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Artificial intelligence (AI) adoption and its perceptions among smallholder women farmers in Kenya

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Abstract
Artificial intelligence (AI) can reduce soil compaction, cost, labor, and resource savings in agriculture. Despite visible benefits, AI and many other related technologies are not adopted by farmers. Although existing studies examine the socioeconomic and farmer characteristics that determine adoption of AI majority ignore the perceptions of AI despite the fast development of AI technologies particularly in agriculture. This study purposely sampled and interviewed 100 smallholder farmers in Kiambu County, Kenya, to identify their adoption and perceptions toward AI. The study adopted principal component analysis (PCA) to analyze the data. The findings show that the farmers were aware of AI (62%). Overall, farmers perceive AI and digital technologies positively, citing benefits such as they facilitate easy access to information, loans, and markets; enhance output; revolutionize agriculture/agribusinesses; and increase household income among other benefits. However, some respondents strongly disagreed with the statements that AI has ambiguous data input requirements (17%), has low adaptability to peculiar business situations (19%), and does not consider the challenges women farmers experience (21%). Additionally, the PCA technique grouped the 20 variables into eight categories: increased returns, access to productive resources, information access and decision-making, AI technology and women's access, functionality, specific requirements, availability, and lack of knowledge factors. The determinants of AI adoption were marital status, land size, and education level. These findings contribute to the existing literature by shedding light on how preexisting sex -based factors, such as land ownership and size, marital status, and education level, shape AI adoption in Agriculture. These findings offer helpful suggestions for policymakers: not to treat AI technology as a magic bullet, but to implement measures that would increase the use of AI in agriculture, reducing the sex, economic, and technological gaps in Agriculture.

Keywords Artificial intelligence, Perceptions, Women, Agricultural, Kiambu, Kenya

1 Introduction

The agricultural sector is vital to the economies of both developed and developing nations since it provides food and is a means of livelihood for a number of households [1, 2, 3]. The agriculture sector is the backbone of the economy of Kenya with the sector accounting for the largest share of poverty reduction. According to the 2023–2024 national agriculture production report, the agriculture sector remains a crucial cornerstone of Kenya's food security, directly contributing 21.8% of the country's GDP [4]. The sector is dominated majorly by the smallholder type of farming system with the farm size ranging between 0.2 and 3 hectares; this accounts for 78% of total agricultural production and 70% of commercial production [4]. The food crop production in Kenya plays an important role in Kenya's economic development as a major source of food, income, employment creation, and saving on foreign exchange expenditures through import substitution.

As per the 2022 Kenya National Bureau of Statistics report, women make up to 60% of Kenya's agricultural labor force, while males make up to 40% [5]. Additionally, women oversee almost 40% of small farms, which means they are heavily involved in food preparation and preservation [6]. Furthermore, with the exodus of males from rural areas, women have increasingly taken up agriculture as their primary profession. Female farmers make up over 25% of the world's population. In developing nations, women make up an average of 43% of the agricultural workforce [7].

Artificial Intelligence (AI) advancements not only in agriculture but in sectors such as education [8, 9, 10], health care [11, 12, 13]; banking [14, 15, 16, 17, 18, 19]; manufacturing [20, 21, 22, 23, 24]; hospitality [25, 26]; plant disease [27, 28] and security [29, 30, 31, 32, 33]. Block-chain technology has shown to be a dependable response to Cybersecurity concerns since it allows for decentralized, transparent, and immutable data transactions [34] and marketing [35, 36, 37, 38] among other sectors. In the agriculture sector, AI is playing a key role in revolutionizing the industry and thus offering enormous benefits such as combating climate change, population growth, labour engagement issues, and food safety. Automated technology has transformed agriculture by improving processes such as tillage, planting, irrigation, crop selection, fertilization, pest management, harvesting, storage, and supply chain management [39]. Thus, the AI technologies save the excess use of water, pesticides, and herbicides; maintain soil fertility; help in the efficient use of workforce; elevate the productivity, and improve the product quality [40].

AI applications, especially in agriculture, remain limited. There are few review papers available on the implementation of AI in the field of agriculture [41, 42, 43, 44, 45, 46, 47, 48, 49]. The available papers highlight specific areas of agriculture, such as weed identification and pesticide spraying, irrigation planning, crop yield monitoring and prediction, greenhouse automation, navigation and planning, disease identification, segmentation, harvesting of crops and fruits, etc. Few studies focus on AI techniques and robots used in growing, monitoring, and harvesting crops. They aim to compare each method based on its usefulness and popularity in agriculture [42]. Other papers review various automation practices, including internet of things (IoT), wireless communications, machine learning, and artificial intelligence [48]. The authors provide a brief overview of the current implementation of automation in agriculture. Further, some authors review various AI techniques used in agriculture, including fuzzy logic (FL), artificial neural networks (ANN), genetic algorithms (GA), particle swarm optimization (PSO), artificial potential fields (APF), simulated annealing (SA), ant colony optimization (ACO), artificial bee colony algorithms (ABC), harmony search algorithms (HS), bat algorithms (BA), cell decomposition (CD), and firefly algorithms (FA) [42]. The review specifically focused on expert systems, robots designed for agricultural use, and sensor technology for data collection and transmission to reveal the potential impact of these techniques in agriculture. Other researchers considered the experimental development of collaborating robots that can work within fields of crops [47]. The authors investigate the application of AI principles to the agricultural domain and the role of user involvement in such a system. Some papers review the modern approaches to agriculture machinery movement optimization with applications in sugarcane production and present the algorithms for the division of spatial configuration, route planning, or path planning, as well as approaches using cost parameters, e.g., energy, fuel, and time consumption [43]. Various hi-tech computer-based systems determine multiple important parameters like weed detection, yield detection, and crop quality, among other techniques [28, 49, 50]. Although employing AI in agriculture offers many advantages, most people worldwide are unfamiliar with its applications in agricultural solutions and machinery and specifically the farm business still lacks enough agricultural technology support.

AI applications, especially in agriculture in developing countries, remain limited. Although the adoption process of agricultural technologies is evident in several studies, most research focuses on an empirical, technological, policy, or governance standpoint. The focus is primarily on how prices, farmer traits (including income, risk aversion, time preferences, and education), and characteristics of technology significantly influence the prediction of agricultural technology performance. None of the existing literature highlights whether smallholders are aware of AI techniques and the perception towards its adoption. The adoption of agricultural technologies correlates with farmers' perceptions and expectations [51]. This study explores female farmers' perceptions of AI technology in agriculture, including the norms, factors, and determinants that influence their adoption of AI technologies. The study also examines the barriers that may emerge and the interventions that can be put in place to enable the effective and inclusive adoption of AI technologies for Agriculture among women smallholder farmers. Thus, examining farmers' perceptions is not only important to ensure the adoption and scaling up of technologies, but also to ensure gender inclusion at the adoption and benefits levels. This ensures sustainable growth and development of the agriculture sector, centering women in agricultural digital transformation and considering their demographics in agricultural labour and production in Kenya and across Africa. This study is a unique contribution to the field of agriculture and the adoption of artificial intelligence.

2 Materials and methods

2.1 Study area and sampling

This study focused on Kiambu County. Five (5) sub-counties were selected to be the area of study, namely, Juja, Ruiru, Githunguri, Laari, and Kabete sub-counties. Among these sub-counties, the study randomly selected the following wards for the survey: Ikinu, Biashara, Kalimoni, Nyathuni, Kijabe, Murera, Muguta, and Kaari. The study employed the snowball sampling technique to select a sample of 100 smallholder farmers from women's farmer groups in these wards. The snowballing process started with a small group of initial respondents (seeds). The snowball sampling technique involved asking initial respondents to refer others who met the study's criteria, allowing researchers to expand their sample through social networks [52]. These initial respondents then referred us to other potential respondents they know within the target population. Those respondents then referred us to others, and so on. This process continued until we obtained the desired sample size [53, 54]. The study used a well-structured questionnaire to collect data from the respondents. The questionnaire covered information on demographics, perceptions about AI and the socioeconomic attributes of the smallholder farmers. The perceptions involved 20 statements that were derived from a review of pre-existing literature [55, 56, 57].

2.2 Theoretical model

This study is anchored on the household utility maximization theory to explain the adoption of AI among smallholder farmers. The theory critically examines the farmer's decision to adopt or not to adopt an innovation, depending on the utility they expect from it. Utility is a central concept in the microeconomics theory of consumer behavior, in which consumers choose among bundles of goods from a given set. Despite the challenges farmers face, they must choose to adopt AI to increase their productivity. The smallholder farmer will choose a bundle of AI and digital technologies that maximizes utility subject to their budget (see Appendix 2). The choices to be made are entirely determined by the benefits derived from the selected alternative. Such benefits include: improved yields and profitability, reduced growth period, better use of soil and water, and improved resistance to diseases, among others. According to the utility maximization theory, the farmer's choice of a particular AI package is guided by random factors [58]. The utility of a choice is composed of two components: a deterministic component and an error component. The error component is independent of the deterministic part and follows a predetermined distribution. This implies that the farmer may not be able to predict with certainty which alternative he/she will select. However, the farmer can express that the perceived utility of a particular AI technology is likely to exceed that of other available alternatives. The utility that the smallholder farmer gains from the adoption of AI comprises an observable deterministic component (the utility function) and a random component, and can therefore be defined as follows:

$$U_{mn} = V_{mn} + \mathcal{E}_{mn} \tag{1}$$

We assume that utility depends on choices made from some set of AI strategies. The individual is assumed to have a utility function of the form:

$$U_{mn} = V\left(V_{mn,} \; Z_n\right) \tag{2}$$

Where U is the utility function, Vm is the AI attributes while Zn represents the farmer's attributes. A smallholder farmer seeking to maximize the present value of AI benefits for agriculture over a specified period must thus choose among available AI technologies. The utility derived from AI technology is assumed to depend on its attributes and the farmer's socioeconomic characteristics. However, a farmer may not choose the preferred AI technology. To explain such variations in choice, a random element is included as a component of the utility function in Eq. 2 such that:

$$U_{mn} = V\ (X_n) + \varepsilon(X_n z_m) \tag{3}$$

The probability that the smallholder farmer will thus choose AI technology among the set of AI technologies could be defined as follows:

$$P\left[m\left(CS\right)\right]=p\left[U_{n}>U_{q}\right]$$

where

$$n\cdot\varepsilon\cdot CS\;=\;P\left[\left(V_{n}+\varepsilon_{n}\right)>\left(V_{q}+\varepsilon_{q}\right)\right] \tag{4}$$

$$P\left[\left(V_{n}-V_{q}\right)>\mu\right]$$

where *CS* represents the complete choice set of AI ttechnologies adopted. In order to estimate Eq. 4, assumptions must be made over the distributions of the error terms. A typical assumption is that the errors are Gumbel-distributed (maximized error terms) and independently and identically distributed i.e. (they have the same probability distribution and are mutually independent) [58].

2.3 Analytical model

The study aimed to analyze and categorize the factors that contribute to the various perceptions about artificial intelligence in the study area using the principal component analysis (PCA) technique. Principal Component Analysis is essential for streamlining complicated datasets and improving the performance of machine learning models in the field of artificial intelligence. Through the process of dimensionality reduction, PCA preserves critical patterns in the data, thereby improving computational efficiency and model correctness. The study preferred PCA since it helps to reduce the dimensionality of the input variables and identify significant factors that influence perceptions of artificial intelligence in agriculture in the study area. PCA does this using a linear combination (basically a weighted average) of a set of variables. The index variables created are called components. When data sets contain a large number of variables that require accounting, conducting a PCA is advantageous. Since the study identified many variables, this approach helps create groups that are homogenous within themselves and heterogeneous between each other. The objective of using the PCA technique for analysis was to condense the information contained in the original variables into a smaller set of variates (factors) with a minimal loss of information. PCA can be represented as follows: Let the principal components in the study be Z1, Z2 … Zi, then the principal components (Z1, Z_2…$Z_{i)}$ are generated through linear combination of variables X's as:

$$Z=\alpha^{T}X \tag{5}$$

Where; Z = Z_1, Z_2, Z_p are vector of principal component and α^{T}- is matrix of coefficients α_{ij} for i, j = 1, 2,. . ., p

$$Z1=\;\alpha 11X1+\;\alpha 12X2+\ldots+\alpha 1pXp \tag{6}$$

Z1 is the largest combination of p features under the condition that:

$$\alpha^{2}11+\alpha^{2}12+\ldots+\alpha^{2}1p=1 \tag{7}$$

The second principle component Z_2 has the second-largest possible variance in X_1, X_2,. . ., Xp, which is orthogonal and uncorrelated with Z_1. The j^t principal component with the largest possible variance is defined similarly, provided it is uncorrelated with the i^{th} principal component for i < j. The principal components obtained are in decreasing order, i.e., variance (Z_1) > variance (Z_2) >. . > variance (Zp). If λi is the variance (eigenvalue) for Zi and αij is the eigenvector for Zi then the following conditions hold:

$$\lambda 1 \ \geq \lambda 2 \ \geq \lambda i \quad \geq 0$$

$$\alpha^T 1 \alpha = 1$$

$$\alpha^T 1 \alpha = 0$$

The eigenvalue represents the level of variation caused by the associated principal component. The variance for the principal component for k-retained principal components is computed by

$$\mathrm{tk} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{k}} \lambda 1}{\sum_{\mathrm{i}=1}^{\mathrm{p}} \lambda 1} \tag{8}$$

In the second stage, the retained factors were used in cluster analysis to characterize the farmers. The process involved hierarchical and partitioning clustering to identify the number of clusters. This method was chosen due to its ability to cluster based on both categorical and continuous variables. Later, one-way Analysis of Variance (ANOVA) was employed to identify the differences between the groups and the factors influencing the variations in adoption of AI and digital technologies.

3 Results

3.1 Descriptive characteristics of the respondents

Table 1 lists the sample's characteristics. This study interviewed a total of 100 respondents. Among the respondents, there were 83 women and 17 men. The findings show that the respondents were 44 years old on average. The average number of members in the households interviewed was five. The average number of years of schooling was 12. The land size was small, averaging 1 acre. The average distance from the farm to the primary market was 8 km. The average farming experience of the respondents was 16 years. Regarding the gender of the household head, 51% of the respondents indicated that males headed their households, while 49% indicated that females headed them. For

Table 1 Sample's descriptive characteristics

Variable	Description	Mean	SD
Age	Age of the household head in years	44	13
Household size	Number of household family members	5	2
Education	Number of years of schooling	12	4
Farming experience	Years of farming experience	16	14
Land size	Total land size owned in acres	1	1
Distance to main market	Number of Kilometres from farm to main market	4	3
Frequency %			
Gender of respondent	Male	17	17
	Female	83	83
Gender of household head	Male	51	49
	Female	49	49
Marital status	Married	65	65
	Single	13	13
	Divorced/Separated	12	12
	Widowed	10	10

marital status, the majority of the respondents were married (65%), 13% were single, 12% were divorced or separated, and 10% were widowed. To deal with outliers especially of land size, distance to the market and number of household members the study conducted winsorization. Winsorization is a statistical technique that replaces extreme outlier values in a dataset with values from a selected percentile range, such as replacing values below the 5th percentile with the 5th percentile value and those above the 95th percentile with the 95th percentile value, thereby preserving degrees of freedom. This method results in means and standard deviations that are typically closer to the corresponding population parameters than those derived from the original data [59, 60]. In this study, the nearest value of distance to the market to the outliers is 10, while that of land size is 4 and number of household members is 9. This study therefore replaced the former with the latter through winsorizing where all the outliers were identified through a box plot as shown in Appendix 1.

3.2 Awareness about artificial intelligence (AI) technologies in agriculture

Table 2 presents the descriptive statistics on farmers' awareness of artificial intelligence (AI) agricultural technologies. The findings indicate that the majority of the farmers were aware of artificial intelligence technologies (62%), while 38% were not aware. The media was the primary source of information on artificial intelligence technologies, accounting for 54%, with fellow farmers following closely at 21%.

3.3 Farmers perception about agricultural technologies

Table 3 presents the descriptive statistics of the farmers' perception of agricultural technologies. 59% and 35% of the respondents strongly agreed and agreed, respectively, that digital technologies provide easy access to information. 55% and 28% of the respondents strongly agreed, respectively, that it was easy to access loans through digital technologies. 50% and 28% of the respondents strongly agreed and agreed, respectively, that it was easy to access markets through digital technologies. 50% and 34% of the respondents strongly agreed and agreed, respectively, that digital technologies help increase output. 49% and 20% of the respondents strongly agreed and agreed, respectively, that agriculture/agribusinesses would be revolutionized by AI. 48% and 34% of the respondents strongly agreed and agreed, respectively, that digital technologies help increase household income. On the other hand, 17% of the respondents strongly disagreed that AI has ambiguous data input requirements, 19% strongly disagreed that AI has low adaptability to peculiar business situations, and 21% strongly disagreed that AI and digital technologies consider the challenges women farmers experience.

Table 2 Awareness about artificial intelligence technologies in agriculture

Variable	Description	Frequency	%
If they have heard about AI technologies in agriculture	Yes	62	62
	No	38	38
Source of information on AI technologies in agriculture	Fellow farmers	21	21
	Researchers	8	8
	Non-Governmental Organizations	6	6
	Ministry of Agriculture Extension agents	3	3
	Media (TV, Radio, Mobile phones, etc.)	54	54

Table 3 Descriptive statistics on perception about agricultural technologies

Attitudinal Statement	Strongly agree (%)	Agree (%)	Neutral (%)	Disagree (%)	Strongly disagree (%)
Digital technologies are not readily accessible	28	28	6	22	16
There is unequal access to digital technologies among smallholder male and women farmers	28	33	12	19	7
Digital technologies are complicated to use	18	14	8	42	18
There is inadequate knowledge on digital technologies	30	24	7	31	8
Digital technologies require specific skills to use	24	33	10	28	5
Digital technologies will discourage the use of indigenous knowledge and skills	24	20	8	31	17
It is easy to access loans through digital technologies	55	28	9	14	4
It is easy to access markets through digital technologies	50	28	8	13	1
It is easy to access extension services using digital technologies	30	31	17	17	5
Digital technologies help easy access to information	59	35	1	3	2
Digital technologies help increase output	50	34	10	4	2
Digital technologies help increase household income	48	34	13	5	0
Agriculture/Agribusinesses would be revolutionized by AI	49	20	19	9	3
AI has unfriendly user interface	20	23	41	15	1
AI has ambiguous data input requirements	17	24	39	17	3
AI has low adaptability to peculiar business situations	19	21	35	23	2
AI and Digital Technologies articulates the needs and values of women farmers	23	31	32	11	3
AI and digital technologies consider the challenges women farmers experience	21	29	30	13	7
I use these technologies to make decisions about the farm or business every time.	26	33	20	15	6
I trust AI and digital technologies to provide me with relevant advice for decision making	36	33	23	5	3

Table 4 Kaiser-Meyer-Oklin and Bartlett's Test of Principal Components

Kaiser Meyer –Oklin Measure of Sampling Adequacy	0.687
Bartlett Test of Sphericity Chi-square	605.62
Degree of Freedom	190
P- value	0.000

3.4 Principal component analysis

3.4.1 Kaiser-Meyer-Oklin (KMO) and Bartlett's test of sphericity

The study conducted a Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity before performing Principal Component Analysis (PCA), with the results presented in Table 4. The results show a KMO of 0.687, meaning that each variable was sufficient for analysis. The BTS value was 605.62, with a P-value of 0.00, indicating that the data, was sufficient for PCA analysis.

3.5 Components resulting from PCA analysis

Kaiser's rule for principal component analysis provides that only factors with eigenvalues that are greater than one should be retained. The table shows the various components resulting from PCA analysis. The results showed that AI and digital technology adoption can be classified into seven components based on the given perception factors. The seven components are economic benefits; access to productive resources; digital technology and women's access, decision-making support and trust in AI; skills and

Table 5 Components and total variance explained

Component	Eigenvalue	Proportion	Cumulative	Variance
Component 1 – Economic benefits	4.291	21.457	21.457	2.606
Component 2 - Access to productive resources	2.236	11.179	32.636	2.263
Component 3 – Digital technology and women's access	1.761	8.805	41.441	1.928
Component 4 - Decision- making and trust in AI	1.514	7.569	49.010	1.831
Component 5 – Skills and cultural aspects	1.428	7.142	56.152	1.812
Component 6 – AI technical constraint	1.278	6.391	62.543	1.763
Component 7 – Knowledge gap	1.056	5.281	67.823	1.362

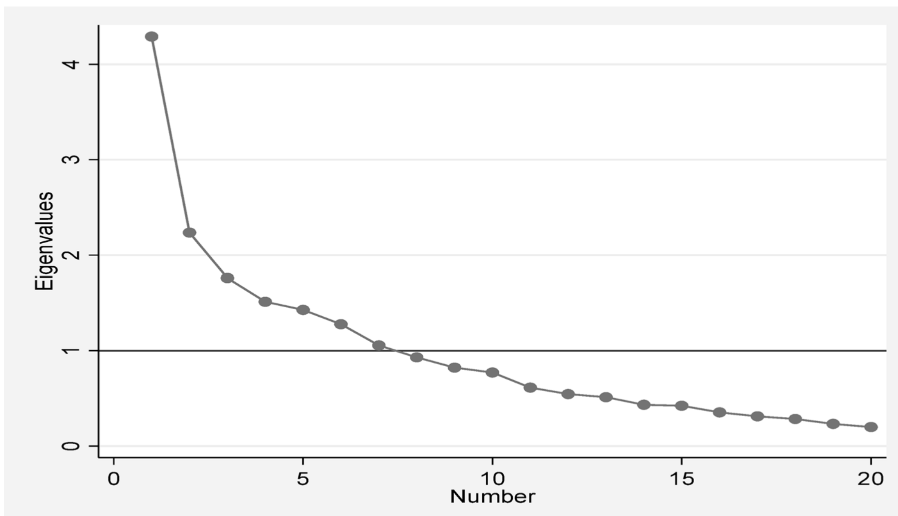


Fig. 1 A scree plot of the retained components

cultural aspects; AI technical constraints and knowledge and awareness gap, as they had eigenvalues greater than 1 (Table 5). AI adoption is assessed by identifying the factors that contribute most to overall variation in AI adoption. This was identified using an eigenvector derived from the covariance matrix. The number of coefficients in each Eigen vector is equal to the number of variables that were subjected to PCA analysis. Similar to the regression coefficient, which indicates the contribution of each variable to the dependent variable, the eigenvalue coefficient indicates the relative importance of each variable to the total variation. In this scenario, the economic benefits accounted for a meaningful variation in AI adoption, followed by access to productive resources and digital technology and women's access, since they had higher coefficients. The positively higher coefficient value indicates a higher contribution of a particular factor to the total variation in a positive direction (Fig. 1).

3.6 Results of exploratory factor analysis

Table 6 provides the results of exploratory factor analysis of smallholders' perception of digital technology adoption. The principal components analysis reduced the twenty variables into seven sets of uncorrelated components. Digital technologies are often used interchangeably with AI, particularly in Kenya, as many agricultural tools are transitioning to AI-enabled systems.

The first retained factor was the economic benefits -related factor. It accounted for 21.46% of the variance. The factor comprises three items with their associated factor

Table 6 Exploratory factor analysis of smallholder farmers' perception on adoption of digital technology

Factor and item description	Factor loading	% Variance explained
Factor 1: Economic benefits related factor	0.533	21.46
Digital technology helps easy access to information	0.827	
Digital technology helps increase output	0.847	
Digital technologies help increase household income	0.639	
Agriculture/Agribusiness would be revolutionized		
Factor 2: Access to productive resources related factor	0.890	11.18
It is easy to access loans through digital technologies	0.776	
It is easy to access markets through digital technologies	0.693	
It is easy to access extension services through digital technologies		
Factor 3: Digital technology and women's access-related factor	0.860	8.81
AI and digital technologies articulate the needs and values of women farmers	0.853	
AI and digital technologies consider the challenges women farmers experience		
Factor 4: Decision-making and trust in AI related factor	0.591	7.57
I use these technologies to make decisions about the farm or business every time	0.450	
I trust AI and digital technologies to provide me with relevant advice for decision making		
Factor 5: Skills and cultural aspects related factor	0.605	7.14
Digital technologies are complicated to use	0.769	
Digital technologies require specific skills to use	0.780	
Digital technologies will discourage the use of indigenous knowledge and skills		
Factor 6: AI technical constraints related factor	0.551	6.39
AI has unfriendly user interface	0.857	
AI has ambiguous data input requirements	0.696	
AI has low adaptability to peculiar business situations		
Factor 7: Inadequate knowledge related factor	0.830	5.28
There is no adequate knowledge on digital technologies		

loadings, i.e., digital technology helps increase output, digital technology helps increase household income, digital technology helps easy access to information and AI would revolutionize agriculture/agribusiness. The second retained component was the access to productive resources-related factor, which accounted for 11.8% of the total variance. The factor comprises three items, each with its associated factor loading: it is easy to access loans, markets, and extension services through digital technologies. The third retained component was the AI technology and women's access related factor, which accounted for 8.81% of the total variance. The factor comprises two items with their associated factor loading, i.e., AI and digital technologies articulate the needs and values of women farmers, and AI and digital technologies consider the challenges women farmers experience. The fourth retained component was decision making and trust in AI related, which accounted for 7.57% of the total variance. The factor comprised of two items with their associated factor loading, i.e., I use these technologies to make decisions about the farm or business every time, and I trust AI and digital technologies to provide me with relevant advice for decision making. The fifth retained component was the skills and cultural aspects -related factor, which accounted for 7.14% of the total variance. The factor comprises three items with their associated factor loading, i.e., digital technologies require specific skills to use, digital technologies are difficult to use, and digital technologies will discourage the use of indigenous knowledge and skills. The sixth retained component was the AI technical constraints-related factor, which accounted for 6.39% of the total variance. The factor consisted of three items with their associated factor loading: an unfriendly user interface, ambiguous data input requirements, and low adaptability to peculiar business situations in AI. The last retained component was the inadequate knowledge-related factor, which accounted for 5.28% of the total variance. The factor comprises one item with its associated factor loading, indicating a lack of adequate knowledge on digital technologies.

3.7 Determinants of adoption of AI technologies

The seven retained components were used in the next stage, cluster analysis, to identify farmer profiles and the factors driving variation in the adoption of AI technologies. The cluster analysis produced 3 categories of farmers highlighting the heterogeneity in farmers as shown by Fig. 2.

Table 7 shows the profiles of smallholder farmers based on their perceptions of AI and the socioeconomic characteristics of farmers determined by the ANOVA test. The findings revealed that farmers were largely homogeneous in their perceptions of digital technology, except for knowledge sufficiency. Socioeconomic characteristics showed differences among the three types. Profile 1 was composed of older, highly experienced farmers who lived farthest from the market. Profile 2 comprised moderately educated farmers, and had bigger household sizes, while cluster three had more educated, less experienced, and younger farmers, with shorter distances to the market. Similarly, the results identified factors that caused variations in the adoption of AI technologies, namely, age, years of schooling, household size, distance to the market, years of experience in farming, and information sufficiency (Table 7).

4 Discussion of the results

The findings indicate that the majority of the farmers were aware of artificial intelligence technologies (62%), while 38% were not aware. The media was the primary source of information on artificial intelligence technologies, accounting for 54%, with fellow farmers following closely at 21%. This shows a disconnect between those designing technologies and those using them. This can lead to the creation of technologies that are not compatible with the realities of farmers, because while the media may provide information about the AI technologies being designed for agriculture, it is only when farmers interact with designers that they can understand what technologies to adopt, as well as discuss issues around risks, viability and usability [61]. Smallholder farmers need access to information about agricultural technologies to make informed adoption decisions [62]. But the information needs to be balanced between the benefits and the risks, so

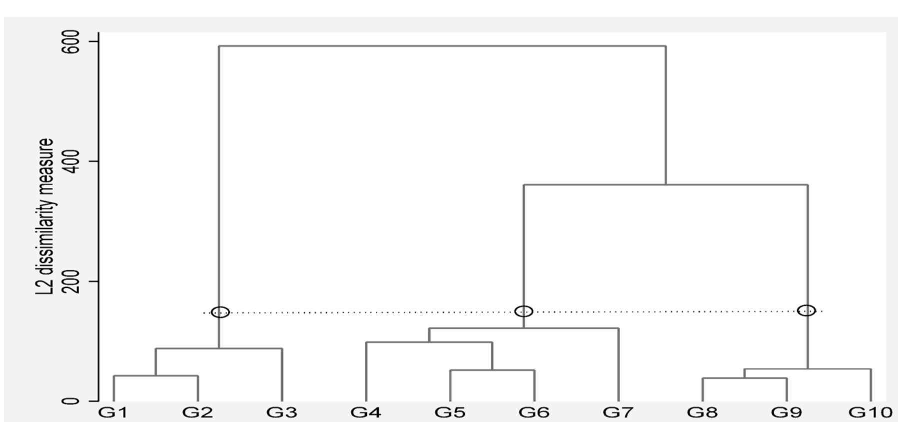


Fig. 2 Dendrogram

Table 7 Profile of smallholder farmers and factors affecting the adoption of AI technologies in decision making

Factor	Cluster 1	Cluster 2	Cluster 3	F	Sig
Digital technologies are not readily accessible	4	3	3	0.15	0.85
There is unequal access to digital technologies among smallholder male and women farmers	4	3	4	0.47	0.62
Digital technologies are complicated to use	3	3	3	0.59	0.56
There is inadequate knowledge on digital technologies	3	4	3	4.03	0.02
Digital technologies require specific skills to use	4	4	3	1.26	0.29
Digital technologies will discourage the use of indigenous knowledge and skills	3	3	3	0.25	0.78
It is easy to access loans through digital technologies	4	4	4	0.45	0.64
It is easy to access markets through digital technologies	4	4	4	0.40	0.67
It is easy to access extension services using digital technologies	4	4	4	0.78	0.46
Digital technologies help easy access to information	4	4	5	3.08	0.05
Digital technologies help increase output	4	4	4	0.26	0.77
Digital technologies help increase household income	4	4	4	0.06	0.94
Agriculture/Agribusinesses would be revolutionized by AI	4	4	4	0.73	0.48
AI has unfriendly user interface	3	3	4	2.87	0.06
AI has ambiguous data input requirements	3	3	4	1.30	0.28
AI has low adaptability to peculiar business situations	3	3	3	0.60	0.55
AI and Digital Technologies articulates the needs and values of women farmers	4	4	3	1.09	0.34
AI and digital technologies consider the challenges women farmers experience	4	3	3	0.25	0.78
I use these technologies to make decisions about the farm or business every time	4	4	4	0.13	0.88
I trust AI and digital technologies to provide me with relevant advice for decision making	4	4	4	0.36	0.70
Socioeconomic characteristics					
Age	64	48	32	113.17	0.00***
Gender	0	1	0	0.99	0.38
Education	10	11	13	5.43	0.00***
Household size	4	5	4	4.63	0.01***
Distance to the market	5.9	4.2	2.4	8.90	0.00***
Land size	1.55	1.40	0.99	1.62	0.20
Experience	44	17	5	175.19	0.00***
Frequency(N)	14	48	38		

increased adoption does not stem from hype but from decisions shaped by the farmer's agency [63]. The use of media as the primary source of information on AI implies that farmers are shifting from relying on traditional sources of information such as research institutions, extension agents, and NGOs for information about new technologies. This finding coincides with the study on the awareness level of understanding of AI technology in agriculture among the farmers in Villupuram district, Tamil Nadu [57]. It shows a potential undermining of the rich information that can emerge from preexisting relationships and channels, also observed in New Zealand [64]. This may lead to the loss of otherwise important knowledge that can add value to agricultural production [65]. The authors found that the media was a key strategy for communication and education that motivated farmers' learning interest. Similarly, another study investigating the impact of artificial intelligence on agriculture and its level of awareness among farmers in India found that although majority of the farmers were aware of a few techniques and tools of artificial intelligence, AI adoption was still a challenge since very few farmers had adopted those techniques for their use in their farms [66]. It is evident that preexisting sociomaterial of farmers is important in building trust in AI and emerging technologies [65]. The study recommended the use of social media platforms and mobile applications by farmers to spread AI awareness more effectively, while combining this with preexisting social networks for improved trust and adoption. Another study shows that women are more likely to be found on social platforms such as WhatsApp groups and Facebook, while as a norm, they trust their informal networks and the information that emerges from them [63]. Thus, improved perception and hence adoption can be achieved by tapping into these networks, which are also increasingly integrated into digital spaces.

Using the exploratory factor analysis, the study found that AI adoption can be classified based on the following 7 factor categories as follows: economic benefits; access to productive resources; digital technology and women's access; decision-making support and trust in AI; skills and cultural aspects; AI technical constraints and knowledge and awareness gap. Existing evidence identifies five categories of factors that influenced AI technology adoption as follows – individual characteristics, environmental factors, structural factors, technology factors and demographic factors. Further, the study concludes that the conditions that facilitate AI adoption and features of AI based solutions particularly its compatibility directly influenced its adoption intention [67]. There is a direct, positive association between perceived value and IoT adoption, which indicated that a combination of perceived economic, environmental and epistemic value motivates farmers to adopt IoT technology [51]. Further, farmers are motivated to adopt technologies that will help them better manage their land and increase sustainable production [68]. This implies that the only AI technology deemed useful to smallholder farmers is that which brings economic and epistemic value while serving their sustainability goals [65]. This serves as a great avenue for introducing AI technologies in Agriculture that can help reduce the gender economic gap, contributing to gender, economic, and development goals in Kenya. The study investigated the perceptions of AI technology adoption, and it revealed that the characteristics of the technology shaped their decisions whether to adopt or not. The findings reveal that perceptions were majorly shaped by the characteristics of the technology and more so its perceived benefits, for example it makes it easy to access information, it is able to increase output among other benefits. This finding is in line with a study in Ghana on how farmers adopted improved varieties based on its characteristics and cost [69]. Further, some farmers perceived digital technologies to be expensive, digital technologies led to a digital gap between the farmers, and hindered the exploitation of indigenous knowledge, although digital technologies generally boosted production in Eastern Cape Province, South Africa [70]. These findings suggest a need for AI literacy among farmers, one that fosters critical discussion and addresses their concerns.

Regarding the determinants of the adoption of AI and digital technologies, age differs significantly among farmers. Farmers in type I were the oldest, while those in type 3 were the youngest. Age is widely recognized as an important factor influencing the adoption of technology. Older farmers tend to rely on conventional farming methods and may demonstrate less comfort with digital technology. In contrast, younger farmers are generally more receptive to technology, more technologically literate, and more willing to experiment with digital tools. The findings show that younger farmers are more likely to adopt digital technology, whereas older farmers may need extra assistance, targeted instruction, or simplified digital interfaces. There was a notable variation in education among the farmers. Farmers in cluster 3 had the highest education levels, followed by cluster 2, while cluster 1 had the lowest. This implies that farmers with a higher level of education were more likely to adopt AI and digital technologies than their less-educated counterparts. This finding coincides with the findings of similar studies that find a positive relationship between the level of education and technology adoption [71, 72 73, 74, 75] among others. Household size varied considerably. Farmers in cluster 2 had the largest sizes. Larger households can influence technology adoption by providing labor and resources.

An increased number of household members provides additional income and labor resources, which can support the adoption of new technologies. Additionally, the distance to the market varied across the three groups. Farmers in Cluster 1 lived from markets, whereas those in Cluster 3 lived near the markets. Market proximity influences adoption in several ways.

Farmers located closer to markets typically have greater access to digital service providers, mobile networks, infrastructure, and extension services. In contrast, those in more remote rural areas often face challenges such as limited connectivity, insufficient digital infrastructure, and limited opportunities to acquire knowledge of digital technologies. Similarly, the years of farming considerably varied among farmers. Farmers in clusters 1 and 2 were more experienced compared to their counterparts in cluster 3. Less experienced farmers may be more willing to adopt digital technologies, whereas more experienced farmers tend to rely on conventional wisdom and established practices. However, experienced farmers may also adopt digital technologies if clear benefits are evidenced in areas such as farm management, market access, or production efficiency.

There is an inferential positive relationship between technology implementation and youth farming [76]. Additionally, younger smallholder farmers that had attained higher education levels, who interacted with scientists and owned large farms were better off in adopting digital technologies of the internet and connectivity/wireless, mobile applications and digital platforms than their older smallholder farmers' counterparts who had lower education levels, did not interact with scientists and owned small farms as evidenced by the study on perception of adoption of digital technologies in Vietnam [77]. Most rural women farmers lack a modest education, and hence, effective adoption of AI technologies may be a problem. This may also limit their participation in AI literacy training. The same study also found that smallholder farmers who took part in training programs, were members of community-based organizations, reached out to extension workers, and lived far from local markets adopted and used digital technologies such as the internet, connectivity/wireless, and mobile applications.

5 Conclusion

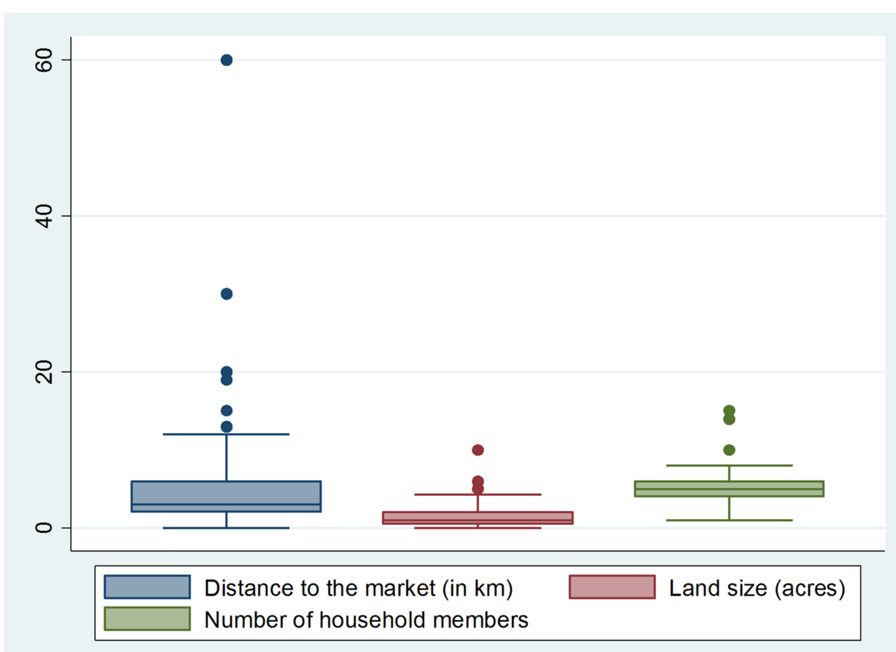
This study investigated the adoption of artificial intelligence and its perceptions among smallholder farmers in Kenya, using a sample of 100 smallholder women farmers. The analysis employed descriptive, principal component, and cluster analysis techniques. From the study findings, it is evident that the majority of the farmers were receptive to artificial intelligence and thus held positive attitudes towards it. The level of education, age, household size, and distance to market were significant determinants of AI and digital technology adoption. Although most farmers were aware of artificial intelligence, they primarily obtained information from the media and through conversations with fellow farmers. The farmers were receptive to AI and digital technology adoption due to several key factors, including increased returns, access to productive resources, information access and decision-making, AI technology, women's access, functionality, specific requirements, availability, and use, as well as inadequate knowledge. In line with the above findings, the study suggests the following recommendations. First, it is essential to empower farmers, especially the men, to be involved in the adoption of AI and digital technologies. Policymakers need to be involved in sensitizing and supporting the farmers to adopt AI and digital technologies.

6 Study limitations

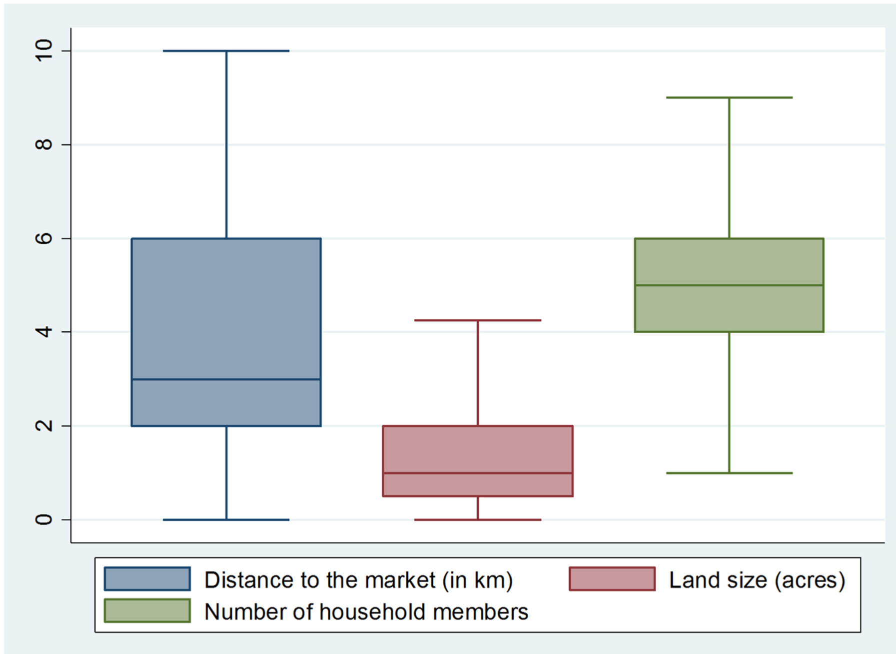
Despite its contributions, this study presents some limitations. First, the sample of 100 smallholder farmers from Kiambu County limits the extent to which the findings apply elsewhere in Kenya or to large-scale farmers who may adopt or perceive AI differently. Second, the study used self-reported perceptions and AI awareness, which may be subject to response or social desirability biases or to misunderstandings of AI. Finally, the cross-sectional design captures only one point in time, so it cannot show how attitudes or adoption might change as AI evolves. This study thus recommends that future studies should use larger, more diverse samples, longitudinal designs, and mixed-methods approaches to provide a fuller view of AI adoption in agriculture.

Appendix 1

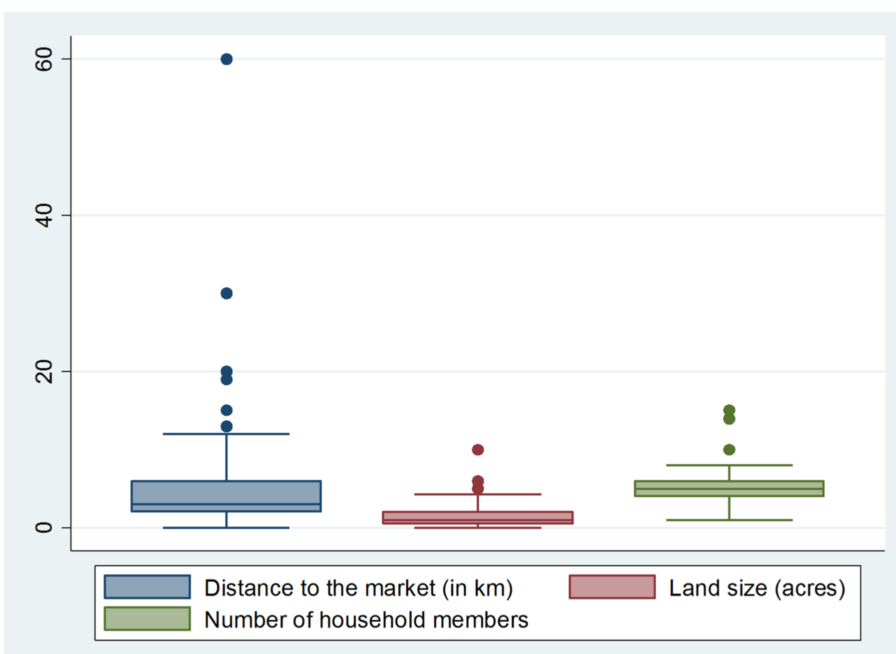
Box plot of the data-set



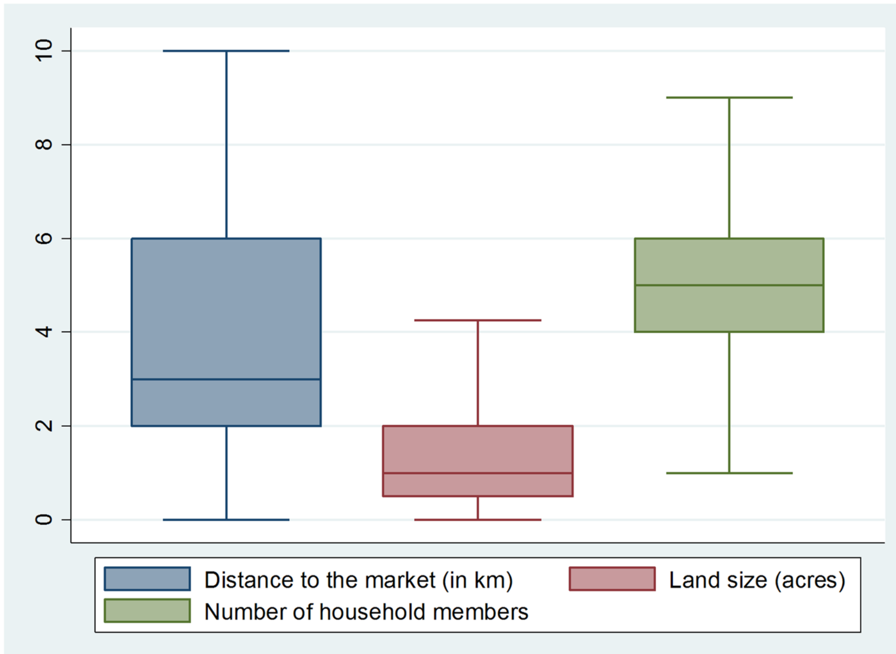
Box plot of the data set after winsorization process



Box plot of the dataset



Box plot of the data set after winsorization process



Appendix 2

Although AI was the original focus of this study, at the time of this study, Agtech digital tools were transitioning to AI for farm-level decision-making, with some tools remaining AI-unenabled while others were AI-enabled. Because we were dealing with rural female farmers with low literacy levels, our questionnaires began with what they knew and ended with what they didn't know. An assumption that they could differentiate the two would lead to invalid data. It is only fair to use AI and digital technologies together, rather than AI or digital technologies alone. Furthermore, our interviews were expert-supported, so the participants got explanations about the difference.

Author contributions

We acknowledge the enormous contributions by the authors towards this manuscript. Eucabeth Majiwa and Angela Ndaka did conceptualization. Eucabeth Majiwa, Angela Ndaka, and Harriet Ratemo did data collection. Eucabeth Majiwa did data analysis. Sourcing for funding was done by Angela Ndaka. Eucabeth Majiwa prepared the first draft of the manuscript. Angela Ndaka and Harriet Ratemo critically reviewed the manuscript. Evans Agembo reviewed the final manuscript thereafter. All the authors reviewed and approved the final manuscript.

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Data availability

The datasets used for this study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

The study performed all procedures for data collection in compliance with relevant laws and institutional guidelines that the Institutional Scientific and Ethics Review Committee of the Jomo Kenyatta University of Agriculture and Technology has approved. The ethical approval was issued on 19th January 2024, referenced as JKU/ISERC/02316/0807. The privacy rights of human subjects were observed, and informed consent was obtained during the data collection. The data was anonymous to protect the privacy of the respondents. Clinical trial number: not applicable.

Consent for publication

The authors confirm that they have read the Nature Portfolio journal policies on author responsibilities and submit this manuscript in accordance with those policies. All the authors approve this manuscript for publication.

Competing interests
The authors declare no competing interests.

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