Sustainable Food Technology

REVIEW

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Can agriculture technology improve food security in low- and middle-income nations? a systematic review

Robert Brenya, *[a] Jing Zhu[a] and Agyemang Kwasi Sampene[b]

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The application of agriculture technology (AT) has been a reliable panacea for meeting the urgent demand for quality and healthy food. Technology has enabled efficiency and effectiveness in swift decision-making, farmers' fiscal and economic sustainability, and food security. However, challenges, such as low adoption, capital intensiveness, technical know-how, climate change, malfunction, and rules and regulations, threaten the precise application of agriculture technology in low and middle-income nations (LMINs). In this review, we have followed the PRISMA guidelines to generate a novel dataset from 60 peer-reviewed articles and we used the Howard Computation Matrix to assess authors' contributions *via* the institution, country and the trend of publication from 2011 to 2020. We further assessed agriculture technology, utilization, and challenges, and operationalized the variables using the linear regression model to establish the causal inference. The findings revealed that the American and European nations emerged as the highest in terms of agriculture technology research as compared to LMIN. This review recommends policies for LMIN to start massive investments into agriculture technology, as it is the only means to uphold food security.

Introduction

A vast body of knowledge in agriculture unearths the relevance of the impact of agriculture technology (AT) on the quest to be food secure in the 21st century. Digital farming has shown the decades of labor intensiveness of farmers in the low-and middle-income nations (LMINs) before the introduction of AT. This study defines AT as the machinery, electronic devices, digital equipment, *etc.*, that are used in the agricultural sector to support food cultivation and decision. On the one hand, the literature argues that agriculture technology is a major contributor to climate variabilities, land degradation, deforestation, pollution due to the overuse of machinery, and excessive carbon emissions, particularly from large-scale farming, among others.[1–4] On the other hand, agriculture technology has been the panacea that can withstand the impact of the growing population and uncertain climate changes such as drought and excessive rainfall, among others. AT is among the principal components that can match the plummeting rate of food insecurity in the LMIN owing to its ability to boost agricultural productivity.[5] AT prevents pests and diseases, and nutrient leaching, enables fertilizer manipulation, and supports decision-making and dairy production systems.[6–8] A study conducted in Africa, Asia, and Latin America asserted that AT directly assisted in decreasing poverty by improving the welfare of poor household farmers who adopted technological innovation.[9]

However, there are numerous problems when adopting agriculture technology in both LMIN and developed nations. Although the incomes of LMIN for food consumption and assurance of physiological needs emanate from agriculture,[10] they are unable to employ agriculture technology farming due to low capital, lack of technical know-how, climate change, malfunctions, and rules and regulations. Thus, the implication is high-rate poverty and food insecurity, among other issues. Koyanagi *et al.*[11] conducted research among 179 771 adolescents in 44 countries and asserted that moderate (46.7%) and severe (7.0%) food insecurity has grave consequences. Household undernourishment escalated in 2015 from 777 million to 815 million individuals in 2016.[12] Statistics indicated by FAO *et al.*[13] asserted that households experiencing moderate and severe hunger in Sub-Saharan Africa moved from 50% to 57% in 2014 and 2019, respectively. Similarly, Ndlovu *et al.*[14] postulated that 33.3% of farmers were food insecure, mildly insecure (17.65%), moderately insecure (7.84%), and 7.84% were severely insecure. It was further postulated that more than 2.37 billion people experienced severe food insecurity in 2020 and the African continent took the highest portion, with 21% of hungry households. The intriguing questions are as follows: can agriculture technology improve food security in low- and middle-income nations? What challenges impede the efficient use of agriculture technology? What policies are needed to facilitate agriculture technology adoption in LMIN? Based on these questions, we propose the technology adoption theory by Kamrath *et al.*[15] This

[a]*College of Economics and Management, Nanjing Agricultural University, Nanjing, 210095, China. E-mail: brenyarobert@yahoo.com*
[b]*School of Management, Jiangsu University, Zhenjiang, 212013, China*

theory provides insight into global agriculture technology adoption, benefits, and challenges. Carolin Kamrath further expatiated that technology adoption is required for structural transformation to achieve food security. We selected the theory of Kamrath *et al.*[15] because the study merges the technology acceptance and the adoption behavior towards its implementation. Omotilewa *et al.*[16] added that adopting agriculture technology expands agricultural production and the financial status of the farmer at adoption promotes household welfare, proceeds, and sustainability. Technology adoption theory and its confirmed benefits have also been established as the sole panacea to meet the demand for food sustainability.[17–20]

Herein, we examine how LMINs can use agriculture technology tools to improve their food security and overcome the challenges encountered in practising agriculture technology. We have conducted a systematic review to evaluate the contributions of institutions and countries using the computation matrix of Howard *et al.*,[21] agriculture technology publication trends, LMIN adoption and times of citation, devices used, and the challenges encountered. Also, we operationalized the challenges to creating the platform for future correlation studies. To do so, we followed the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) in generating the agriculture technology and food security articles for analysis (Fig. 2), based on the studies and the results obtained from the Americans and the Europeans spearheading the agriculture technological research. This review fills the gap in the literature on agriculture technology application in LMIN. The theory adopted improves the understanding of agriculture technology practice, and the method employed to compute the ranking score is a novel accepted matrix. Based on 60 peer-reviewed articles, we have deduced a new ranking for journals whose scope is within the review subject.

This review covers the key terms, materials and methods, and the results and discussion of modern devices used in agriculture settings, themes, and operationalization. We also address the challenges and conclude with policy recommendations, limitations, and future research.

Overview of key terminology and future agriculture sustainability

Agriculture technology

As highlighted above, agriculture technology is the way for agricultural stakeholders to have a firm grasp to match food security.[17] Most farmers in LMIN practice subsistence agriculture, farming using cutlasses, shovels, spades, and hoes, among others, thus hindering mass agricultural production, having low-income generation, and a negative impact on the socioeconomic living standard of farmers, *etc.*[22,23] Nowadays, modern agricultural farming has reduced the drudgery of farmers *via* automatic seed sowing, irrigation application, harvesting, chemical pest control, and fertilizer application, among others.[7,24–26] Old methods such as salting, drying, and the like, used for preserving agricultural products during post-harvest, have been replaced with modernized technological innovations such as canning, freeze-drying, *etc.*[27,28] Below is a graphical representation of sample studies that used agriculture technology devices in the field (Table 1).

Food security

The principal elements of food security, including availability, accessibility, utilization, and stability, have caused a wider spectrum of stakeholders to continue the debate as to what constitutes a food-secure household.[31,32] According to the United Nations (UN) scope, "food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life".[33] However, during the analysis for this review, we found that there are little or no empirical studies to support the eradication of food insecurity in the LMIN, and these regions are also accustomed to old farm tools such as hoes, cutlasses, rakes, *etc.*, which are less than ideal for the fight against food insecurity.[34,35] This review considers the positive effect of global agriculture technology on household food security. For instance, in the study conducted in Malaysia by Abdullah and Samah,[36] agriculture technology enforced the total eradication of inadequate crops and animal production in the region, thereby enhancing their food consumption and stability. Similarly, agriculture technology, according to Partel *et al.*,[37] provided a platform for farmers to reduce the cost of production while increasing food sustainability.

Nanotechnology

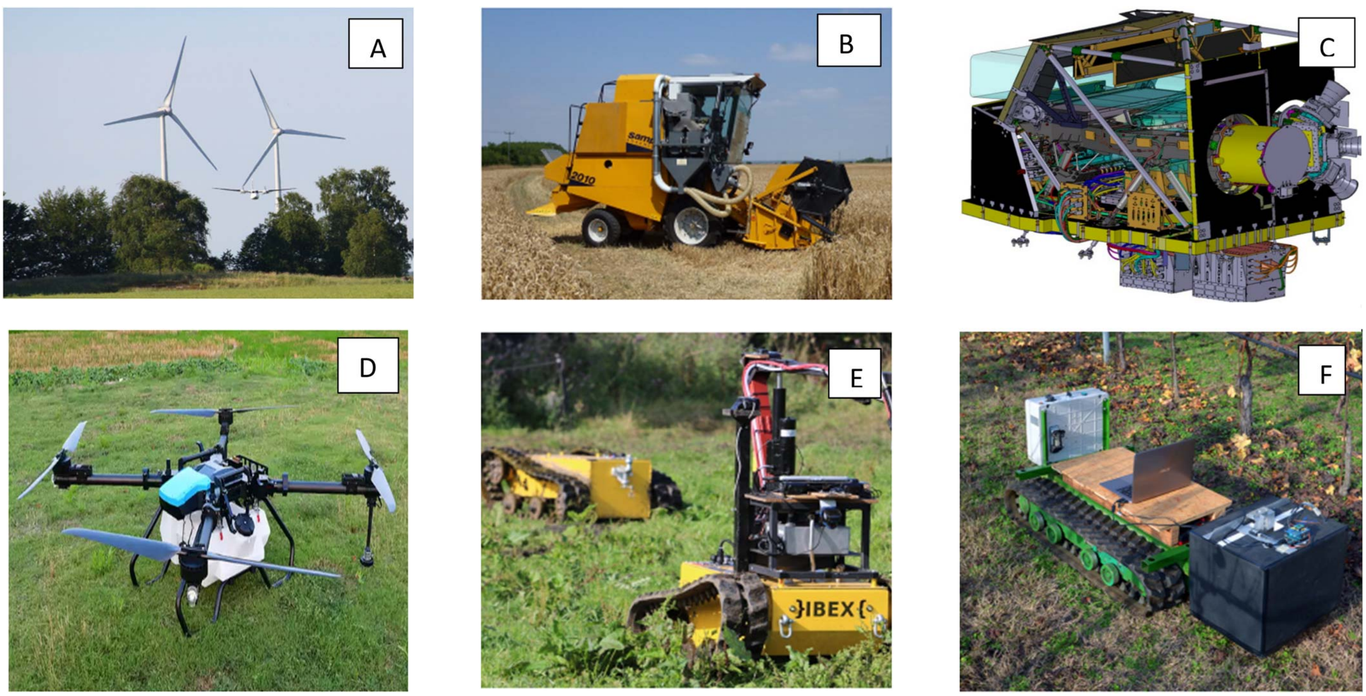
This study selected nanotechnology as a principal component to promote future agriculture sustainability as well as food security. The use of nanomaterials is growing in the food and agriculture industry due to their effectiveness. Nanotechnology manipulates nanoparticles such as ceramics, metals, nanofibers, *etc.*, which are within the measurement of 1 to 100 nanometers, to enhance agricultural production. The nanotechnology application enables farmers to kill weeds, pests, and diseases without hurting the plants.[38–40] Also, nano-research is imperative in preventing the negative effects of crop cultivation and animal farming *via* genetic engineering, which inadvertently increases the strength of crops and the production of farm animals.[41–43] Agricultural technology, including nanotools, enable stakeholders such as farmers, scientists, and policymakers to sustain agriculture through plant nutrients, nanocopper, and nano-nitrogen fertilizer production.[44–46] Consequently, nanotechnology adoption saves farmers money in fighting pests and diseases by enabling scientists to use microscopes to diagnose pests and diseases that are not visible before they spread to other parts of the farm. Nanotechnology provides a dynamic platform for sustaining agriculture, long-lasting seeds after post-harvest, enhancing the soil's water-holding capacity, healing sick animals, and detecting bad foods.

Materials and methods

To avoid bias in reporting, this study follows the PRISMA guidelines for conducting a systematic review (Fig. 2). The study

Table 1 Modern agriculture machinery and their functions

Diagram	Name	Function	Reference
A	Airborne gamma-ray spectrometry sensing	It provides accurate content mapping and spatial variability of soil potassium, uranium, and thorium	Ameglio *et al.*[29]
B	Combine harvester	It is used for reaping, threshing, and winnowing grains into a single process	Marchant *et al.*[24]
C	Multispectral instrument	It performs thermal imaging of crops and assists in detecting and tracking waves	Zhang *et al.*[30]
D	Drone	It is used to estimate low plant nutrients, poor soil health, and water stress	Klauser *et al.*[25] Alibaba.com
E	Agribot	It is used for precision weedicide spraying, sowing, and covering of seeds	Basu *et al.*[26] (photo: Ibex Automation Ltd)
F	Visual odometry system	It is used to assist agricultural field robots in enhancing navigation accuracy	Zaman *et al.*[7]



also used expert opinions regarding article selection and analysis.[47] The objective is to evaluate existing studies *via* scientific and repetitive strategies as to how agriculture technology utilization affects LMIN food security.

Articles selection and procedures

Identification and screening. The Scopus and Web of Science (WoS) databases help find peer-reviewed papers. These databases are generally accepted for their rigorous methods of indexing peer-reviewed articles. Identification began with keywords such as "*Agriculture Technology*", "*Smart Agriculture*", "*Agriculture Science*", "*Agriculture Automation*", "*High-tech Agriculture*", and "*Food Security*" (Fig. 1). This initial search gave more than 10 000 papers. Next, the syntax editing and double scanning reduced the selected articles massively. The Microsoft Excel template provided the foundation for validating and cleaning the downloaded articles using details, *inter alia*, the journal, title, authors, year of publication, and citations.

Eligibility – inclusion, and exclusion. Full-text titles and abstract screening were conducted to determine the eligibility of articles. Agriculture and food disciplines were also highly

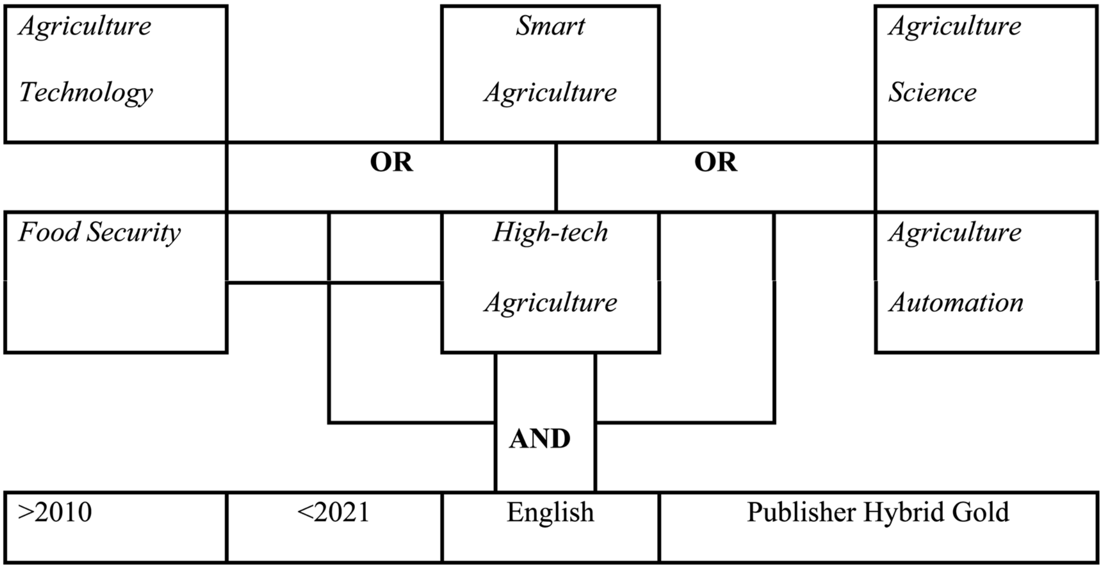


Fig. 1 A framework for assessing the database keyword search.

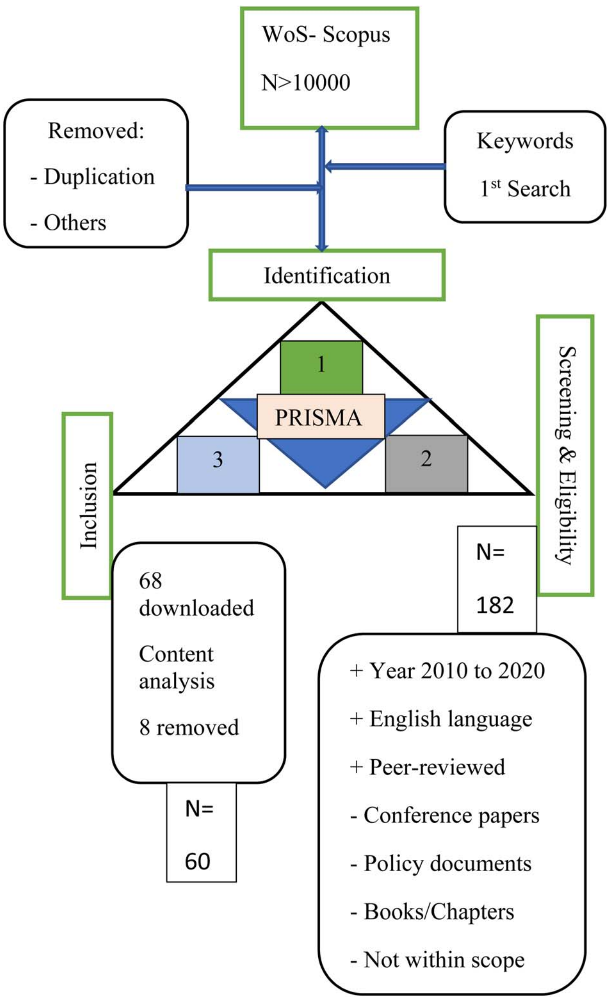


Fig. 2 PRISMA flow chart.

considered since this study aims to establish the effects of the usage of agriculture technology tools on food security while operationalizing the challenges. As a result, 182 articles with publication years ranging from 2011 to 2020 were obtained. However, based on inclusion criteria such as english language preference, peer-reviewed articles, and excluding elements such as conference papers, policy documents, books, chapters, published papers outside the years 2011–2020, and subjects outside the scope of agriculture technology and food security, most articles were ignored.

Included review articles. Thus, the 68 downloaded papers were subject to rigorous content analysis, of which 60 peer-reviewed papers were accepted for data interpretation, analysis, and discussions. Moreover, the accepted papers gave sufficient information to answer the research questions as to why farmers especially those on the LMIN are reluctant in adopting AT.

Coding and operationalization. This review operationalized the variables to employ a regression model to infer the causal relationships between agriculture technology utilization and challenges that affect food security (Table 8). The purpose is to provide the foundation for a future plethora of studies about AT utilization and the predictive power of the independent variables. Thus, AT utilization (Y) changes based on the unit of change in the explanatory variables (X), malfunctions, and climate change, among others. The representation below signifies the model relationship:

$$y = \beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5 + \beta_6 + \varepsilon_{it} \quad (1)$$

Hence, the estimation *via* linear regression is indicated in eqn (2):

$$\text{AT-utilization } (Y) = \beta_0 + \beta_1\text{LA}_{it} + \beta_2\text{LC}_{it} + \beta_3\text{TKH}_{it} + \beta_4\text{CC}_{it} + \beta_5\text{MF}_{it} + \beta_6\text{RR}_{it} + \varepsilon_{it} \quad (2)$$

where β_0 = intercept; β_1 = low adoption (LA), β_2 = low capital (LC), β_3 = technical know how (TKH), β_4 = climate change (CC), β_5 = malfunctions (MF) and β_6 = rules and regulations (RR). The error term = ε_{it} at a time (t).

Evaluation of contributing papers. Various scholars generally use the score matrix formula by Howard *et al.*[21] to assess the contribution of authors on a particular subject within academic settings.

$$\text{Score} = \frac{1.5^{n-i}}{\sum_{i=1}^{n} 1.5^{i-1}} \tag{3}$$

Note: n = number of authors, i = the rank of author, m = maximum score of 1.00; minimum score of 0.08.

Results and discussion

This study aimed to assess peer-reviewed papers on agriculture technology utilization in the direction of food security in LMIN households. We used the method of Howard *et al.*[21] to assist in identifying institutions and countries that participate in publishing the subject. Table 2 indicates the mark assigned to each author based on the author's position.

Background analysis of accepted papers

Institution contribution. The purpose of Table 3 is to summarize the institutional contribution to agriculture technology publications. Research institutions provide the platform for researchers to investigate matters of essence to the scientific world; as a result, we found strong indicators that authors without institutional backing contributed less to agriculture technology than those with backing. Table 3 denotes that Wageningen University is ranked first with a 4.68 index score (19 researchers). Likewise, the following institutions from the United States (US), namely, the United States Department of Agriculture-Agricultural Research Service (USDA-ARS) with a 2.26 score, the University of Florida with a 2.00 score, Iowa State University with a 1.21 score, and South Dakota State University with a 1.00 score were ranked 2nd, 5th, 6th, and 12th, respectively. The Swedish University of Agricultural Sciences was ranked 3rd with a 2.12 score. Table 3 indicates the rest of the ranking; however, it is worth noting that the Universiti Putra Malaysia ranked 4th with a 2.00 score as the only institution from the Asian continent contributing to the subject.

Contributions of countries. In Table 4, the highest index score during the ranking was 13.40 points, attained by the US occupying the first position. Consequently, among the 1st and 2nd ranked countries, the Netherlands had 5.98, a 7.42 index score difference. This signifies that the US has superior knowledge and scientific research contribution towards agriculture technology publication more than any other country in the world. China was ranked 3rd with a score of 3.88, showing a committed interest in agriculture technology research as

Table 2 Matrix score for author's calculation[a]

Number of author(s)	Order of author(s) 1	2	3	4	5
1	1.00				
2	0.60	0.40			
3	0.47	0.32	0.21		
4	0.42	0.28	0.18	0.12	
5	0.38	0.26	0.17	0.11	0.08

[a] Source: Howard *et al.*[21]

Table 4 The contributions of each country's researchers, papers, and average score

Ranking	Country	Institution	Researchers	Papers	Score
1	USA	19	60	17	13.40
2	The Netherlands	3	22	7	5.98
3	China	6	12	5	3.88
4	India	4	15	4	3.53
5	Sweden	3	10	3	3.00
6	UK	8	15	5	3.2
7	Brazil	5	12	3	2.11
8	Italy	3	8	2	2.00
9	Malaysia	1	4	2	2.00
10	Germany	4	9	4	2.16
11	Australia	3	7	3	1.46
12	Canada	3	3	2	1.26

Table 3 The contribution of each institution's researchers to the average score

Rank	Institution	Country	Researchers	Score
1	Wageningen University	Netherlands	19	4.68
2	USDA-ARS	USA	6	2.26
3	Swedish University of Agricultural Sciences	Sweden	6	2.12
4	Universiti Putra Malaysia	Malaysia	2	2.00
5	University of Florida	USA	7	2.00
6	Iowa State University	USA	7	1.21
7	Universidade Tecnológica Federal do Paraná	Brazil	4	1.20
8	Loughborough University	UK	4	1.00
9	Tuscia University	Italy	2	1.00
10	University of Bremen	Germany	3	1.00
11	Erasmus University	Netherlands	1	1.00
12	South Dakota State University	USA	4	1.00

Table 5 Modern agriculture technology adoption in agriculture in African countries

Country	Citation	Year	Technology	Food	Status	Citation
Ghana	3	2020	Zai Tech	Seed	Adoption	Dagunga *et al.*[17]
Uganda	25	2019	Hermetic	Grain	Adoption	Omotilewa *et al.*[16]
Kenya	8	2020	Climate-smart	Livestock	Adoption	Maina *et al.*[18]
Tanzania	18	2016	Fertilization	Maize	Adoption	Magrini and Vigani[49]
Cameroon	10	2011	Hybridization	Banana	Adoption	Temple *et al.*[50]
Southern Africa	40	2019	Climate-smart	Cereals	Adoption	Mutenje *et al.*[51]

compared to the remaining Asian countries ranked among the first twelve in this review. Researchers such as Chanana-Nag and Aggarwal[48] contributed to India's 4th position with an index score of 3.53. Table 4 further denotes the rest of the ranking, however, Brazil, with an index score of 2.11, is the only country from the South American continent that entered the review ranking.

As shown in Tables 3 and 4, agriculture technology research publication is dominated by economically developed countries. Thus, it needs to be emphasized that no LMIN country had the opportunity to join this grading status; why is that? Upon discovery, this review accepted papers on agriculture technology adoption in Africa (Table 5). The study observed that although the households see the significance of adoption, constraining factors prevented them from practising agriculture technology.

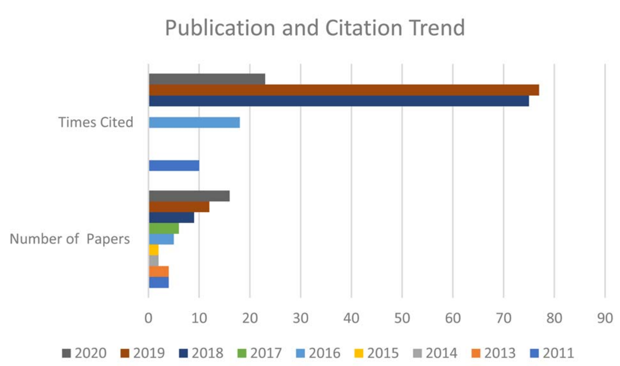


Fig. 3 Annual trends and citations from 2011–2020.

Articles, methods and annual publication trends. As indicated in Table 7, most of the methodologies used for data collection were surveys, experiments, monitoring, image capturing, observation, *etc.* These methods examine and record the zonal characteristics the researchers need to make constructive decisions. Trout and DeJonge[52] postulated that the experimental data collection method enables a reliable balance of water systems *via* crop evapotranspiration. Fig. 3 indicates the number of African agriculture technology-adopting articles cited and the trends of 60 scientific peer-reviewed papers published from the year 2011 to 2020. Our analysis shows the intensity of studies on agriculture technology from the onset of 2011 and 2013 with 6% and 8%, respectively. Nevertheless, the number of publications dropped to 4% in the year 2015. In 2016, agriculture rose remarkably to 8%, doubling the previous year's publications. From that moment, it can be seen that agriculture technology publications continued to upsurge in the years 2017, 2018, 2019 to 2020, representing 12%, 14%, 18%, to 26%, respectively. Still, the study observed that agriculture technology implementation is the central determinant of economic growth, yet countries with agricultural acclaim are unable to adopt it.[10] This review further looks at the challenges that impede the countries.

Journals, citations, the impact factor (IF), and corresponding articles. We further ascertained the scientometric journal index that denotes the average number of citations based on a journal's last two publications. The study selected the first 12 highest impact factor quartile (Q1) journals that contributed to agriculture technology. Web of Science Clarivate 2021 IF report (Table 6) and Google Scholar (Table 7) showcased the journal

Table 6 Sample journals and JIF that contributed to the study

No.	Journal name	2021 IF	Quartile	Articles
1	*Journal of Cleaner Production*	11.072	Q1	1
2	*International Journal of Applied Earth Observation and Geoinformation*	7.672	Q1	1
3	*Geoderma*	7.422	Q1	1
4	*Computers and Electronics in Agriculture*	6.757	Q1	6
5	*Agricultural Water Management*	6.611	Q1	1
6	*Agriculture Ecosystems & Environment*	6.576	Q1	1
7	*Environmental Science and Policy*	6.424	Q1	1
8	*Field Crops Research*	6.145	Q1	1
9	*Precision Agriculture*	5.767	Q1	11
10	*Computer Networks*	5.493	Q1	1
11	*Climatic Change*	5.174	Q1	2
12	*Irrigation Science*	3.519	Q1	1

Table 7 A synopsis of the application of agriculture technology in the selected countries

No.	Authors	Citations	Method	Origin	Technology (T)	Technology usage	Agri-Relation
1	Groher *et al.*[62]	36	Survey	Switzerland	Driver assistance systems	Physical workload reduction	Vegetables and grapes
2	Xu *et al.*[63]	43	Surveillance	China	Quadcopter aerial images	Livestock counting	Livestock
3	Branca and Perelli[64]	15	Survey	Italy	Climate smart technology	Crop diversification	Cereal legume
4	Qayyum *et al.*[65]	1	Surveillance	Germany	H_2O sense	Monitor and alert water-tanks	Fish
5	Radoglou-Grammatikis *et al.*[55]	306	Survey	Greece	Unmanned aerial vehicles (UAV)	Soil mapping	Crops
6	Faling[66]	22	Interviews	Netherlands	Transformative tool	Smart climate adopting	Crops and livestock
7	Basu *et al.*[26]	37	Robot data	UK	Robots	Legal-robot-adoption	Spray weeds
8	Kolady *et al.*[67]	20	Survey	USA	Embodied-knowledge-and information-intensive PAT	Automatic-fertilizer-and seeds applications	Crop land size
9	Chanana-Nag and Aggarwal[48]	51	Rural-level data	India	Climate-smart agriculture (CSA)	Prioritizing climate change adaption and interventions	Crops and livestock
10	Groeneveld *et al.*[68]	7	Controlled experiment	Netherland	Domain-specific-language (DSL)	Farm-management information system (FMIS)	Fertilizers and pesticides
11	Wang *et al.*[6]	4	Simulation experiments	China	Global-navigation satellite-system (GNSS)	Farm-vehicle positioning	Farm vehicle
12	Khatri-Chhetri *et al.*[34]	55	Census	India	Laser land leveling (LLL)	Leveling land	Crops
13	Clapp and Ruder[69]	63	Synthesizes of studies	Canada	Plant genome editing	Technology lock-in relations	Crops
14	Eastwood *et al.*[56]	157	Interviews	Netherlands	Smart dairying R&D	Assess dairy development	Cow
15	Piikki and Söderström[70]	40	Clustering farms	Sweden	Digital soil map (DSM)	Produce-soil-raster-maps	Arable land
16	Ampatzidis *et al.*[71]	61	Survey	USA	UAVs	Phenotyping and grafting	Orange trees
17	Young *et al.*[72]	63	Field observation	USA	TERRA-MEPP robotic	Stereo imaging	Crop fields
18	Zaman *et al.*[7]	36	Experiment	Italy	Monocular visual odometry system (MVOS)	Crop monitoring	Crops
19	Zhang *et al.*[30]	39	Monitoring	UK	Sentinel-2A satellite	Remote sensing images	Crop/tree/soil
20	Partel *et al.*[37]	208	Experiment	USA	Smart sprayer (IA)	Simulating vegetable field	Agrochemicals
21	Thomas *et al.*[73]	7	Detection monitoring	USA	Automated-oestrus-detection-technology system (AODTS)	Reducing manual oestrus detection	Diary production
22	Marchant *et al.*[24]	31	Experiment	UK	Yield sensor development	Ensures precise distinction treatment effects	Crop-small-grain cereals
23	Huuskonen and Oksanen[59]	147	Image capturing	Finland	Drone imaging	Automatic-detection of soil samples	Soil sampling
24	Hunt Jr and Daughtry[58]	197	Monitoring	USA	Unmanned aircraft systems (UASs)	Light-sensing-image calibration	Crop management
25	Dunnett *et al.*[74]	53	Toolkit	India	CSA-prioritization toolkit	Support-multiple analysis	Crop production
26	González Perea *et al.*[75]	49	Case study	Spain	Variable rate irrigation (VRI)	Irrigating management-zones	Soil water-management
27	Ghosal *et al.*[53]	318	Image capturing	USA	UAV	Large-scale scouting	Plant breeding
28	Morota *et al.*[60]	105	Monitoring	Canada	Machine-learning and data-mining	Collecting farm-level-information	Livestock
29	Ward *et al.*[76]	8	Observation	USA	CropSyst-microbasin	Simulating f-scale-variability	Crops and soil
30	Kempenaar *et al.*[77]	52	Spatial-data: soil maps	Netherlands	Inter-intra-field variability	Variable rate applications	Potato crops
31	Navulur and Prasad[61]	132	Wireless sensors	India	Internet of things	Monitoring soil moisture	Crop growth
32	Lindblom *et al.*[54]	259	Knowledge framework	Sweden	ICT systems	Nitrogen fertilization	Crop production
33	Trout and DeJonge[52]	89	Experiment	USA	Crop evapotranspiration	Balancing the water system	Maize production

Table 7 (*Contd.*)

No.	Authors	Citations	Method	Origin	Technology (T)	Technology usage	Agri-Relation
34	Snyder[78]	79	Experiment	USA	Enhanced N-fertilizers	Lessening nitrogen loss	Crop production
35	Schenatto *et al.*[79]	7	Management zones	Brazil	Management zones	Reduce processing costs	Crops-soil conditions
36	Olayide *et al.*[80]	89	Time series	Nigeria	CSA-irrigation	Improve water management	Crops-fish-livestock
37	Piikki and Söderström[70]	38	Soil datasets	Sweden	DSM	Predicting soil suitability	Arable topsoil
38	Williams *et al.*[81]	15	Management zone	USA	Soil functional zone management	Managing row-crop-agroecosystems	Maize/soybean
39	Kruize *et al.*[82]	84	Software ecosystem	Netherlands	Crop-R-and-AgroSense	Software integration	Farm produced
40	Bazzi *et al.*[83]	9	Yield map dataset	Brazil	Profit-maps-precision	Facilitating decision	Farm yield
41	Elarab *et al.*[57]	137	Imagery	USA	UAS	Chlorophyll concentration	Plant and crops
42	Zhang and He[84]	1	Imagery	China	Image-processing-tech	Measuring leaf area	Plant leaf
43	Tilly *et al.*[85]	23	Experiment	Germany	Terrestrial laser scanning (TLS)	Capturing small objects	Crops
44	Abdullah and Samah[36]	120	Previous study data	Malaysia	ICT	Surfing agro-based website	Crops
45	Shamshiri and Ismail[86]	17	GPS data	Malaysia	GPS	Calculating field efficiency	Crop production
46	Xu *et al.*[87]	7	Simulation	China	Power-balance AODV	Saving energy	Greenhouse awning
47	Verdouw *et al.*[88]	189	Synthesis of studies	Netherlands	Internet of things	Enhancing virtualization	Floriculture
48	Rodríguez-Pérez *et al.*[89]	69	Borehole observations	Spain	Time-domain reflectometry (TDR)	Determining moisture content	Vineyard
49	Heijting *et al.*[90]	30	Soil data	Netherlands	Real time kinematic (RTK) GPS	GPS receiver providing centimeter leveling	Arable soil
50	Florin *et al.*[91]	16	Monitoring	Netherlands	Agric-production simulator	Estimating soil H_2O capacity	Crop

impact factor (JIF) and the article citations, respectively. The equations are represented below:

$$\mathrm{JIF}_y = \frac{\mathrm{citations}_{y-1} + \mathrm{citations}_{y-2}}{\mathrm{publications}_{y-1} + \mathrm{publications}_{y-2}} \tag{4}$$

Hence, the JIF calculation for 2021 is as follows:

$$\mathrm{JIF}_{2021} = \frac{\mathrm{citations}_{2020} + \mathrm{citations}_{2019}}{\mathrm{publications}_{2020} + \mathrm{publications}_{2019}} \tag{5}$$

Although the *Journal of Cleaner Production* is ranked high with an IF = 11.072, it contributed only one article. In Table 6, *Precision Agriculture* (IF = 5.767) and *Computers and Electronics in Agriculture* (IF = 6.757) were the major contributors with 11 and 6 articles ranked 9th and 4th, respectively. The impact factor serves as an assessment aid that provides the platform as to which journal ought to receive consideration from the research readership. Furthermore, the impact factor's descriptive quantitative measure of the Q1 journal's performance tells us the imperativeness of agriculture technology utilization in promoting food security. Also, the citation of the article equally contributed to the subject under review. As marked in Table 7, some scholars[37,53–55] have had more than 200 citations since the publication, while other citations[36,56–61] are between 100 to 200, and the remaining articles fall below 100 citations. This confirmed the strength and quality of AT research articles synthesized for this review and the global interest.

Overview of an agriculture technology device, authors, origin, type of technology, usage, and agri-relation. Operationalizing the challenges of the review

In Table 8, we operationalized agriculture technology challenges by defining a specific variable and the quantification of that particular variable. The purpose is to provide the platform to answer the review questions (as to what we are looking for and what we are not), give grounds for replication and consistency of the results, and create the basis for agriculture technology's comprehensive understanding of the future.

Themes of agriculture technology devices

Highlighted below are the often-used technologies in Table 7, which are applied in agriculture settings.

Unmanned aerial vehicles (UAVs). Our review denotes that UAVs are one of the most frequently used technologies investigated, according to Radoglou-Grammatikis *et al.*[55] UAVs have provided a platform that can operate autonomously or remote-controlled without a human pilot.[59] Bazzi *et al.*[83] suggested that UAVs collect analytical data on a large scale as compared to hand-held devices, which take time. Thus, this technology facilitates strategic decisions with the sole purpose of transforming yield-map datasets into profit maps. Furthermore, UAVs with multispectral cameras enable the farmers to detect plant breeding diseases in their early stages and control the spread before it affects the whole tree; this is done by capturing the images.[71] The evidence suggests that UAV sensors can monitor, identify, and apply precision injections to crops and

Table 8 A synopsis of the challenges and variable operationalization of agriculture technology

Variable	Operationalization: Observable (A = include definition; B = exclude definition)	Operationalization: Measurement	Citation
Farmers	A = any person who considers the growing of crops and the rearing of animals as their occupation. B = otherwise	Yes = 1, no = 0: dummy, if the person grows crops and rears farm animals	Khatri-Chhetri *et al.*[34]
Technology utilization	A = the kind of farm technology that is available and useable by the farmer. B = the purpose of technology is not for the agricultural sector	Software = 1, hardware = 2, both = 3, none = 4): the kind of technology	Kolady *et al.*[67]
Low adoption	A = farmers who do not use technology in their farms due to one or two challenges. B = farmers who have no difficulty using technology but decided not to use it	Yes = 1, no = 0: dummy if the farmer finds using technology on the farm	Groher *et al.*[62]
Low capital	A = farmers who have low capital to acquire agriculture technology. B = farmers who have means but decided not to buy AT	Yes = 1, no = 0: dummy, if the farmer has no capital for investment in agriculture technology	Groher *et al.*[62]
Technical know-how	A = farmers who lack the practical ability to use agriculture technology. B = otherwise	0 = have no knowledge, 1 = have little knowledge, 2 = have knowledge but no technology device	Elarab *et al.*[57]
Climate change	A = climate conditions that prevent the efficient use of AT devices. B = otherwise	0 = no rain, 1 = rain often, 2 = rain very often	Faling[66]
Malfunctions	A = the farm machine is defined as malfunctioning if the technological device is not able to perform the specific task assigned to the farm. B = technological device that is unable to work at a place either than on the farm	0 = 5 times a week within 52 weeks. 1 = 3 times a week within 52 weeks. 2 = 1 time a week within 52 weeks: the number of times the machine is unable to work	Ward *et al.*[76]
Rules and regulations	A = guidelines that prevent the efficient utilization of AT devices on the farmland. B = guidelines that do not relate to agricultural farming	0 = complex guidelines. 1 = medium guidelines. 2 = lower guidelines	Basu *et al.*[26]

animals before the symptoms start to show up.[55,58,71] This has a significant positive effect on the health of farmers' crops and animals, thus increasing their agricultural production and inadvertently enhancing food security.

Sensors. This study observed sensors as a key component of agriculture technology. Its hyperspectral camera, for example, presents sensing applications such as H_2O sensing for monitoring the parameters in the fish tank and signals to the farmer.[65] Also, a variety of sensors such as wireless sensor networks enable the accurate isolation of actual data from noise. In contrast, others use an electrochemical cell to offer yield signals by which the existence of an analyte can be determined.[6,92] Sensor application has brought massive innovations such as the absence of cable transmission, accurate data distribution, target plant diseases, and accurate sensor power. Hunt Jr and Daughtry[58] expressed that in the US, sensors assisted in the light-sensing image calibration for crop nutrient management. The study results demonstrated that sensor application was effective for assessing and capturing specific content of crop data from the large-scale agricultural field. Hence, sensor microchip technology is established for measuring an analyte parameter in a host.[93]

Digital soil map (DSM). The soil is the natural lifeblood that maintains humans and other living organisms. Lagacherie *et al.*[94] described the DSM as, "the creation and population of spatial soil information systems by the use of field and laboratory, observational methods coupled with spatial and non-spatial soil inference systems". Thus, spatially and statistically 3D DSM provides the accurate effective disposition of precision soil map applications and technologies as well as advanced crop analytics.[95] Piikki and Söderström[70] postulated that the DSM enables them to access a large authenticated dataset of soil analyses at the farm level, which assisted in their constructive decision-making. According to Radoglou-Grammatikis *et al.*,[55] DSM based on geographic information systems provides the understanding of soil variability within a terrain attribute. Thus, "digital soil mapping has been used for applications such as lime requirement estimations to address subsoil acidity issues and therefore changing/improving the soil's capability" according to Boorowa Agricultural Research Station, Southern New South Wales.[96]

Global positioning system (GPS). We observed that GPS technology is used to estimate field indexing and random sampling and enable centimeter-level accuracy.[90] The GPS prospect of satellite networks sends endlessly coded information to the receivers to enable easy location detection.[86] Governments provide satellite data *via* radio navigation to agricultural farmers for free. The GPS estimates the exact position, and velocity, and monitors time-related parameters needed to make a critical assessment of crop and animal management systems.[97] Furthermore, the GPS allows the stakeholders to acquire data that can be manipulated to suit the exact position of the livestock and/or crop production.[90] In research conducted in Malaysia, GPS provided the opportunity for accurate management decisions and precision agriculture for supporting the usage of farm resources.[86] Thus, a GPS receiver is connected to a computer that shows the incoming GPS signals with display data to allow farmers to know the exact position of the farm animals.[97]

Robots. Robots play essential roles in agricultural production, *inter alia*, weed spraying, monitoring crops, and temperature assessment. Robots have developed sensors that enable high on-site detection *via* robotic sampling, which mitigates the exposure of farmers and other stakeholders to dangerous chemicals; hence, "to handle sample collection, a robotic manipulator requires tactile feedback, to ensure that no damage will be done to either the robot or the other in contact due to excessive force".[98] Similarly, Young *et al.*[72] asserted that agriculture robots are deployed to ensure the efficient implementation of soil analysis, rice, seeding, planting, harvesting, *etc.* Robots on the field have a direct connection to plants and animals on the farmland, giving a major advantage to synchronizing data at the farmer's end.[26] The study observed that robot utilization in agricultural settings has enormously reduced labor intensiveness on the farm, becoming an indispensable tool to speed up the quest for food security.[72,99]

Lasers. Traditionally, agricultural stakeholders have used various means to level the land (*i.e.*, animal energy, hoes, *etc.*) and assess the height of crops before planting and pre-harvesting. However, in this technological age, the literature tells us that laser technology is used for the same purpose. Table 7 indicates that laser technology brings novelty to topsoil management while reducing operational costs. Rickman[100] indicated that farmers used Laser Land Leveling (LLL) for the leveling of the soil for seed planting, uniform distribution of water, and soil humidity, which enhance germination. Tilly *et al.*[85] said that farmers used their Terrestrial Laser Scanning (TLS) to capture minor items and ascertain plant height. Similarly, a study conducted in Fars Province, Iran, postulated lasers as having economic, social, environmental, and technical effects on farmers' income, erosion reduction, and minimizing chemical fertilizer usage.[101]

Internet of things (IoT). IoT generally refers to the platform that conveys sundry data *via* a common channel for billions of interconnecting intelligent devices.[102,103] Navulur and Prasad indicated that IoT enhances the virtualization of the supply chain, and leverages the remote observation of soil temperature.[61] The various linked devices such as sensors, lasers, drones, and other electronic devices, send information to data centers *via* the internet. According to Verdouw *et al.*,[88] the IoT is an exceedingly promising technology that can serve as a panacea for contemporary agriculture through device synchronization, thus tracking the positions of robots and tractors, and providing the mechanisms in agricultural field networks that function. High-precision agricultural instruments link an array of IoT-based agronomic sensors to provide moisture, humidity, and other ecological monitoring devices.

Smart sprayer. Smart spraying technology is highly recognized as a factor in decreasing the existence of weeds among non-target objects such as vegetable crops without risking quality.[37] Scholars such as Klauser and Pauschinger[25] added that a smart sprayer, *via* its machine vision, can spot and mitigate the agrochemical input by closing individual nozzles in an area that is not targeted. Likewise, a study conducted in Spain used field sensors to depict vineyard canopies and monitor spray drift to enhance vineyard spraying and ensure its resilience.[104] Moreover, smart spraying decreases pollution during spraying, and "the new intelligent variable-rate spray technology automatically controls spray outputs to match plant presence, canopy characteristics, and travel speeds".[105] However, not all countries allow the use of smart spraying, especially with drones.[37] That notwithstanding, researchers encourage farmers to adopt smart spraying technology to enhance their ability to reduce pests and diseases.

Automated oestrus detection technology system. Our literature indicates that manual oestrus detection in a periodic dairy production system has been a constant hindrance to farmers until the inception of automated oestrus detection. According to Thomas *et al.*,[73] detection models for oestrus were created to alert cows that require the farmer's care due to a probable incident such as the cows' intake activity, the electrical conductivity of milk, *etc.* The timely detection of oestrus in dairy production is an imperative course of proper management that provides the foundation for large-scale milk production and economic viability.[106] More so, wearable sensors attached to or within cows enable farmers and field researchers to estimate oestrus detection, pH, rumination, disease detection, and other animal activities on the field.[107] The researchers agreed that farmers are encouraged to adopt this technology in their dairy farming based on improved economic feasibility and labor reduction.

Monocular visual odometry system (MVOS). Zaman *et al.*[7] asserted that MVOS depends on the modernization of structure-from-motion architecture to accomplish the best results concerning accuracy in real-time performance. Visual odometry resolves the scale problem and forecasts the camera path frame by frame using efficient features.[108] Moreover, Firk *et al.*[109] asserted that oestrus detection by visual observation is challenging, particularly in large dairy farms; thus, automatic oestrus detection reduces the drudgery of farmers while enabling active reproduction supervision. Aguiar *et al.*[110] enunciated that the monocular visual odometry method can achieve efficient crop monitoring and harvesting in a steep slope vineyard. The outcomes regarding odometry precision and meting out time accomplished in the terrains proved effective.[7]

Agriculture technology application challenges

There is no doubt about the numerous merits derived from AT; nevertheless, it does come with some challenges. Highlighted below are the known challenges enumerated by the researchers.

Low adoption. In Fig. 4, the review analysis indicated that low adoption is one of the leading challenges of agriculture technology.[67,82] Technology acceptance in the agricultural sector has been a beacon of hope for dairy production, supply chain, *etc.*,[34,88] but the rate of adoption is low as compared to expectations. Scholars have asserted that farmers decline the use of technological tools due to their lack of knowledge about the benefits.[36,111,112] As a result, it was confirmed that low acceptance of technology is a threat to LMIN's food security in the near future.[14,66]

Lack of initial capital. Massive financial resources injected into the agriculture industry create a solid foundation for building a strong production scheme in agriculture farming. Fig. 4 depicts the lack of initial capital investment as a challenge that prevents farmers from practising agriculture technology,[16] which makes expensive and energy-hungry UAVs, sensors, robots, *etc.*, difficult to obtain by LMIN farmers. Kruize *et al.*[82] confirmed that farmers are unable to buy advanced software to assist in production due to a lack of financial investment. This makes the initial capital investment relevant to the startup application of agriculture technology.

Technical know-how. Stakeholders who know how to use these technologies reap enormous benefits. However, studies have postulated that not only do farmers not know how to use the technology devices on their land but they are also not aware of the existence of these technologies that can ease their farm drudgery.[6,82] For example, some technologies entail precise hardware and expertise to operate,[25] making it difficult for uneducated farmers, predominantly in LMIN. In 2015, Elarab *et al.*[57] mentioned the difficulty of using Support Vector Machines due to their complex computation. Farmers' inability to use agricultural devices efficiently is an impediment to food security in the long run.

Climate change (CC). Recurrent weather changes to extremely dry and/or rainy days force farmers to either abandon their acquired climate-smart technology tools and wait for better weather conditions, or overuse them and expect quick deterioration.[64] Trout and DeJonge[52] expounded that climate change mitigates mountain snowpack accumulation, making it difficult for efficient technological irrigation. Farmers are unable to fly drones when the weather is windy or use machinery on the farmlands during bad weather conditions.[59] Farmers' inability to work directly on their farmlands due to climate change indirectly affects food security.

Malfunctions. New technology comes with numerous efficacy and precision benefits with initial utilization. However, as the years go by, almost all spare parts of that particular technology device may begin to malfunction.[82] We define malfunction as destruction, repair and maintenance, risk, and errors that occur during the use of agriculture technology devices. As shown in Fig. 4, malfunctions have been recognized in this review as a challenge to farmers' ability to operate technological devices.[24,82] Errors in GPS representation, inherent uncertainty within the irrigation ballistics, *etc.*, contribute to malfunction.[75,86]

Rules and regulations (RR). Rules and regulations guide farmers concerning ethics, health, and safety issues when using agriculture technology tools. This review points out rules and

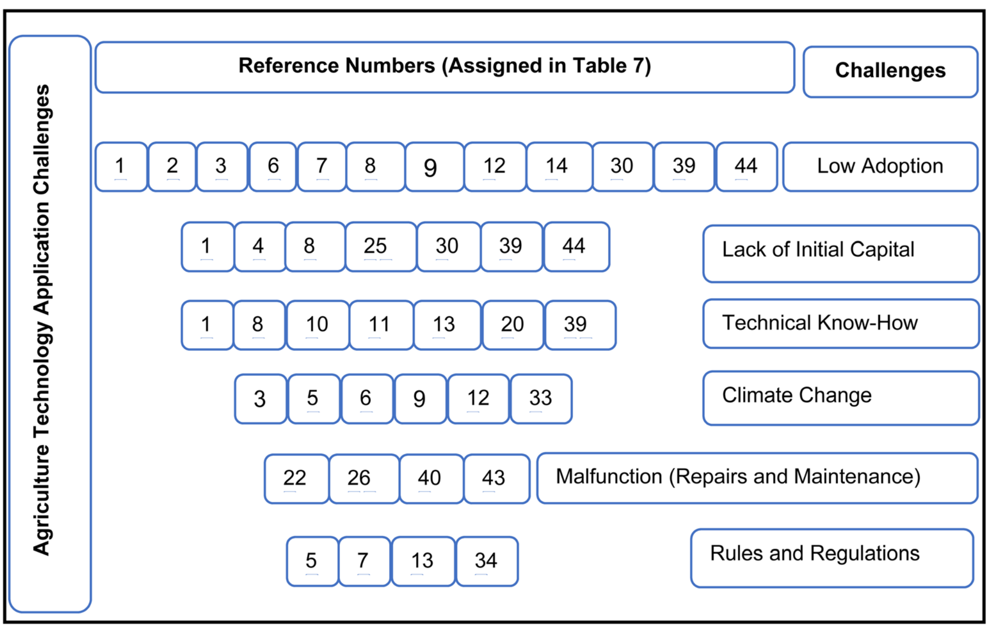


Fig. 4 Common agriculture technology challenges associated with selected review articles.

regulations as a hindrance to agriculture technology tools application; see Fig. 4. Laws control using drones to engage in mass spraying in Europe,[55] while others require UAS operators to renew their certificates every two years. Furthermore, in the UK, farmers are subject to statutory penalties should their device, 'agribot', cause damage to a person or property.[26,113] These constraints stipulated in the review indicate the struggle farmers go through to use their technologies efficiently.

These constraints above form the basis for the reluctance of farmers, especially those in Africa, to adopt agricultural technology. Evidence indicates that these barriers are the main causes of food insecurity in LMIN as they are hard for poor farmers to overcome.

Conclusions, policy directions, limitations, and future research

LMIN is struggling with growing food insecurity impacts and how to respond. Developed nations have synthesized studies to support their policy decisions to fight against food insecurity. In this review, the authors have reflected on the challenges, provided an overview, and operationalized, and analyzed worldwide empirical publications on agriculture technology. The review shows the LMIN agriculture technology publication gap and the urgent need to achieve food security *via* agriculture technology.

Considering the global scores and ranking depicted by the various institutions and countries in this study, we make the following policy directions for governments. Firstly, the study realized that most farmers and agricultural stakeholders are reluctant to adopt agriculture technology to improve farm production. We recommend massive digital advertisements to educate stakeholders about the merits of agriculture technology. Secondly, the review shows farmers' difficulty in raising capital to acquire these technologies. It is recommended that both government and non-governmental institutions, domestic or abroad, and all those with financial resources in LMIN invest in agriculture technology. Similarly, agriculture technology cannot be applied if stakeholders do not know how to operate the devices and/or have no standby experts to teach them. We recommend that farmers must be willing and make an effort to learn while experts in the field must be provided by the government and other non-governmental organizations. Above all, workable policies prioritizing sustainability and resilience must be laid down to restructure and further reduce the impacts of climate change, and strict rules and regulations that prevent the use of certain kinds of technological devices on the farm. This will loosen the stringent nature of technology applications and motivate farmers in their implementation.

This review has some limitations despite its contributions. We only used Web of Science and Scopus databases to search for english peer-reviewed papers from 2011 to 2020. This implies that our discoveries may not fully reflect the total publications on agriculture technology since some publications might have been missed. However, we followed a rigorous selection procedure within the appropriate period since it was within that time that research on agriculture technology started to emerge. Also, the scope of this review is limited to 60 articles and excludes LMIN papers that were not peer-reviewed. However, accepted articles give detailed information about the parameters of agriculture technology applications globally. We analyzed one technological device for the first 50 articles though some articles had more than one device. Nevertheless, selecting and analyzing one device enhanced the understanding of the interpretation. The indicated limitations can form the basis for future researchers to comprehensively deliberate and review each of the challenges in depth regarding why they exist even though agriculture technology benefits outweigh the shortcomings. Future studies should also focus on agricultural innovation tools, adoption of agricultural techniques, and related field criteria.

Author contributions

Robert Brenya: conceptualization and writing. Jing Zhu: conceptualization and supervision. Agyemang Kwasi Sampene: reviewing and editing.

Conflicts of interest

There are no conflicts of interest to declare.

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