

Mapping Synergies and Trade-offs between Digital Agriculture Outcomes and Inequalities among Farmers in Uasin-Gishu County, Kenya

Evans Kemboi, Prakash Singh Badal, Virendra Kamalvanshi, Sachin Rathour and Bharath Kumar Mannepalli

Department of Agricultural Economics, Institute of Agricultural Sciences, Banaras Hindu University, Varanasi, Uttar Pradesh, India

Abstract

Digital technologies are often regarded as the next agricultural revolution, accelerating sustainable agri-food production. However, research on the synergies and trade-offs of digital practices in agriculture and the determinants of digital inequalities and its economic, societal or environmental implications are lacking. A survey of 384 farming households was conducted in Uasin Gishu County of Kenya. Higher synergistic interactions were found over trade-offs, indicating that a focus on one aspect of digital technology may result in spillover effects on other outcomes, although some farmers may struggle to reap the benefits in the short term. The biggest synergies exist between increased credit availability, entrepreneurial skills and weather updates/alerts access, while the biggest trade-off occurs between farm workers reduction, increased credit availability and high data bundles/devices costs. The age, geographical location, education level and accessibility to extension services were key determinants of digital inequality. This contribution emphasizes the need for integrated digital strategies that promote both innovation and inclusivity for equitable socio-economic outcomes.

Keywords: Synergies, Trade-offs, Digital tools, Digital agriculture, Digital inequality

JEL Classification: Q12, Q16, D63, O33

Introduction

Over the past decade, digital agriculture (DA) has garnered considerable interest attributed to the rapid emergence of new technologies worldwide (Hackfort, 2021; Mouratiadou et al., 2023). “Digital farming technologies cover a broad spectrum, from small mobile apps for decision support, over in-field sensors and remote sensing technologies for data collection and to drones and robots for the automation of processes” (Shang et al., 2021). Shepherd et al. (2020) and Addison et al. (2024) describe DA as the application of digital technologies to support decisions and undertake tasks across all the stages of the agricultural value chain. This study adopts this approach, focusing on the utilization of basic digital tools (mobile and web-based applications) by farmers to access services such as personalized e-extension, digital payment, market information, and farm management services, among others. The smartphone, as a key component of DA, has considerably accelerated its expansion and has become an indispensable tool for farmers (Luo et al., 2023). Digital advisory services are more widespread in Sub-Saharan Africa, offering farmers services such as weather and market

price information all of which are readily available through mobile phones (GSMA, 2020). The need for timely access to reliable information has grown as a result of climate change or unpredictable weather conditions (Omulo and Kumeh, 2020). DA not only introduces new technology, but its application also improves and streamlines farm management and information integration. They are viewed as revolutionary for smallholders because of their ability to improve information access, increase output, and improve food security (Abdulai et al., 2023).

Kenya is often regarded as a “Silicon Savannah” (technology ecosystem), due to its number of ICT start-ups (Stroisch, 2018). With a mobile connection index score of 56.8, it is one of Sub-Saharan Africa’s top performers (GSMA, 2024). The utilisation of smartphones is rising in both urban and rural area, aided by enhanced management techniques and agricultural information systems (Balasundram et al., 2023). According to Aker and Ksoll (2016), farmers who utilised shared mobile phones had better agricultural outputs through cultivating a wider range of crops. DA’s positive contributions can enhance information dissemination, production, profitability and climate change response by enhancing smallholders’ and community resilience (Abdulai,

2022). Digital finance and its capabilities have been shown to positively increase agricultural income by fostering entrepreneurship skills among farmer households (Wang et al., 2023; Zhang et al., 2024). However, digitalization may also be associated with a range of detrimental effects or threats (Zscheischler et al., 2022). The disparities in access to new technologies, power shifts that benefit global agrosuppliers and tech companies, data misuse risks, asymmetries and rural employment patterns intensify inequalities and power imbalances (Fleming et al., 2018; Jayashankar et al., 2018; Regan, 2019; Rotz et al., 2019; Klerkx and Rose, 2020). Some of these outcomes may be regarded as having synergic and trade-off interactions.

Kenya's digital transformation agenda is essential; however, investigation on the implications of digital tool usage in farming is lacking. It is of prime concern to explore how the basic digital tools utilisation and their services in farming can create synergies and trade-offs from farmers' perspectives. Smartphones serve as the most accessible and economical entry point for agricultural extension information, digital marketing, financial services, and the use of farm management applications. The present investigation adds the understanding of DA by exploring the interconnected outcomes of digital practices and the determinants of digital inequalities. According to Breuer et al. (2019), "When progress on one objective adds to progress on other goals, the relationship is regarded as a synergy; when progress on one goal has a negative impact on other goals, the relationship is considered a trade-off". Understanding the intricate interactions that arise from digital tool usage is vital for informing policy that ensures inclusiveness while balancing economic, environmental, and societal implications. In this study, we aim to identify possible synergies and trade-offs arising from the application of digital practices in farming and to assess digital inequalities and their determinants among farmers in Uasin Gishu County of Kenya.

Data Sources and Methodology

The research was undertaken in Uasin Gishu County, Kenya, an agriculturally high-potential area located in the Kenyan highlands. The county features elevations between 1,500 and 2,700 meters with a land area of 3345.2 Km². There are two distinct rainfall seasons: 'long rains from March to September', and 'short rains from October to December' (Kibii and Kipkorir, 2018). The research utilised primary data from interviews alongside secondary information from journals and published sources. Respondent selection for the study was carried out through a multi-stage sampling process. At first, Uasin Gishu County of Kenya was selected purposively due to its consideration as an agriculturally high-potential region "food basket" of the country (KNBS, 2021). In the second stage, the six sub-counties (Moiben, Ainabkoi, Kesses, Kapseret, Turbo, and Soy) were chosen due to their proximity to the county headquarters, Eldoret city, which

allows access to agricultural institutions and companies that provide agricultural interventions to farmers. Next, two wards from each sub-county were randomly selected to capture farming household characteristics from each region. From these wards, 32 households per ward were selected for data collection. The uniform distribution method was chosen to represent the general farming characteristics of the county. The 2019 Kenyan population census revealed that around 77120 farming households in the county have mobile phone access (KNBS, 2019) resulting in a sample size of 384 households based on the Cochran (1977) formula for finite population.

$$n_0 = \frac{z^2 pq}{e^2} = \frac{(1.96^2)(0.5)(1-0.5)}{0.05^2} = 384.16$$

$$n = \frac{n_0}{\left(1 + \frac{n_0}{N}\right)} = \frac{384.16}{\left(1 + \frac{384.16}{77120}\right)} = 382.3$$

Where n_0 is the estimated sample size, N =population size, p represents the proportion of the population (the study assumed that $p=0.5$, which was about 50 per cent of smallholders using phones or ICT), q equal to $1-p$, z represents a 95 per cent degree of confidence level (1.96) and e is the acceptable error (precision).

Principal component and correlation analysis

A literature review aided in categorising digital practices into economic, social and environmental domains (Figure 1). Eighteen indicators were identified and a field survey was conducted to gather farmers' perceived outcomes of digital practices using a 5-point Likert scale. Principal component analysis (PCA) was used to refine variables into sixteen key outcome dimensions following the methodology approach adopted by Appelt et al. (2025). PCA is a statistical technique for reducing a data set's variables into smaller 'dimensions'. Spearman's rank correlation analysis was then employed to map inter-linkages across outcomes, interpreting positive and negative correlations as synergies and trade-offs respectively.

$$r_s = 1 - \frac{6 \sum d_i^2}{n(n^2 - 1)}$$

Where, r_s = 'Spearman's rank correlation coefficient', d_i = 'difference between the two ranks of each observation' and n = 'number of observations'

Digital inequality index

Study utilised Li, (2023) methodology to calculate the digital inequality index, which is a multidimensional construct involving digital access and usage. Six indicators were normalized on a binary scale, with the number of devices normalized using min-max scaling. All other indicators were already binary (Table 1). The digital inequality (DI_i) for each household was calculated as the average of these indicators, representing the overall digital utilization level. The formula for normalized value and digital inequality index is provided as follows.

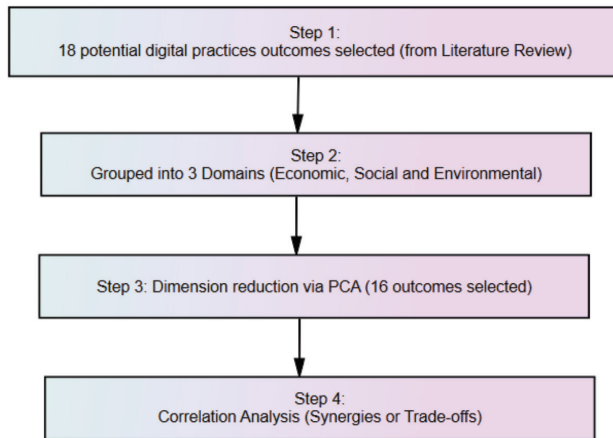


Figure 1: Conceptual steps

$$X' = \frac{X_i - X_{min}}{X_{max} - X_{min}}$$

$$DI_i = \frac{\max(Digital_{ci}) - Digital_i}{\max(Digital_{ci}) - \min(Digital_{ci})}$$

where, X' denotes the normalized value for the number of devices, X_i represents the original indicator value for household i , and X_{max} and X_{min} indicate the maximum and minimum values of the indicator at the household level, respectively. $Digital_{ci}$ denotes the level of digital use among households within the same county, while 'max' and 'min' refer to the highest and lowest observed values. A larger DI_i score reflects a higher level of digital disparity experienced by the household.

Regression analysis model

A multiple regression model was applied to examine determinants of DI. The formula is given as follows,

$$DI_i = \beta_0 + \beta_1 Age_i + \beta_2 Gender_i + \beta_3 Location_i + \beta_4 Educ_i + \beta_5 Farmsize_i + \beta_6 Income_i + \beta_7 Coop_i + \beta_8 Ext_i + \varepsilon_i$$

Where, DI_i captures the degree to which the household experiences digital gaps, which is considered as a dependent variable, β_i are the parameters ($i = 0, 1, 2, \dots, 8$). Age_i indicates the age characteristics of the household respondent. $Gender_i$ is a dummy variable that indicates whether 1=female, or otherwise 0. $Location_i$ shows the geographical location of the household respondent using the dummy variable 1=Rural, or otherwise 0. $Education_i$ was coded as 1=literate, otherwise=0, $Farmsize_i$ in acres, $Income_i$ indicates the income characteristics of the household respondent in Kenyan shilling (Ksh), $Cooperative_i$ and $extension services_i$ were coded as 1=Yes or 0=No. ε_i represents the error or random disturbance term.

Results and Discussion

Demographic profile of the respondents

The respondents were composed of 58.85 per cent male and 41.15 per cent female, while the respondents' mean age was about 42.39 years. This is consistent with traditional family systems in which men often play a role as the head of the household. The average farming experience was around 14.67 years. 33 per cent of the respondents had primary schooling, while 26.04 per cent had secondary education and 17.71 per cent had certificate/diploma qualifications. The mean household size was around 6 people, with a mean farm size of 8.6 acres. Moreover, the majority of respondents (52.08%) utilise family land, with only 27.86 per cent and 20.05% owning private land and rented land, respectively (Table 2).

Figures 2 and 3 reveal diverse patterns in farmers' access to digital tools. Smartphones were the most common device (63.28%), followed by feature phones (56.77%), while tablets (12.24%) and laptops (5.73%) were less common. This may be associated with affordability and digital skill constraints (Mwansa et al., 2025). According to Krell et al. (2021), mobile phone ownership among households was nearly

Table 1: Dimension and indicators for assessing digital inequality index

Dimension	Indicator	Descriptions	Scale
Digital access	Number of devices	Proportion of farmers owning digital devices-how many digital tools does your household have? (Number)	Continuous (normalized)
	Network condition	How is the network condition at your HH? 1=Good; 0=Presence of network disruptions	Binary
Digital usage	Device usage	Barrier free- do you have any difficulties using digital tools? 1= Yes, 0=No	Binary
	Usage frequency	How frequency to you use digital tools for farming purposes? 1=Frequently, 0= Otherwise	Binary
	Info adequacy	Does the internet access satisfy your daily needs? 1=Yes, 0=No	Binary
	Literacy skill	Ability to perform basic digital tasks, can you send a text or browse the internet on your device; 1=Yes, 0=No	Binary

Table 2: Summary demographic profile of the respondents

Particulars	Value (n=384)
Gender (%)	
Male	58.85
Female	41.15
Age (year)	42.39
Education level (%)	
No formal schooling	8.33
Primary schooling	33.33
Secondary schooling	26.04
Certificate/Diploma	17.71
Graduate	11.46
Postgraduate and above	3.13
Farming experience (Years)	14.67
Farm size (Acres)	8.60
Household size (Number)	6.24
Land Ownership (%)	
Own private land	27.86
Family land	52.08
Rented land	20.05

universal (98%), but only one-quarter use it for agricultural purposes. On the other hand, digital financial services such as mobile money were most widely used (40.89%), whereas adoption of digital extension (19.01%), digital marketing (15.10%), and farm management tools (8.07%) remained comparatively low. Notably, 39.58 per cent of respondents did not use any digital agricultural services, highlighting persistent barriers to adoption. These findings concur with those of Parlasca et al. (2022), who discovered that mobile money usage was significant while its application in agriculture remained limited.

The adequacy of the factor reduction was verified through the Kaiser–Meyer–Olkin (KMO) test, which yielded a value of 0.913 and Bartlett’s test of sphericity ($\chi^2(153) = 4729.143$, $p < 0.000$). The correlation matrix was found to be sufficient for PCA, indicating its suitability for evaluating trade-offs

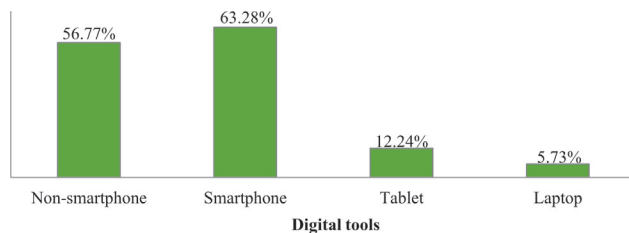


Figure 2: Patterns of digital tools usage among respondents. Note; the percentage do not add up to 100 as some respondents use more than one type of digital tools

and synergies associated with digital tools in agriculture (Table 3). Variables were selected based on their significant contribution to the component (Rangaswamy, 1995) and the principal components were determined using the “Kaiser-Guttman criterion of eigenvalue >1 ” (Chen et al., 2022; Sun et al., 2022). The initial four components of DA usage accounted for 68.65 per cent of the overall variation, with the first component accounting for 32.4 per cent, followed by the second dimension at 24.84 per cent, the third component at 5.77 per cent, and the fourth dimension at 5.64 per cent (Table 3).

Relationships between selected digital practices outcomes

Figure 4 shows the correlation between the DA outcome matrix 16x16, demonstrating 56 significant interactions between variables, with positive correlations indicating synergies and negative correlations indicating trade-offs. The strongest positive correlation was found between credit access and the initial high costs of acquiring digital devices/internet bundles ($r_s = 0.868$, $p < 0.01$), emphasizing the importance of credit facilities (Parlasca et al., 2022; Kamal and Bablu, 2023). Similarly, a high correlation between credit access and weather updates access ($r_s = 0.857$, $p < 0.01$). An inclusive credit can support CSA, enabling farmers to acquire real-time weather information. Farmers may need immediate access to credit to adopt CSA technologies Villalba et al. (2024), which can enhance their farm productivity. Credit facilitates easy procurement of inputs and technologies (Haryanto et al., 2023), enhancing agricultural performance and farm productivity through the synergies between credit access and other goals. Entrepreneurial skills positively correlate with the initial cost of acquiring digital devices ($r_s = 0.850$, $p < 0.01$) and credit access ($r_s = 0.836$, $p < 0.01$), indicating that farmers may invest in reliable tools when perceived benefits outweigh the costs (Fabregas et al., 2019). The application of digital services is linked to better decision-making capabilities among farmers particularly in weather updates. Digital financial services in rural areas may improve farmers’ entrepreneurial skills, market access and agricultural supply chain management (Deichmann et al., 2016; Xu and Yang, 2025).

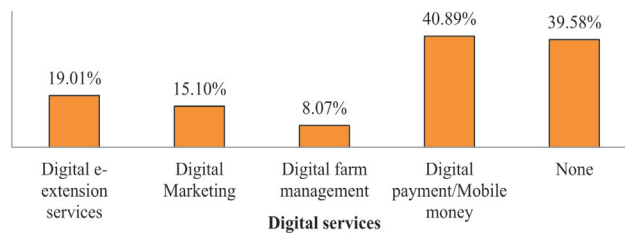


Figure 3: Patterns of digital services usage among respondents. Note; the percentage do not add up to 100 as some respondents use more than one type of digital services

Table 3: Rotated component matrix table with Eigen values and percentage of variance

Particulars	Principal Component			
	1	2	3	4
1. Reduce transaction cost	.623	.045	.549	-.032
2. Increased farm income	.629	-.042	.473	-.097
3. High costs data bundles/acquiring digital devices	.012	.957	-.016	-.054
4. Increased access to loan/credit facilities	-.016	.960	.019	-.013
5. Reduce farmers’ search cost	.710	.031	.209	-.137
6. Fosters knowledge sharing	.717	.023	.143	-.048
7. Promotes entrepreneurial skills among farmers	.024	.943	-.025	-.030
8. May bring changes in the farming culture among farmers	-.013	-.005	-.709	-.088
9. Strengthens social bonds	.721	.038	.132	-.013
10. Displace labourers/reduce need for more farm worker	-.008	-.955	.011	.020
11. Risk of misinformation/Privacy and data ownership issues	-.006	-.074	.063	.951
12. Promotes efficient use of inputs like fertilizer	.790	.031	-.036	.014
13. Increased access to weather updates/alerts	-.008	.896	.024	.012
14. Supports early warnings e.g floods/pest outbreaks	.732	.008	.015	.203
15. Enhancement of biodiversity	.765	.003	.022	.174
16. Increases awareness of CSA practices	.623	-.080	.070	-.126
Eigen values (>1)	5.83	4.47	1.04	1.02
Percentage of Variance (%)	32.4	24.8	5.77	5.64

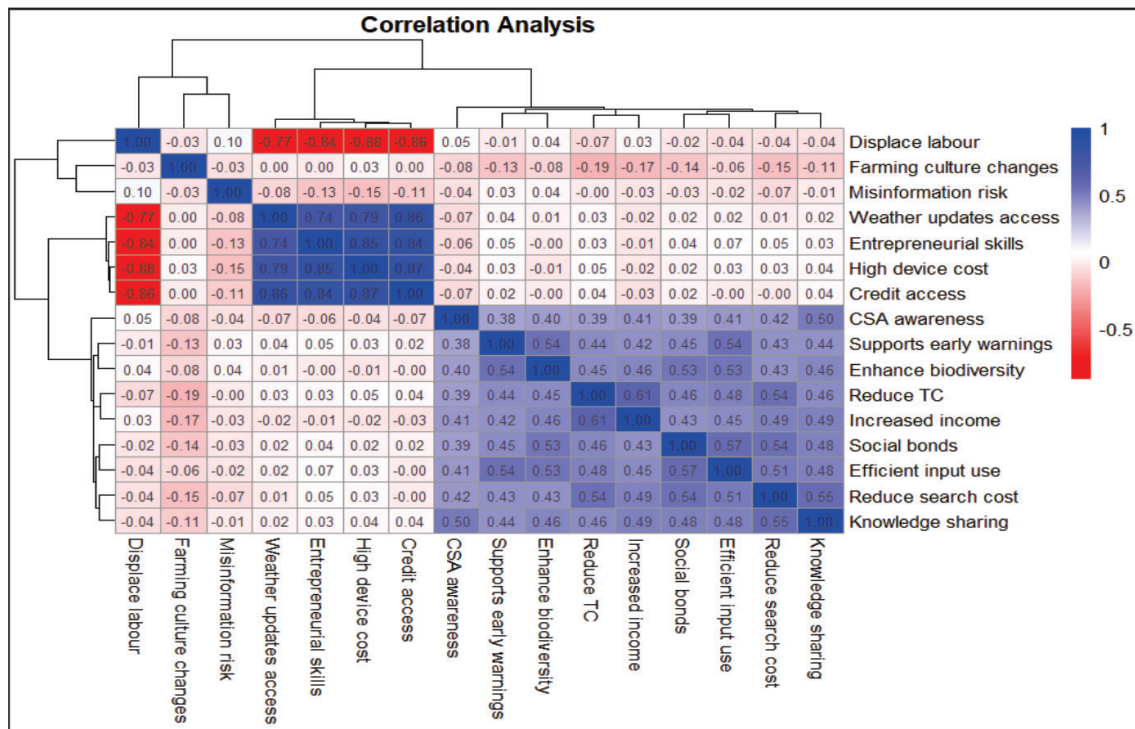


Figure 4: Correlation analysis between outcomes of digital tools usage

Table 4: Calculated digital inequality index for household respondents

Variable	Category	Digital inequality Index
Geographical location	Rural	0.55
	Urban	0.49
Gender	Male	0.51
	Female	0.54
Age	Younger farmers	0.49
	Older farmers	0.53
Overall DI Index		0.52

On the other hand, the high initial investment required for accessing digital tools negatively correlates with the reduction in farm workers ($r_s = -0.88$, $p < 0.01$), highlighting the significant barrier faced by smallholder farmers. Negative correlations were also observed between credit access and reduced farm workers, entrepreneurial skills and access to weather updates. Digital technologies can improve agricultural efficiency, but they may also lead to job losses and widen sectoral inequalities (Rotz et al., 2019). Moreover, changes in farming culture negatively impact transactional costs, income and search costs, highlighting trade-off dynamics. Digital engagement enhances market exchanges and information accessibility, although it may undermine traditional norms, result in uneven gains, create knowledge gaps and raise security and privacy concerns (Van Campenhout et al., 2021; Coggins et al., 2022; Choruma et al., 2024; Dibbern et al., 2024).

Digital inequality indices across different demographic categories of farmers

Table 4 presents calculated digital inequality indices across different demographics. Rural households exhibited a higher digital inequality (0.55) compared to urban households

(0.49). This digital gap may be attributed to differences in infrastructure, internet connectivity and digital service availability. Fu et al. (2024) and Wang et al. (2023) found that differences in information infrastructure availability and ICT adoption rate are more significant in urban areas. Gender-based disparities also emerged, with female respondents reporting slightly higher inequality (0.54) than male respondents (0.51). This may highlight how social norms, unequal resource distribution and lower digital literacy hinder women's participation in digital settings (Choruma et al., 2024). A similar observation was reported by Gustafsson and Nielsen (2017), who demonstrated that mobile phone availability significantly intensifies gender inequality in rural areas, in contrast to metropolitan settings. Older farmers displayed higher digital inequality (0.53) relative to younger farmers (0.49), implying that younger respondents were more digitally engaged and adaptive to emerging technologies.

Estimated coefficients for the determinants of digital inequality

The regression model's R-squared was 0.1229, indicating that all explanatory variables explained approximately 12.29 per cent of the variation in digital inequality. Among

Table 5: Determinants of digital inequality

Variables	Coefficients	Standard Error	P-value
Intercept	0.591***	0.131	0.000
Age	0.002**	0.001	0.042
Gender	0.018	0.018	0.339
Geographical location	0.060***	0.018	0.001
Education level	-0.114***	0.036	0.002
Farm size	-0.006	0.011	0.631
Farm income	-0.004	0.012	0.757
Cooperative membership	-0.018	0.022	0.392
Extension services	-0.051**	0.020	0.013
R-Square	0.1229		
No of observations	384		
Dependent variable:	Digital inequality (Calculated index)		

Note: ***and ** indicate $p < 0.01$ and $p < 0.05$, respectively

all the exogenous variables, age, geographical location, education level and access to extension services emerged as significant determinants of digital inequality (Table 5). Age had a positive and significant influence with the p-value falling below 0.05. This implies that older farmers may experience higher levels of digital inequality by 0.002. The younger farmers exhibit higher digital literacy and familiarity with emerging technology compared to older individuals. The findings aligned with previous research conducted by Ding et al. (2025), Wayagi et al. (2025), Gouthon et al. (2024), and Bontsa et al. (2023), which found that older farmers were more susceptible to the digital divide. The geographical location of the respondents was positively and highly significant ($\beta = 0.060$, $p < 0.01$). Rural households may experience greater digital inequality than those in urban areas, likely due to disparities in infrastructure, internet connectivity, and exposure to digital initiatives (Fu et al., 2024).

Education level indicated a negative and highly significant relationship with digital inequality ($p < 0.01$). The literate individuals may exhibit considerably lesser digital inequality by 0.114 in contrast to their counterparts, emphasizing the role of literacy and digital competence in bridging digital gaps. A similar result was reported by Gouthon et al. (2024) in Ghana, who recognize that educational level greatly influences digital inequalities. Extension service access exhibited a negative effect on digital inequality ($p < 0.05$). The digital inequality can be reduced by 0.051 with households receiving agricultural extension support. This suggests that extension programs, particularly those integrating digital tools like e-extension platforms, enhance farmers' awareness and capacity to engage with digital technologies. Ledermann et al. (2024) noted that increased capacity building and the farmers' adoption of digital tools and technologies are likely to reduce inequalities.

Conclusions and Policy Implications

Evidence of both synergistic and a trade-off relationship between different outcomes of agricultural digitalization was identified. The study shows the existence of more synergistic interactions than trade-offs; this contributes to understanding how progress in one goal may potentially strengthen or diminish another. The most significant synergies include increased access to credit facilities, enhanced entrepreneurial skills and access to weather updates, while the trade-offs involve farm labour reduction, high cost of digital device/internet bundles and access to credit. The positive relationships observed in some interlinkages imply a trade-off. The development of one goal of digital agriculture may provide a spillover effect to other goals, though those benefits may be difficult to achieve for some farmers in the short run. Digital financial education can enhance farmers' digital financial literacy and entrepreneurial abilities, enabling better farming decisions. The age, geographical location,

education level and access to extension services were key determinants of digital inequality, with older and rural respondents experiencing higher inequality. The results stress the critical need for integrated efforts that foster innovation, inclusion and affordability, while simultaneously strengthening digital infrastructure in rural areas, promoting digital literacy programs and enhancing digital agricultural extension services. Some limitations of this study are that we concentrated on a limited range of economic, social and environmental factors associated with digital tool usage in farming operations, neglecting some other technological and institutional-related aspects. Moreover, the study focused on generic digital tools, offering services such as digital marketing, digital payment, farm management decision-making and advisory services commonly accessible to farmers and did not include advanced digital technologies such as drones, robots, and sensors. Future research should take into account all effects of digital services on farmers, considering both generic and advanced tools in both developed and developing countries for a comprehensive comparative analysis.

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