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## SOCIOECONOMIC FACTORS ASSOCIATED WITH THE USE OF SMART DIGITAL PLATFORMS FOR AGRICULTURAL EXTENSION SERVICES AMONG FARMING HOUSEHOLDS IN CENTRAL KENYA

Anestine M. Ringera\*, Hezron R. Mogaka, Florence K. Kirimi, Scholastica K. Mutungi

Department of Agricultural Extension and Economics, University of Embu, Kenya.

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### ABSTRACT

Persistent inefficiencies in agricultural extension in Kenya, particularly within Afromontane agroecosystems, have hindered information dissemination among farming households. Smart digital platforms (SDPs) offer scalable, cost-efficient extension access, yet uptake remains limited. This study examined socioeconomic and access-related correlates of SDP use among 393 farming households across four purposively selected counties in the Central Kenya highlands, using a cross-sectional, multistage sampling design. Awareness of SDPs was a virtual precondition for use: none of 287 unaware households reported use, versus 34.9% of 106 aware households ( $\chi^2 = 61.19$ ,  $p < 0.001$ ); overall, 37 of the 393 households (9.4%) reported using at least one SDP. A Multivariate Probit model estimated on the aware subsample by composite likelihood, with a ridge penalty, showed platform-specific associations: age and education favored iShamba use, education also favoured Apollo Agriculture use, gender effects diverged by platform, land size favoured DigiFarm/e-Kilimo use, and farmer-group extension access was negative for iShamba use. Cross-equation correlations were not statistically significant (LR = 8.65,  $p = 0.194$ ). The study recommends prioritizing awareness-building alongside platform-specific, gender-responsive digital-literacy and extension strategies.

Corresponding Author: Anestine M. Ringera

Email: [anestineringera@gmail.com](mailto:anestineringera@gmail.com)

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### INTRODUCTION

Agriculture remains the cornerstone of rural livelihoods in Sub-Saharan Africa, providing food, income, and employment for most of the population. In Kenya, the sector contributes about 21–23% of GDP and sustains roughly 70% of the rural population, mostly smallholder farmers (Kenya National Bureau of Statistics [KNBS], 2024; FAO, 2024). Farmers nonetheless face persistent challenges, including limited access to timely, reliable agricultural information (Kyambo et al., 2021), as extension services remain underfunded and constrained by low staffing and poor infrastructure (Mapiye et al., 2023; Okello et al., 2023). Smart digital platforms (SDPs)

have emerged as a mechanism for delivering agricultural information more efficiently. Here, SDPs are defined as mobile application-based, SMS/USSD-based, or web-based tools that farming households use to access agricultural extension information. App-based platforms such as iShamba, WeFarm, Apollo Agriculture, and DigiFarm/e-Kilimo require internet-enabled smartphones, SMS/USSD services are accessible on basic phones without internet, and web-based portals are accessed via computers or mobile browsers. These platforms provide real-time data on weather, pest and disease alerts, market prices, agronomic and financial services (Khatri et al., 2024; Singh et al., 2023). Smart

Digital Platforms represent a promising solution to the mounting extension demands associated with rapid population growth and evolving farmers' needs. By leveraging widespread mobile phone ownership, SDPs enable the cost-effective dissemination of timely, location-specific and actionable agricultural information to large numbers of farming households (Raghunath et al., 2024).

These platforms have the potential to ease pressure on overstretched conventional extension systems, (Kyambo, 2021) accelerate technology adoption, and support productivity enhancement necessary to meet rising food demand. Their integration into the agricultural extension landscape is consistent with key national development policies, including Vision 2030 and the Digital Superhighway agenda (2023-2030), which emphasize the modernization of agriculture, inclusive service delivery and enhanced food security under increasing demographic and climate pressures (Bonilla et al., 2024). In Kenya, platforms including DigiFarm/e-Kilimo complement traditional extension (Tabe-Ojong et al., 2023). Despite the increased availability of these technologies, their adoption and effective use among farming households remain relatively low, particularly in underserved areas like the Afromontane agroecosystems of Mount Kenya.

Emerging evidence suggests that attributes such as age, gender, education level, income, household size, and digital literacy significantly influence the likelihood of using SDPs (Sumo et al., 2022; Abdulai et al., 2023). However, little is known about how these factors operate in highland ecosystems where terrain, connectivity, and resource limitations exacerbate access disparities. This study investigates the influence of selected factors on the use of SDPs for agricultural extension services among farming households in the Central Kenya highlands, providing empirical evidence to inform inclusive digital agriculture policy and programming.

Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh et al. (2003), has been positioned to explain how age, education, farmer group membership, and access to digital devices are associated with the use of agricultural technologies through its core constructs of performance expectancy, effort expectancy, social influence, and facilitating conditions. Age and education may shape farmers' performance and effort expectancies, influencing how useful and easy they

perceive the technology to be. Farmer group membership may strengthen social influence through peer learning, shared experiences, and encouragement to use agricultural technologies. Access to digital devices and extension personnel represents a key facilitating condition that enables actual technology use. Thus, UTAUT provides a framework for linking farmers' socioeconomic characteristics and enabling conditions to their perceptions and use of agricultural platforms.

### Literature review

Digital-technology adoption in agriculture is increasingly recognized as a strategy for modernizing extension, improving productivity, and building climate resilience (Balogun et al., 2022; Steinke et al., 2021). Socioeconomic characteristics have been identified as key determinants of uptake (Kyalo et al., 2025). Age, for example, has been shown to have mixed effects: while older farmers may possess valuable farming experience and social capital (Beshir et al., 2022). Farming households are often less comfortable with digital interfaces compared to younger counterparts. Gender also plays a significant role; male-headed households are more likely to adopt agricultural technologies, partly due to greater decision-making authority and access to productive resources (Ngaiwi et al., 2023). Education is consistently cited as a positive driver of SDP use, as it enhances farmers' capacity to understand, evaluate, and apply digital content (Wawire et al., 2021). Income and landholding size further influence SDP adoption by shaping a household's ability to invest in mobile devices, internet data, and complementary technologies (Karanja et al., 2020). Studies also suggest that awareness and digital literacy are critical enablers; even when platforms are available, usage remains low if farmers are unaware of their existence or unable to navigate their features (Nyagango et al., 2023).

Despite this growing body of research, there is a notable gap in empirical evidence from mountainous and remote agricultural regions, such as the Afromontane agroecosystems of Central Kenya. These areas face unique challenges including infrastructural constraints and ecological variability that may affect SDP adoption differently from lowland zones. This study contributes to the literature by examining how socio-economic characteristics associated with the use of SDPs among highland farming households, helping bridge a critical knowledge gap in digital agricultural extension.

## METHODOLOGY

### Study area

The study was conducted within the Afromontane agroecosystems of the Central Kenya highlands, in Meru, Embu, Tharaka Nithi, and Kirinyaga counties. These agroecosystems span altitudes of 1,200–3,000 metres above sea level, with bimodal rainfall and sub-humid conditions favourable to smallholder agriculture, predominantly rain-fed, with key crops including tea, coffee, maize, bananas, and horticultural produce. The area was purposively selected for its ecological importance, vulnerability to climate change, and the emerging presence of smart digital platforms (SDPs) for agricultural extension.

### Research design and sampling

A cross-sectional survey design was used to collect primary data at a single point in time from a selected sample in the four counties. A multistage sampling procedure was used. First, four counties with regions of 1,200 m altitude and above were purposively selected. Second, one sub-county within those regions was purposively selected from each county: Imenti South (Meru), Embu East (Embu), Maara (Tharaka Nithi), and Kirinyaga Central (Kirinyaga). Third, one ward was randomly selected from each subcounty: Igoji West, Kyeni North, Muthambi, and Kanyekini. A sampling frame in each ward was compiled with the assistance of local extension officers. Generalisation is limited to farming households in ecologically similar afromontane wards of these four counties. Fieldwork was conducted between 4 and 22 December 2025.

Network connectivity across the four sampled wards reflects the varied Afromontane terrain: access is generally more reliable near lower-altitude market and administrative centres, while mobile network and internet connectivity become more variable and at times intermittent in the steeper, higher-altitude sections, consistent with national reporting on persistent rural network-quality gaps in Kenya's mountainous counties (Communications Authority of Kenya, 2024). Households were then selected from each ward's sampling frame using simple random sampling. The minimum required sample size was determined using Cochran's (1977) formula:

$$n = Z^2 pq / d^2 \dots\dots\dots (1)$$

where  $n$  is the desired sample size,  $Z = 1.96$  is the standard normal deviate at the 95% confidence level,  $p =$

0.5 is the estimated proportion of farming households with the characteristic of interest,  $q = 1 - p = 0.5$ , and  $d = 0.05$  is the desired margin of error, yielding a minimum sample of  $n = (1.96)^2(0.5)(0.5)/(0.05)^2 \approx 384$  households, allocated to the four wards using probability-proportional-to-size (PPS) sampling:

$$M_h = (n_h / N) \times n \dots\dots\dots (2)$$

where  $M_h$  is the number of households to be interviewed in ward  $h$ ,  $n_h$  is the total number of farming households in ward  $h$ , and  $N$  is the total across the four wards. Because PPS allocation was rounded up, and every reachable household, using a return-visit protocol when the head was initially unavailable, completed the questionnaire, the achieved sample was 393 households, a 2.3% oversample relative to the Cochran minimum of 384, distributed as 145 in Tharaka Nithi (36.9%), 113 in Meru (28.8%), 83 in Embu (21.1%), and 52 in Kirinyaga (13.2%), reflecting each ward's sampling-frame size under the proportional-to-size rule. No household had missing data on the core socioeconomic items.

### Data collection instrument

Data were collected using a semi-structured questionnaire administered via KoboToolbox, capturing household demographics and socioeconomic characteristics (age, gender, education, household size, income, land size), phone ownership and digital skills, awareness of SDPs, farmer-group and extension engagement, and SDP use. The household head, or the adult member most knowledgeable about farming and digital-technology decisions where the head was unavailable, was interviewed.

The dependent variables were four binary indicators of SDP use: iShamba, WeFarm, Apollo Agriculture, and DigiFarm also referred as e-kilimo. Use was measured as current or recent self-reported use as of the survey date, not frequency or duration; SDP-use experience in years, in Table 2, captures how long a household has used any SDP among those with any use.

The questionnaire contained two overlapping multi-select items on SDP use; a review of the raw KoboToolbox data confirmed these were a duplicated question block, and the earlier block, following the gating question on mobile-app use, was used as the analytic measure. Key independent variables were age, gender, education level, household size, annual income, land size, phone ownership, awareness of SDPs, and farmer-group extension access.

### Analytical model

The Multivariate Probit (MVP) model was used to jointly estimate the four platform-use equations while allowing their error terms to be correlated, which separate probit models assume away. For household  $i$  and platform  $j$  ( $j = 1, \dots, 4$ : iShamba, WeFarm, Apollo Agriculture, DigiFarm/e-Kilimo), the model is specified in latent-variable form as:

$$y_{ij}^* = x_i \beta_j + \varepsilon_{ij}, \quad y_{ij} = 1[y_{ij}^* > 0], \quad j = 1, \dots, 4 \quad (3)$$

where  $y_{ij}^*$  is the unobserved latent propensity of household  $i$  to use platform  $j$ ,  $y_{ij}$  is the observed binary indicator,  $x_i$  is a vector of covariates common across equations,  $\beta_j$  is the platform-specific coefficient vector, and  $(\varepsilon_{i1}, \dots, \varepsilon_{i4})$  follow a joint multivariate normal distribution,  $N(0, \Sigma)$ , with unit variances and off-diagonal elements  $\rho_{jk}$  ( $j \neq k$ ) representing the correlation between unobserved determinants of using platforms  $j$  and  $k$ . Correlations near zero would suggest separate probit models are adequate, while non-zero correlations would indicate platform choices are linked by unobserved household-level factors not captured by the observed covariates.

Covariates were age (years), gender (male = 1, female = 0, reference), education level (5-point ordinal scale, 1 = no formal education to 5 = tertiary/university, treated as continuous), annual income (KES, rescaled to units of 100,000), land size (acres), access to extension services through farmer groups (yes = 1, no = 0, reference), and phone ownership (yes = 1, no = 0, reference). All models include a constant term.

A preliminary specification pooling the full sample ( $N = 393$ ) with awareness as a covariate could not be reliably estimated: no household unaware of any SDP reported using one, so awareness perfectly predicted non-use in that subgroup, quasi-complete separation. Because using a platform one does not know exists is not behaviorally meaningful, awareness is better treated as a scope-defining condition than an estimated covariate. The MVP model was therefore estimated on the 106 households (27.0% of the full sample) that reported awareness of at least one SDP; awareness itself is reported descriptively in the Results (Table 3). Because standard statistical packages available in R, the software environment used for all data analysis in this study, did not provide a full-information multivariate probit estimator for four correlated equations, the model was estimated by maximum pairwise composite likelihood (Cox and Reid, 2004), an approach also used for multivariate and multinomial probit models with more than two or three

alternatives (Bhat, 2011), around the joint likelihood as the sum, over all six equation pairs, of exact bivariate-probit log-likelihoods at a common set of coefficients  $\beta_j$  and correlations  $\rho_{jk}$ , yielding consistent estimates without four-dimensional numerical integration. Given the small number of platform users in several equations (6 iShamba, 8 WeFarm, 6 Apollo Agriculture, 21 DigiFarm/e-Kilimo, among 106 aware households), a small L2 (ridge) penalty was applied to stabilise estimation (Firth, 1993); coefficients and standard errors should be read as approximate, obtained from the numerical Hessian of the penalised composite log-likelihood at convergence. Because the design has only four primary sampling units, design-based cluster-robust standard errors would be unstable and are not reported. No missing data were present in the 106-household sample, so the same observations entered every equation.

Table 1. Variance Inflation Factor (VIF) Diagnostics for the Explanatory Variables Used in the Probit Model.

| Variable                              | Variance Inflation Factor (VIF) | Tolerance (1/VIF) |
|---------------------------------------|---------------------------------|-------------------|
| Education level                       | 1.39                            | 0.72              |
| Land size (acres)                     | 1.30                            | 0.77              |
| Age of household head                 | 1.26                            | 0.79              |
| Annual income (per KES 100,000)       | 1.25                            | 0.80              |
| Phone ownership                       | 1.13                            | 0.89              |
| Gender (male = 1)                     | 1.09                            | 0.91              |
| Access to extension via farmer groups | 1.08                            | 0.93              |
| Mean VIF                              | 1.21                            | n/a               |

### Diagnostic tests

Variance Inflation Factors were recomputed for the seven explanatory variables actually entered in the final model (Table 4), estimated on the same 106-household sample, rather than for the extension-access, phone-skills, cost-concern, and distance variables used in an earlier diagnostic table that did not correspond to the estimated model. All VIFs are well below the threshold of 5, with a mean of 1.21 and a maximum of 1.39, indicating no problematic multicollinearity.

### Ethical considerations

Participation was voluntary, and informed consent was obtained after the study's purpose, academic nature, and

the right to withdraw without penalty were explained. The household head, or the most knowledgeable available adult member, was interviewed, with a return visit scheduled where the head was unavailable. Data collected through KoboToolbox were stored on a password-protected, encrypted server accessible only to the research team, and respondent identifiers were separated from the analytic dataset before analysis. The study protocol was reviewed and approved by the Tharaka University Institutional Scientific and Ethics Review Committee (ISERC) (Ref. No. TUNISERC/NSEC/EM001; Approval No. ISERC04023).

## RESULTS

### Socioeconomic attributes of farming households

This section summarizes the characteristics of the 393 surveyed farming households. Education was measured on a 5-point ordinal scale (1 = no formal education, 2 =

primary, 3 = secondary, 4 = middle-level college, 5 = university), so a mean of 2.64 indicates primary-to-secondary schooling on average. Annual income is highly right-skewed (mean KES 163,935 versus median KES 90,000, SD KES 303,970 exceeding the mean, maximum KES 5,000,000), so median and interquartile range are reported alongside the mean and SD. Many households reported zero off-farm income, for which the natural log is undefined.

Monthly income, also in Table 2, was collected separately to capture regular recurring cash income (wages, casual labour, remittances), whereas annual income captures total household income, including farm produce, over the preceding twelve months; its median of KES 0 reflects the largely subsistence-oriented nature of this sample rather than a data error. Annual income, not monthly income, was the covariate used in the multivariate probit model as described in Table 4.

Table 2. Summary of Demographic and Socioeconomic Characteristics.

| Variable                                       | Mean    | Median                                    | Std. Dev. | Min | Max       |
|------------------------------------------------|---------|-------------------------------------------|-----------|-----|-----------|
| Age (years)                                    | 51.75   | 51                                        | 14.39     | 21  | 85        |
| Education level (1-5)                          | 2.64    | 3                                         | 1.06      | 1   | 5         |
| Annual income (KES)                            | 163,935 | 90,000                                    | 303,970   | 0   | 5,000,000 |
| Interquartile range (KES)                      | n/a     | IQR = 140,000 (Q1 = 50,000, Q3 = 190,000) |           | n/a | n/a       |
| Monthly income (KES)                           | 14,211  | 0                                         | 56,177    | 0   | 600,000   |
| SDP use experience (years)                     | 0.31    | 0                                         | 1.06      | 0   | 10        |
| Farm size (acres)                              | 1.40    | 1.00                                      | 0.88      | 0   | 5         |
| Household size                                 | 3.50    | 3                                         | 1.10      | 1   | 7         |
| Perceived cost of extension services (1 = yes) | 0.10    | 0                                         | 0.30      | 0   | 1         |
| Proximity to extension services (1 = yes)      | 0.015   | 0                                         | 0.12      | 0   | 1         |

The average age of household heads was 51.75 years, mid-to-late adulthood. Average education, 2.64 on the 1–5 scale, corresponds to primary-to-secondary schooling, a plausible enabler of digital literacy. Income is highly unequal and right-skewed, suggesting affordability of smartphones and data varies substantially across households. The mean land holding of 1.4 acres and household size of 3.5 members are consistent with a smallholder profile. The low mean SDP-use experience of 0.31 years (median 0) reflects that only 37 of 393 households (9.4%) reported using any of the four platforms, so most are non-adopters rather than long-tenured users.

Pairwise Pearson correlations among the continuous variables in Figure 1 support the visual patterns: age and

education are weakly to moderately negatively correlated ( $r = -0.31$ ); education and income are weakly positively correlated ( $r = 0.28$ ); and farm size and income are only weakly correlated ( $r = 0.14$ ). None of the pairwise correlations exceeds  $|r| = 0.31$ , corroborating the low VIFs in Table 1. These are simple pairwise associations from cross-sectional data and are not evidence of causal relationships.

### Distribution of selected socioeconomic variables

Figure 2 shows the gender distribution of household heads, phone ownership, and awareness of SDPs, all categorical, alongside the distribution of farm sizes in acres, presented as a box plot rather than a bar chart because it is continuous.

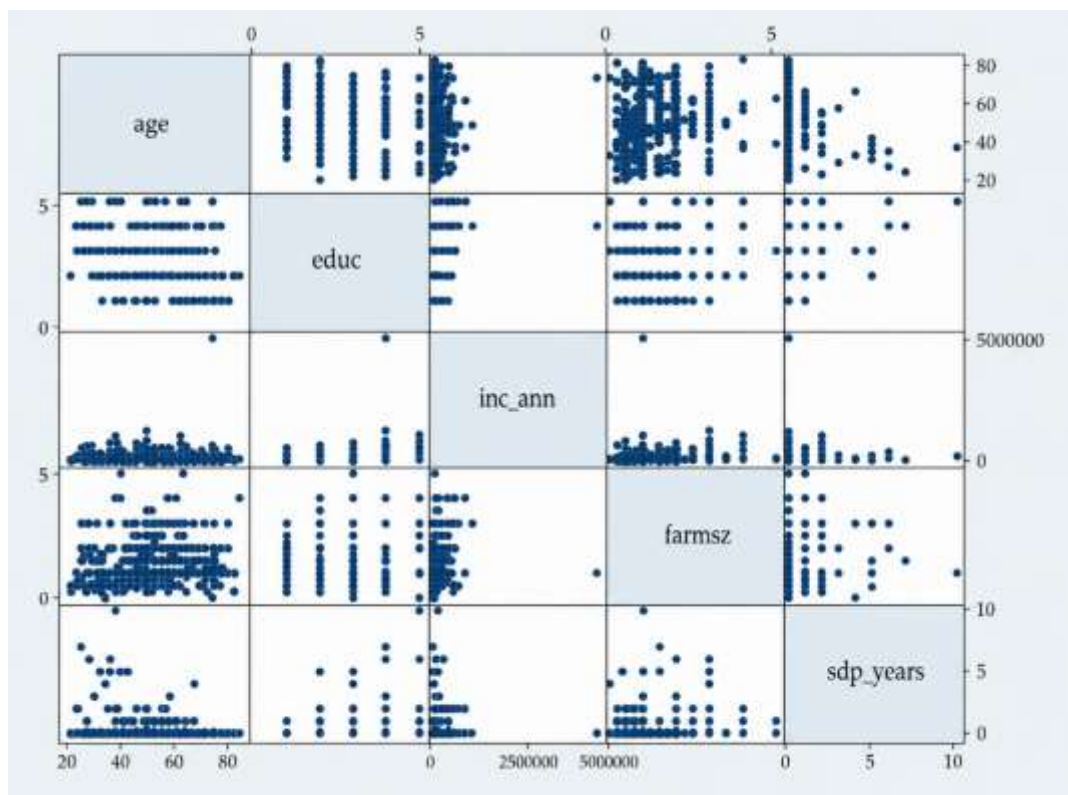


Figure 1. Scatterplot Matrix of Continuous Socioeconomic Variables.

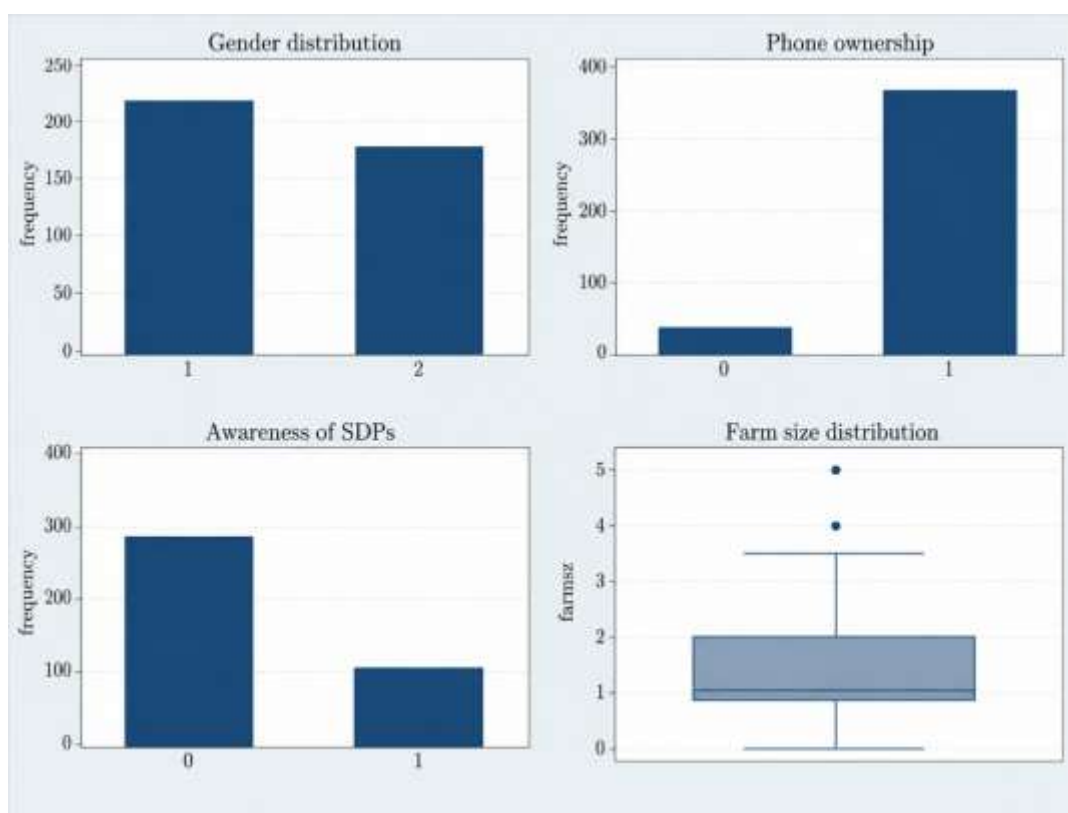


Figure 2. Distribution of Selected Socioeconomic Variables (Gender, Phone Ownership, Awareness of SDPs, and Farm Size).

### Association between socioeconomic characteristics and use of smart digital platforms

SDP use was defined, consistently with Table 4, as a household reporting use of at least one of the four platforms studied. 9.4% of households met this

definition, 90.6% did not. Because several sub-groups have <5 expected users under independence, Fisher's exact test (two-sided) is reported alongside chi-square for every row of Table 3, and the exact p-value is treated as authoritative where the two diverge.

Table 3. Association Between Socioeconomic/Access Variables and Use of Smart Digital Platforms.

| Variable                                   | Category | Overall n (%) | SDP users n (row %) | Non-users n (row %) | $\chi^2$ | Fisher's exact p |
|--------------------------------------------|----------|---------------|---------------------|---------------------|----------|------------------|
| Gender                                     | Male     | 213 (54.2)    | 25 (11.7)           | 188 (88.3)          | 2.38     | 0.155            |
|                                            | Female   | 180 (45.8)    | 12 (6.7)            | 168 (93.3)          |          |                  |
| Phone ownership                            | No       | 26 (6.6)      | 0 (0.0)             | 26 (100.0)          | 1.83     | 0.155            |
|                                            | Yes      | 367 (93.4)    | 37 (10.1)           | 330 (89.9)          |          |                  |
| Electricity access                         | No†      | 37 (9.4)      | 0 (0.0)             | 37 (100.0)          | 3.13     | 0.036*           |
|                                            | Yes      | 355 (90.6)    | 37 (10.4)           | 318 (89.6)          |          |                  |
| Awareness of any SDP                       | No       | 287 (73.0)    | 0 (0.0)             | 287 (100.0)         | 61.19    | <0.001***        |
|                                            | Yes      | 106 (27.0)    | 37 (34.9)           | 69 (65.1)           |          |                  |
| Extension service engagement               | No       | 165 (42.0)    | 2 (1.2)             | 163 (98.8)          | 20.81    | <0.001***        |
|                                            | Yes      | 228 (58.0)    | 35 (15.4)           | 193 (84.6)          |          |                  |
| Extension access via farmer groups         | No       | 220 (56.0)    | 14 (6.4)            | 206 (93.6)          | 4.67     | 0.023*           |
|                                            | Yes      | 173 (44.0)    | 23 (13.3)           | 150 (86.7)          |          |                  |
| Became aware of SDPs via radio/TV          | No       | 328 (83.5)    | 20 (6.1)            | 308 (93.9)          | 23.29    | <0.001***        |
|                                            | Yes      | 65 (16.5)     | 17 (26.2)           | 48 (73.8)           |          |                  |
| Became aware of SDPs via extension officer | No       | 389 (99.0)    | 35 (9.0)            | 354 (91.0)          | 3.74     | 0.046*           |
|                                            | Yes      | 4 (1.0)       | 2 (50.0)            | 2 (50.0)            |          |                  |

†One response with an invalid multi-value entry for electricity access was recoded as missing from the "Yes" total reported in Table 2 and treated as "No" here for completeness of the cross-tabulation. This does not affect any substantive conclusion.

Every row above uses the same definition of SDP user, any of the four platforms, and the same denominators of 37 users and 356 non-users out of 393, so row percentages are internally consistent and comparable. This corrects the earlier draft, in which user counts varied by row because different, undocumented definitions of user had been used.

Note: significance stars (\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ ) are shown after the Fisher's exact p-value in each row for ease of scanning; the dagger (†) above is unrelated and marks the data-recoding note.

The single strongest pattern is that awareness of SDPs is a virtual precondition for use: none of the 287 unaware households reported using one, versus 34.9% of the 106 aware households ( $\chi^2 = 61.19$ , Fisher's exact  $p < 0.001$ ), which is why the model in Table 4 is estimated on the aware subsample rather than the full sample with awareness as an ordinary covariate (see Methodology). Extension engagement was also strongly associated with use (15.4% versus 1.2%,  $p < 0.001$ ), as was farmer-group extension access (13.3% versus 6.4%,  $\chi^2 = 4.67$ ,  $p = 0.023$ ) and becoming aware through radio or television (26.2% versus 6.1%,  $p < 0.001$ ) or direct extension-officer contact (50.0% versus 9.0%,  $p = 0.046$ , only four exposed households). Gender and phone ownership were non-significant ( $p = 0.155$ ); electricity

access significantly associated (Fisher's exact  $p = 0.036$ ). Phone ownership was, however, near-universal among users, all 37 owning a phone, which is why it is retained as a covariate, rather than a scope restriction, where non-ownership is rare but not perfectly separating.

### Factors influencing the use of smart digital platforms

The model was estimated by maximum pairwise composite likelihood (see Methodology), with a small ridge penalty for stability; the composite log-likelihood at convergence was -302.87. To test whether the four equations' error terms are correlated, the justification for a multivariate rather than four separate probits, a composite-likelihood-ratio test compared the fitted model with a constrained version fixing all six  $\rho_{jk} = 0$ : LR

$= 2 \times (-302.87 - (-307.19)) = 8.65$  on 6 df,  $p = 0.194$ . Individually, none of the six pairwise correlations in Table 4b reaches conventional significance (all  $p > 0.10$ ), despite some large point estimates ( $|\rho|$  up to 0.95). With only 106 aware households, the data do not provide significant evidence against independent errors, though negative correlations among iShamba, WeFarm, and

Apollo Agriculture are qualitatively consistent with substitution between similar platforms.

Coefficients as tabulated in Table 4 should be read as indicative rather than definitive; results were materially similar when the equations were estimated as separate ridge-stabilised probit models, offered as a robustness check.

Table 4. Multivariate Probit Estimates of Socioeconomic Factors Associated with Use of Smart Digital Platforms, Conditional on Awareness ( $n = 106$  households aware of at least one SDP).

| Variable                           | iShamba                                  | p      | WeFarm                                  | p     | Apollo Agric.                           | p      | DigiFarm/e-Kilimo                      | p      |
|------------------------------------|------------------------------------------|--------|-----------------------------------------|-------|-----------------------------------------|--------|----------------------------------------|--------|
| Age (years)                        | 0.034<br>(0.014)*<br>[0.007, 0.061]      | 0.018  | 0.025<br>(0.010)*<br>[0.005, 0.045]     | 0.013 | 0.016<br>(0.010)<br>[-0.004, 0.036]     | 0.110  | -0.001 (0.008)<br>[-0.017, 0.015]      | 0.933  |
| Gender (male = 1)                  | 1.242<br>(0.529)*<br>[0.205, 2.279]      | 0.019  | -0.770<br>(0.246)**<br>[-1.252, -0.288] | 0.002 | -0.189<br>(0.259)<br>[-0.697, 0.319]    | 0.465  | 0.770<br>(0.197)***<br>[0.384, 1.156]  | <0.001 |
| Education level                    | 0.349<br>(0.160)*<br>[0.035, 0.663]      | 0.029  | 0.129<br>(0.134)<br>[-0.134, 0.392]     | 0.335 | 0.660<br>(0.170)***<br>[0.327, 0.993]   | <0.001 | -0.020 (0.092)<br>[-0.200, 0.160]      | 0.830  |
| Annual income (per KES 100,000)    | -0.041<br>(0.073)<br>[-0.184, 0.102]     | 0.576  | 0.112<br>(0.055)*<br>[0.004, 0.220]     | 0.043 | 0.015<br>(0.066)<br>[-0.114, 0.144]     | 0.822  | 0.058 (0.045)<br>[-0.030, 0.146]       | 0.198  |
| Land size (acres)                  | 0.280<br>(0.157)<br>[-0.028, 0.588]      | 0.075  | -0.172<br>(0.111)<br>[-0.390, 0.046]    | 0.122 | -0.249<br>(0.167)<br>[-0.576, 0.078]    | 0.135  | 0.333<br>(0.097)**<br>[0.143, 0.523]   | 0.001  |
| Extension access via farmer groups | -1.440<br>(0.362)***<br>[-2.150, -0.730] | <0.001 | 0.164<br>(0.251)<br>[-0.328, 0.656]     | 0.513 | -0.476<br>(0.259)<br>[-0.984, 0.032]    | 0.066  | -0.038 (0.185)<br>[-0.401, 0.325]      | 0.839  |
| Phone ownership                    | 0.108<br>(0.892)<br>[-1.640, 1.856]      | 0.904  | 0.480<br>(0.772)<br>[-1.033, 1.993]     | 0.534 | 0.056<br>(0.930)<br>[-1.767, 1.879]     | 0.952  | 0.244 (0.831)<br>[-1.385, 1.873]       | 0.769  |
| Constant                           | -5.331<br>(1.386)***<br>[-8.048, -2.614] | <0.001 | -3.301<br>(1.032)**<br>[-5.324, -1.278] | 0.001 | -3.995<br>(1.212)**<br>[-6.371, -1.619] | 0.001  | -2.170<br>(0.981)*<br>[-4.093, -0.247] | 0.027  |

Note: Coefficients are followed by significance stars (\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$ , based on the exact p-value shown in the adjacent column).

The bracketed italic figures beneath each coefficient are approximate 95% Wald confidence intervals (coefficient  $\pm 1.96 \times \text{SE}$ ).

Table 4b. Cross-Equation Correlations ( $\rho$ ) of the Multivariate Probit Model.

| Equation pair                          | $\rho$ (SE)    | z     | p     |
|----------------------------------------|----------------|-------|-------|
| iShamba - WeFarm                       | -0.616 (1.811) | -0.34 | 0.734 |
| iShamba - Apollo Agriculture           | -0.890 (0.581) | -1.53 | 0.126 |
| iShamba - DigiFarm/e-Kilimo            | 0.269 (0.366)  | 0.73  | 0.463 |
| WeFarm - Apollo Agriculture            | -0.922 (0.731) | -1.26 | 0.207 |
| WeFarm - DigiFarm/e-Kilimo             | -0.945 (0.893) | -1.06 | 0.290 |
| Apollo Agriculture - DigiFarm/e-Kilimo | -0.276 (0.464) | -0.59 | 0.552 |

Table 4c. Average Marginal Effects (Probability Points) on the Likelihood of Platform Use.

| Variable                           | iShamba | WeFarm | Apollo Agric. | DigiFarm/e-Kilimo |
|------------------------------------|---------|--------|---------------|-------------------|
| Age (years)                        | 0.003   | 0.003  | 0.002         | 0.000             |
| Gender (male = 1)                  | 0.067   | -0.103 | -0.019        | 0.173             |
| Education level                    | 0.027   | 0.016  | 0.065         | -0.005            |
| Annual income (per KES 100,000)    | -0.003  | 0.014  | 0.001         | 0.014             |
| Land size (acres)                  | 0.022   | -0.021 | -0.025        | 0.079             |
| Extension access via farmer groups | -0.123  | 0.020  | -0.051        | -0.009            |
| Phone ownership                    | 0.008   | 0.044  | 0.005         | 0.053             |

Significance in the discussion below is evaluated at the conventional 5% level ( $p < 0.05$ ). Results with  $0.05 \leq p < 0.10$  are described as weak or marginal evidence, consistent with a threshold specified a priori and applied uniformly across platforms and variables.

Among the 106 aware households, age was positively associated with iShamba ( $p = 0.018$ ) and WeFarm use ( $p = 0.013$ ), with average marginal effects (AME) of about 0.3 percentage points per year for each platform. Gender effects were platform-specific: male heads were more likely than female heads to use iShamba (AME = +6.7 points,  $p = 0.019$ ) and DigiFarm/e-Kilimo (AME = +17.3 points,  $p < 0.001$ ), but less likely to use WeFarm (AME = -10.3 points,  $p = 0.002$ ), with no significant effect for Apollo Agriculture ( $p = 0.465$ ). Education was positive for iShamba ( $p = 0.029$ ) and, most strongly, Apollo Agriculture use ( $p < 0.001$ , AME = +6.5 points per scale-point), but not for WeFarm or DigiFarm/e-Kilimo. Income (KES 100,000 units) was positive only for WeFarm use ( $p = 0.043$ ); a general income-adoption claim is not supported. Land size was positive for DigiFarm/e-Kilimo use ( $p = 0.001$ , AME = +7.9 points per acre) and weakly so for iShamba ( $p = 0.075$ ), but not for WeFarm or Apollo Agriculture. Farmer-group extension access was negative for iShamba use ( $p < 0.001$ , AME = -12.3 points) and weakly negative for Apollo Agriculture ( $p = 0.066$ ), with no effect for WeFarm or DigiFarm/e-Kilimo; this runs counter to the positive bivariate relationship in Table 3, and may reflect group channels steering households toward other platforms, though this design cannot establish why. Phone ownership,

though essentially a precondition for use in the raw data, was not significant for platform choice among aware households (all  $p > 0.5$ ), since only 1 of the 106 lacked a phone.

## DISCUSSION

The Multivariate Probit results in Table 4 show how key farmer characteristics are associated with the likelihood of using specific SDPs, namely iShamba, WeFarm, Apollo Agriculture, and DigiFarm/e-Kilimo, among households already aware such platforms exist. These platforms offer digitized extension services crucial for improving decision-making and farm productivity in the Afromontane agroecosystems of Kenya.

Age of the household head was positively associated with iShamba ( $p = 0.018$ ) and WeFarm use ( $p = 0.013$ ), and not significantly with Apollo Agriculture ( $p = 0.110$ ) or DigiFarm/e-Kilimo ( $p = 0.933$ ); this differs from the negative association initially suspected when awareness was pooled with the full sample (see Methodology), and may reflect that older, aware household heads have accumulated more social capital and extension experience. Male-headed households were significantly more likely to use iShamba ( $p = 0.019$ ) and DigiFarm/e-Kilimo ( $p < 0.001$ ), but less likely to use WeFarm ( $p = 0.002$ ), than female-headed households. This variable records the sex of the household head who actually makes day-to-day digital-extension decisions. This finding aligns with prior literature indicating that men often have greater access to technological resources and decision-making power within

households (Abdulai et al., 2023). Such disparities point to the importance of gender-sensitive digital inclusion policies to bridge this gap and improve technology access for women in rural households. Gender-related disparities may constrain the uptake of digital technologies because of unequal access to resources, costs, and sociocultural constraints reported in prior studies (Mugisha et al., 2025). Education was a significant positive predictor of iShamba use ( $p = 0.029$ ) and, most strongly, Apollo Agriculture use ( $p < 0.001$ ), though not WeFarm ( $p = 0.335$ ) or DigiFarm/e-Kilimo ( $p = 0.830$ ). These findings are consistent with Krell, (2021), who found educated farmers to be more receptive to new technologies. Annual income was significant only for WeFarm use ( $p = 0.043$ ), not iShamba, Apollo Agriculture, or DigiFarm/e-Kilimo ( $p \geq 0.198$ ); a general income-adoption inference is not supported, since only one of four equations was significant, though consistent with financially stable farmers more readily affording smartphones and data (Addison et al., 2023).

There was an almost deterministic link between awareness and use: none of the 287 unaware households reported using an SDP, versus 34.9% of the 106 aware households. An ordinary covariate approach would have produced quasi-complete separation (see Methodology), so the model is estimated on the aware subsample instead, meaning its coefficients describe what differentiates users from non-users given awareness, not what predicts awareness itself; this also mitigates a simultaneity concern, since households already using a platform might over-report awareness of it. Awareness-building remains necessary, though not sufficient, for adoption, but the case for awareness as the single strongest predictor cannot be made from Table 4 alone. Farmer-group extension access was negatively associated with iShamba use ( $p < 0.001$ ) and weakly negatively with Apollo Agriculture ( $p = 0.066$ ), but not with WeFarm ( $p = 0.513$ ) or DigiFarm/e-Kilimo ( $p = 0.839$ ), contrasting with the positive pathway highlighted in the literature (Mapiye et al., 2021) and the positive bivariate association in Table 3, possibly because groups promote other platforms. Land size showed a similarly uneven association: weak with WeFarm ( $p = 0.122$ ), significant with DigiFarm/e-Kilimo ( $p = 0.001$ ), and absent for Apollo Agriculture ( $p = 0.135$ ), partially agreeing with Betela and Wolka (2021) but not a general farm-size-adoption pattern. Phone ownership was almost a prerequisite for use in the raw data, since every one of the 37 users owned a phone (Mariyono et al., 2022), yet was not a significant predictor of platform choice among aware

households ( $p > 0.5$  in all four equations), since only one of the 106 lacked a phone, and should be understood as a structural gateway condition rather than a platform differentiator.

## CONCLUSION

This study examined socioeconomic and access-related correlates of the use of four Smart Digital Platforms, iShamba, WeFarm, Apollo Agriculture, and DigiFarm/e-Kilimo, among 393 farming households in the Afromontane agroecosystems of Central Kenya. Awareness of SDPs proved a virtual precondition for use rather than an ordinary predictor: none of the 287 unaware households reported use, compared with 34.9% of the 106 aware households. Because pooling awareness with the other covariates produced quasi-complete separation, the model was estimated on the aware subsample using maximum pairwise composite likelihood with a ridge penalty, so its results describe what distinguishes users from non-users among households that already know SDPs exist, not an explanation of awareness itself. Within that subsample, correlates of use were platform-specific: age and education favored iShamba use, education also favored Apollo Agriculture use, gender effects diverged, favoring male heads for iShamba and DigiFarm/e-Kilimo and female heads for WeFarm, land size favored DigiFarm/e-Kilimo use, income favored only WeFarm use, and farmer-group extension access was negative for iShamba use. Phone ownership was a near-universal gateway condition rather than a differentiator. The six cross-equation correlations were not significant, so this study finds no strong evidence the platforms are used as a bundle, though negative correlations among iShamba, WeFarm, and Apollo Agriculture are consistent with some substitution. Overall, closing the awareness gap is the most consequential step toward wider SDP adoption here, but the levers that move adoption once households are aware differ by platform, so strategies should be tailored accordingly.

These findings should be read in light of several limitations. First, the cross-sectional design captures associations at a single point in time and cannot establish causal direction, and the purposive selection of counties, sub-counties, and wards limits generalization to farming households in ecologically similar Afromontane (1,200-3,000 meters above sea level) highland wards rather than Kenya's highland areas as a whole. Second, the model was estimated on only 106 aware households, with as few as 6 users in the iShamba equation, so the coefficient estimates

and standard errors in Table 4 should be read as indicative rather than precise population parameters. Third, because the multistage design has only four primary sampling units, design-based cluster-robust standard errors could not be reliably computed and are not reported, so reported standard errors do not account for within-ward clustering. Fourth, SDP use, awareness, and most covariates were self-reported, which may introduce recall or social-desirability bias, and reverse causality or simultaneity cannot be ruled out. Future research would benefit from panel data, larger aware subsamples across more counties, and, where feasible, experimental or quasi-experimental designs.

The study makes the following specific recommendations; First, because awareness is a near-deterministic precondition for use, county departments of agriculture and platform providers should prioritise and scale up awareness campaigns, including through radio and television and direct extension-officer contact, both strongly associated with awareness and use in this study, before investing heavily in platform-specific features.

Second, because socioeconomic correlates of use differ by platform, extension agencies and providers should tailor digital-skills training and outreach to each platform's actual user profile rather than a single blanket strategy: education-focused outreach may suit Apollo Agriculture and iShamba, while WeFarm outreach may benefit from targeting income-constrained households with affordability support.

Third, because gender effects diverge by platform, with iShamba and DigiFarm/e-Kilimo favouring male-headed households and WeFarm favouring female-headed households, gender-inclusion programmes should be platform-specific rather than assuming a single direction of gender disadvantage; providers of iShamba and DigiFarm/e-Kilimo in particular should investigate and address barriers facing female-headed households.

Fourth, given the positive association between land size and DigiFarm/e-Kilimo use, and the negative association between farmer-group extension access and iShamba use, county extension departments should review how farmer groups are linked to specific platforms and whether group-based channels are inadvertently steering members away from iShamba, so groups can become a channel for iShamba adoption rather than a barrier.

Finally, because phone ownership is a near-universal gateway condition rather than a differentiator among aware households, and network connectivity was more variable in the higher-altitude sections of the study wards,

national and county governments and telecommunications providers should pursue coordinated investment in rural network infrastructure and affordable data access, alongside monitoring of quality-of-service gaps in Kenya's mountainous counties, to ensure gains in awareness translate into actual use.

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