Davis et al., 1989), Computer Self-Efficacy Theory (Compeau & Higgins, 1995), and extended TAM models (Chau & Hu, 2001). These frameworks emphasize behavioural beliefs (e.g., perceived usefulness), facilitating conditions (e.g., infrastructure, support), and individual capabilities (e.g., knowledge and self-efficacy) as key determinants of technology adoption.

H1: Technical Infrastructure (TI) has a positive and significant effect on the adoption of smart farming technologies (ASFT).

Adequate infrastructure such as internet connectivity, hardware, and farm-level digital systems enhance farmers' ability to use and integrate smart technologies. Molieleng et al. (2021) highlighted the importance of enabling infrastructure for communal livestock farmers adopting climate-smart technologies, while Mkhonto and Zuva (2024) found that infrastructure significantly influences the acceptance of smart agriculture technologies.

H2: Farmers' Knowledge and Skills (FKS) positively influence the adoption of smart farming technologies (ASFT).

Knowledge and digital literacy increase farmers' confidence and ability to use new technologies, aligning with computer self-efficacy theory (Compeau & Higgins, 1995). Mbeche et al. (2025) found behavioural factors, including knowledge, to be key predictors of adoption in livestock systems.

H3: External Support (ES) has a positive influence on the adoption of smart farming technologies (ASFT).

Access to extension services, advisory support, and training improves adoption rates. Bodiba and Legodu (2025) emphasize the role of agricultural advisors in knowledge transfer to smallholder farmers, which facilitates digital technology uptake.

H4: Regulatory Environment (RE) positively affects the adoption of smart farming technologies (ASFT).

Policy incentives, regulations, and institutional frameworks shape adoption decisions by creating enabling conditions. Slayi et al. (2023) show how communal feedlot initiatives supported by regulatory structures improve resilience and encourage innovation adoption.

H5: Perceived Usefulness (PU) has a positive and significant effect on the adoption of smart farming technologies (ASFT).

This hypothesis is grounded in TAM (Davis, 1989), which posits that perceived usefulness strongly predicts behavioural intention and actual use. Bontsa et al. (2023) similarly found that perceived benefits influence digital technology adoption among smallholder farmers.

RESEARCH METHODOLOGY

This study adopted a quantitative descriptive research design, suitable for examining relationships between multiple variables in a structured manner (Bell et al., 2022; Stockemer et al., 2019). A structured questionnaire was used to collect data from 110 South African livestock farmers, focusing on technological, behavioural, institutional, and perceptual factors influencing the adoption of smart farming technologies.

The instrument consisted of validated constructs derived from the Technology Acceptance Model (TAM) and Computer Self-Efficacy Theory, measured on a Likert scale to ensure standardization. The data collection approach aligns with the principles of quantitative research, emphasizing objectivity, replicability, and statistical generalization (Hair et al., 2019).

Data were analysed using Structural Equation Modelling (SEM), which enables simultaneous testing of measurement and structural models to evaluate hypothesised relationships between latent constructs (Coe et al., 2021). SEM was employed to assess construct validity, reliability, and the significance of hypothesised paths using p-values. This analytical technique is particularly effective for theory testing and model development in social science research.

The methodology ensured rigour through careful design, appropriate sampling, and advanced statistical analysis, providing robust insights into the factors influencing livestock farmers' adoption of smart farming technologies in the South African context (Busetto et al., 2020).

RESULTS AND DISCUSSION

This section presents the findings from the survey conducted among 110 South African livestock farmers, who responded to a structured questionnaire designed to measure technological, behavioural, institutional, and perceptual factors influencing smart farming technology adoption. The questionnaire used Likert-scale items to assess participants' perceptions regarding infrastructure, knowledge, support, regulation, and perceived usefulness. The results include demographic characteristics, hypothesis testing, and the Structural Equation Modelling (SEM) analysis, providing insights into the key determinants of technology adoption behaviour among livestock farmers.

Demographic results

Figure 1 provides a breakdown of the respondents' gender distribution. Out of a total of 110 participants, 82 (75%) identified as gender category " (Males," while 28 (25%) identified as gender category "2 (Females)". This figure illustrates the majority representation of category "1" in the sample, suggesting that insights derived from the data may predominantly reflect the experiences and perspectives of this group. The balance between categories is adequate for meaningful analysis.

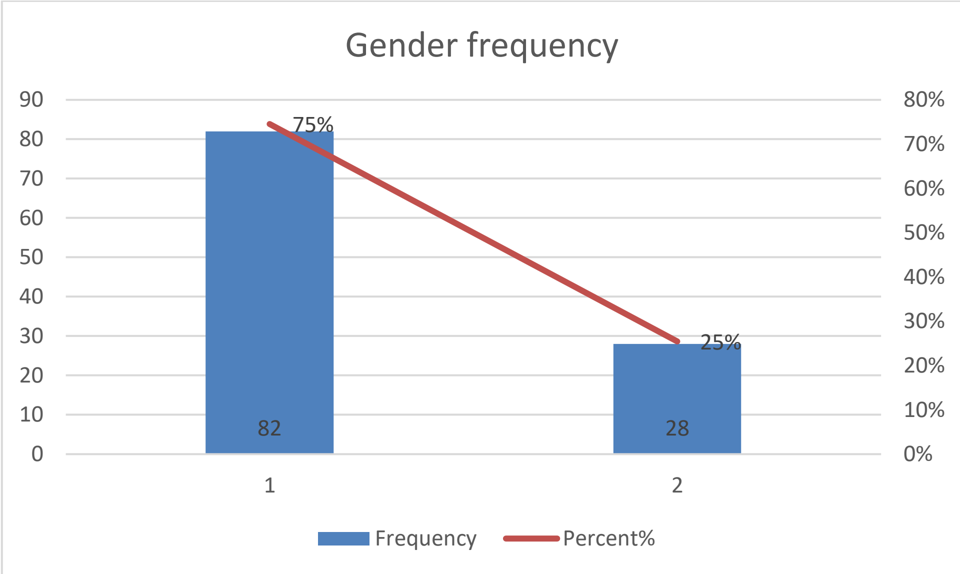

Fig. 1 gender distribution

Table 1 below provides the distribution of participants' ages. A total of 110 respondents participated in the survey. The age categories are defined as follows: Category 1 (18–25 years); Category 2 (26–35 years; Category 3 (36–45 years); Category 4 (46–60 years); and Category 5 (above 60 years) includes senior farmers who are generally slower adopters of new technologies. The most frequent age group was category 2, which included 46 individuals (41.8% of the total sample), followed by category 3 with 40 individuals (36.4%). The next largest group was category 1, with 12 participants (10.9%), while category 5 had 8 respondents (7.3%). Finally, category 4 had the fewest individuals, with just 4 respondents (3.6%). Cumulatively, the percentages increase progressively across the categories, with 52.7% of participants being in category 2 or younger, and by the end, 100% of participants are accounted for across all categories. This distribution provides a snapshot of age diversity in the sample.

Table 1 Age distribution

Age					
		Frequency	**Percent**	**Valid Percent**	**Cumulative Percent**
Valid	1	12	10.9	10.9	10.9
	2	46	41.8	41.8	52.7
	3	40	36.4	36.4	89.1
	4	4	3.6	3.6	92.7
	5	8	7.3	7.3	100.0
	Total	**110**	**100.0**	**100.0**	

Table 2 below outlines the distribution of participants' qualifications. A total of 110 respondents participated in the survey. The largest group of respondents, 69 individuals (62.7%), held a Diploma, making it the most common qualification among the participants. The second largest group, 30 participants (27.3%), had a Certificate qualification. Fewer individuals held higher qualifications, with 8 participants (7.3%) possessing a Degree and 3 participants (2.7%) holding a Postgraduate qualification. The cumulative percentages show that by the time we reach the Diploma category, 90% of the sample is accounted for. This suggests that the majority of respondents have intermediate-level qualifications, while there are fewer individuals with higher or lower qualifications. This distribution provides insight into the educational background of the sample.

Table 2 Qualifications distributions

		Qualifications			
		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Certificate	30	27.3	27.3	27.3
	Diploma	69	62.7	62.7	90.0
	Postgraduate	3	2.7	2.7	92.7
	Degree	8	7.3	7.3	100.0
	Total	**110**	**100.0**	**100.0**	

Hypothesis results

Table 3 is the hypothesis tested results reveal that Technical Infrastructure (H1) and Perceived Usefulness (H5) significantly influence the adoption of smart farming technologies (ASFT), while Farmers' Knowledge and Skills (H2), External Support (H3), and Regulatory Environment (H4) show no significant effects.

The strong effect of Perceived Usefulness aligns with Schukat and Heise (2021), who found that German farmers' adoption decisions are primarily driven by perceived productivity gains and efficiency improvements. Similarly, Kopler et al. (2023) reported that perceived benefits such as improved monitoring and animal welfare strongly shape technology adoption in the EU livestock sector. The significance of Technical Infrastructure reflects findings by Makinde et al. (2022), who emphasized that adequate digital infrastructure is critical for Canadian beef farmers to effectively use digital tools, especially in remote areas.

The non-significant impact of Farmers' Knowledge and Skills contrasts with expectations but may reflect broader systemic issues. Tikasz et al. (2023) found that even when farmers have some awareness, adoption can remain low if the technologies are perceived as complex or costly. Similarly, Silvi et al. (2021) observed that Brazilian dairy farmers' adoption depends more on farm size and expected returns than on technical know-how alone. External Support and Regulatory Environment also did not significantly influence adoption, echoing Marescotti et al. (2021), who noted that technophobia and context-specific attitudes often outweigh external drivers, particularly in traditional livestock systems. Overall, these findings highlight the primacy of infrastructure and perceived benefits over institutional and knowledge-based factors in influencing livestock farmers' adoption behaviour.

Table 3 hypothesis testing results

Hypothesis	P-value	Outcome
H1: Technical Infrastructure (TI) has a positive and significant effect on the adoption of smart farming technologies (ASFT).	0.045	Supported
H2: Farmers' Knowledge and Skills (FKS) positively influence the adoption of smart farming technologies (ASFT).	0.842	Not Supported
H3: External Support (ES) has a positive influence on the adoption of smart farming technologies (ASFT).	0.231	Not Supported
H4: Regulatory Environment (RE) positively affects the adoption of smart farming technologies (ASFT).	0.154	Not Supported
H5: Perceived Usefulness (PU) has a positive and significant effect on the adoption of smart farming technologies (ASFT).	0.000	Supported

The conceptualised Structural Equation Model (SEM)

Figure 2 shows the conceptualized SEM results reveal that Perceived Usefulness (PU) and Technical Infrastructure (TI) are significant predictors of livestock farmers' adoption of smart farming technologies (ASFT), while Farmers' Knowledge and Skills (FKS), External Support (ES), and Regulatory Environment (RE) show weak or non-significant effects.

- ***Perceived Usefulness (PU → ASFT)***

Perceived Usefulness has the strongest positive and significant effect on the adoption of smart farming technologies (path coefficient = 0.345). This indicates that livestock farmers are more likely to adopt technologies when they perceive clear benefits such as improved efficiency, productivity, and animal welfare. Schukat and Heise (2021) found that German farmers' adoption of smart products was driven primarily by perceived productivity gains. Similarly, Kopler et al. (2023) observed that perceived benefits including better monitoring and data-driven decision-making are decisive in adoption decisions. This underscores the central role of PU, consistent with TAM-based studies in agricultural contexts.

- ***Technical Infrastructure (TI → ASFT)***

Technical Infrastructure shows a positive and significant relationship (0.096) with adoption, highlighting that access to reliable digital infrastructure such as connectivity, devices, and data systems is essential. Farmers with adequate infrastructure are better positioned to integrate and use smart farming technologies effectively. Makinde et al. (2022) reported similar findings in the Canadian beef industry, where digital infrastructure gaps significantly constrained adoption, particularly in remote and rural areas.

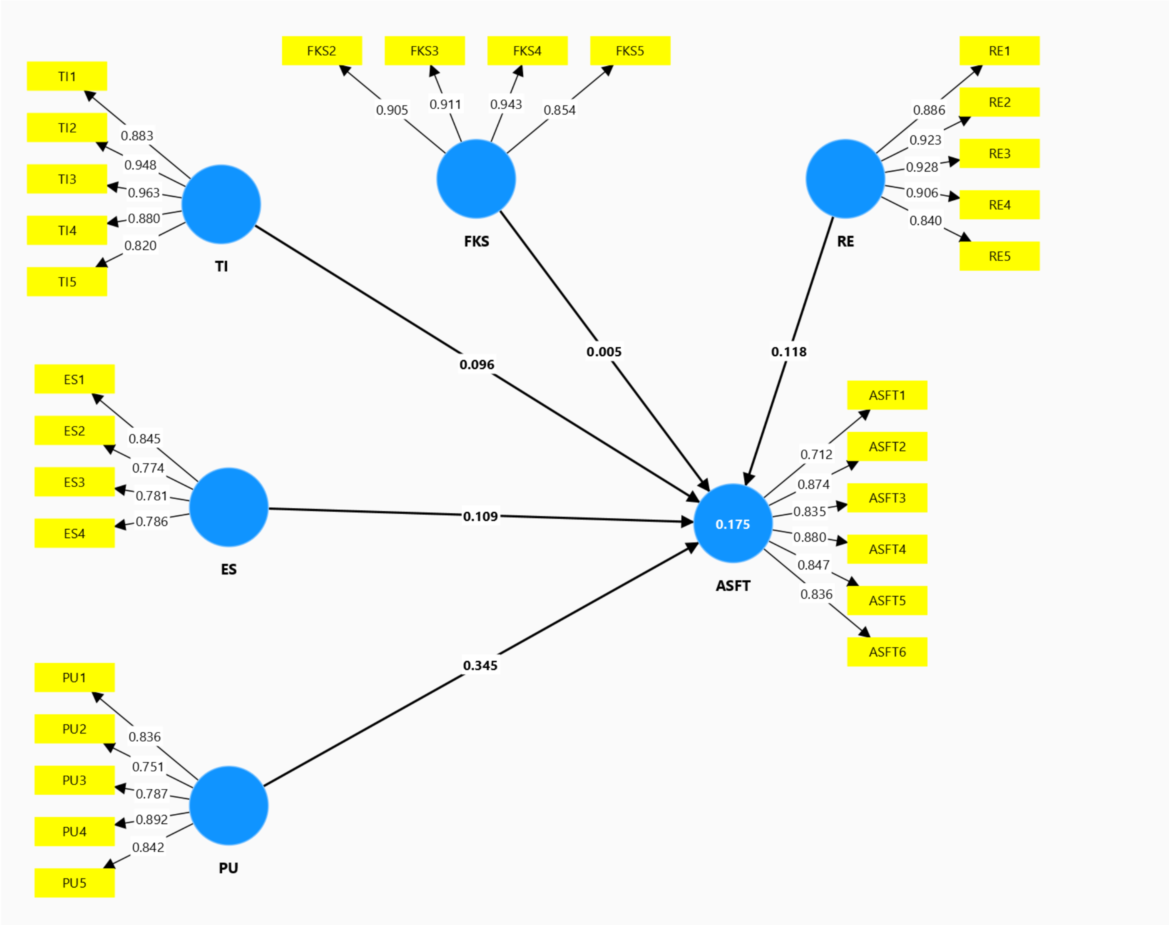

Fig. 2 Conceptualized SEM results

- ***Farmers' Knowledge and Skills (FKS → ASFT)***

FKS exhibits a very weak and non-significant effect (0.005), suggesting that knowledge and skills alone are not sufficient to drive adoption. This may reflect situations where farmers have some awareness but still perceive technologies as complex, costly, or unsuitable. Tikasz et al. (2023) found that readiness among pig and poultry farmers did not always translate into adoption due to perceived barriers and uncertainties.

- ***External Support (ES → ASFT)***

The path from External Support to ASFT (0.109) is positive but not significant, indicating that extension services, advisory inputs, and training programs may not directly influence adoption decisions. Marescotti et al. (2021) found that farmers' attitudes such as technophobia or technophilia often have a stronger influence than external interventions, especially in traditional livestock systems where institutional influence is limited.

- ***Regulatory Environment (RE → ASFT)***

The Regulatory Environment shows a weak and non-significant effect (0.118), implying that policies, regulations, or institutional frameworks currently have limited impact on farmers' adoption behaviour. Silvi et al. (2021) similarly found that Brazilian dairy farmers' adoption decisions were more strongly shaped by expected economic returns and farm size than by regulatory incentives.

The recommendations, Future Work, and limitations

The study recommends prioritizing investment in digital infrastructure to enhance connectivity and technical capacity in rural livestock farming communities, as infrastructure significantly influences adoption (Makinde et al., 2022; Molieleng et al., 2021). Awareness and training programmes should emphasize the practical benefits and usefulness of smart farming technologies to increase adoption (Schukat & Heise, 2021; Kopler et al., 2023). Strengthening agricultural advisory services can support knowledge transfer and farmer engagement, especially among smallholders (Bodiba & Legodu, 2025). Policies should incentivize adoption through targeted support rather than relying solely on regulatory mechanisms (Slayi et al., 2023).

Future research should explore longitudinal and comparative studies to understand behavioural changes over time and differences between crop and livestock farmers. Incorporating behavioural factors and technophobia/technophilia into extended models could deepen understanding of non-technical adoption barriers (Marescotti et al., 2021; Tikasz et al., 2023). Finally, future work should examine context-specific business models for affordable technology adoption among communal and smallholder livestock farmers.

The study is limited by its cross-sectional design, which restricts causal inference, and its focus on a specific geographic context, limiting generalizability. It relies on self-reported data, which may introduce response bias. Additionally, the model does not include cultural or behavioural moderators, which could further explain variations in livestock farmers' adoption behaviours across different contexts.

CONCLUSION

The study concludes that Perceived Usefulness and Technical Infrastructure are the most significant factors influencing the adoption of smart farming technologies among South African livestock farmers. These findings highlight those farmers are more likely to adopt technologies when they perceive clear productivity and efficiency benefits, supported by adequate digital infrastructure. In contrast, Farmers' Knowledge and Skills, External Support, and Regulatory Environment show limited influence, suggesting that institutional mechanisms and knowledge transfer alone are insufficient drivers of adoption. This reinforces the need to shift focus from generalized crop-oriented strategies to livestock-specific approaches that address infrastructural and behavioural dimensions. By applying Structural Equation Modelling (SEM), the study provides a nuanced understanding of the interrelationships between multiple determinants of adoption. Overall, strengthening rural infrastructure, enhancing perceived value through awareness programmes, and developing context-appropriate support mechanisms are critical for accelerating smart technology adoption in the livestock sector. These insights offer valuable guidance for policymakers, agricultural advisors, and technology providers aiming to drive digital transformation and sustainability in South African livestock farming.

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