
**INTERPRETATION OF INDIGENOUS AGRICULTURAL TERMINOLOGIES BY
ALGORITHMIC TOOLS AMONG YOUNG DIGITAL AGRICULTURAL USERS IN
NIGERIA**

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ABSTRACT

This study analysed interpreted indigenous agricultural terminologies used in Nigeria by algorithmic tools from youth and gender perspectives. Data were collected from 396 respondents and analysed using descriptive statistics and regression analysis. Results revealed dominant male respondents (60.4%). Youths aged 21–40 years represented 59.3% of the sample, while adults aged 41 years and above accounted for 40.7%. The majority (33.0%) possessed Master's degrees, Bachelor's degrees (24.3%), PhDs (22.0%), and professorial ranks (12.9%). Results further showed that misinterpretation of indigenous agricultural terminologies recorded an average occurrence of 10.3%–16.2% across all age groups. Indigenous food names (14.9%) and local farming tools (14.9%) were frequently distorted. Lack of localized NLP training data (18.2% youth males; 12.6% adult males; 12.1% youth females) was among the key challenges exacerbating algorithmic misinterpretation. The study concluded that algorithmic tools consistently misinterpreted indigenous agricultural terminologies across all age groups of users, hence, the need to prioritize the creation of inclusive, gender and youth-responsive NLP datasets that integrate indigenous agricultural knowledge, local languages, and contextual variations in Nigeria.

Keywords: Gender, Youth, Algorithmic tools, indigenous agricultural terminologies, Digital Agricultural Users

INTRODUCTION

The increasing use of digital technologies in agriculture is changing how agricultural information is disseminated and/or utilized by the target audience. Agwu *et al.* (2022) observed that beyond the characteristic speed digital agriculture has brought into the food system, the efficiency with which it supports agricultural information distribution across the agricultural value chain actors has remained significant. It has reduced the cost of adoption by shortening the time it takes to collect data, process data, package information, and provide advisory services, method/result demonstration, market linkage, insurance services, tech integration, financial services, software deployment, for extension clientele. By providing an electronic platform to automate several agricultural operations, Yahaya *et al.* (2019) described it as the brainchild of smart agriculture. Through digital integration, agricultural activities such as fertilizer application, pest and disease monitoring, farm survey, security surveillance, hitherto performed with huge labour and budget, are now performed with great speed and precision, improving agricultural efficiency.

Beyond digital tools that assist human decisions in agricultural value chain activities, the sector has since witnessed the integration of autonomous and semiautonomous tools to automate human decisions through algorithmic operations (Akpabio *et al.*, 2021; Junherr, 2023). Algorithms are digital frameworks that employ formal, rule-based procedures to transform inputs into outputs, decisions, explanations, interpretations, or predictions (Powerdrill AI., 2025). They rely on techniques, such as sorting, optimization, pattern recognition, and machine learning, to automate complex decisions without direct human oversight (Tzachor *et al.*, 2023). They are the step-by-step set of instructions that enable Artificial Intelligence (AI) systems to function. Every operation performed by an AI system is controlled by an algorithm. For instance, machine learning algorithms learn patterns from data, searching algorithms navigate through data structures, sorting algorithms arrange data in a particular order, and optimization algorithm finds best solution among possibilities. Rule-based algorithms follow predefined rules rather than learning from data; a graph algorithm analyzes the network and relationships. Hence, electronic tools that are run or operated by algorithms are generally regarded as algorithmic tools.

To enhance agricultural information dissemination through an interactive interface, especially in view of the 1: 25,000 disproportionate ratios of farmer to extension agent in Nigeria (Federal Ministry of Information and National Orientation, 2025), algorithmic tools are increasingly being integrated in agriculture as a virtual extension agent (Okoroma *et al.*, 2025). For instance, **the** Hello Tractor tool uses Internet of Things (IoT) and Machine learning (ML) to connect tractor owners with farmers, track machinery usage, and predict equipment demand (Daudu *et al.*, 2025). AgriPredict uses AI and image recognition to diagnose plant diseases and pest infestations. Apollo Agriculture combines machine learning and remote data to offer tailored input packages, insurance, and credit to farmers through mobile phones in Nigeria, while FarmCrowdy connects farmers to investors, input suppliers, and markets. These tools provide interactive and user-friendly interfaces that make smart agriculture more autonomous and AI-driven.

Like the women, the youth face a similar fate of neglect, exclusion, and low productive resources in Nigerian agriculture. Youth are individuals aged between 18 and 35 years who engage in agribusiness activities across the agricultural value chain, in line with the National Youth Policy (EIDidin *et al.*, 2020; Fasakin *et al.*, 2022). Their willingness to undertake labour-demanding farm operations, venturesome disposition, entrepreneurial enthusiasm, high mobility, adaptability to change, innovative and technology orientation make them a significant workforce for the agricultural sector. However, Osabohien *et al.* (2021); Maisule and Bankole (2023) regretted that while youth contribute significantly to farm labour, produce processing and marketing, their participation in agriculture remains limited by a lack of finance, lack of inputs, lack of access to

credit and loan facilities, environmental issues, market unavailability, lack of production and management skills.

Smartphone penetration and internet usage in Nigeria soared from 11 million to 143 million between 2014 and 2025 (Worldometer, 2025). The number of internet users was also projected to jump from 56 million to 110 million between 2018 and 2025 (Statista, 2024). The upward trend has also spiked the number of people electronically accessing agricultural information and advisory services (Emerhirhi *et al.*, 2020). Algorithmic tools like AgriPredict, Apollo Agriculture, FarmCrowdy, CashtoCrop, as well as other startup agricultural Apps are increasingly being integrated in delivering information and advisory services to farmers. However, despite the potential of these algorithmic tools to deliver virtual and interactive advisory services, most users report their limited capacity to interpret indigenous agricultural terminologies. In a study carried out across 16 States and 6 geopolitical zones in Nigeria, Okoroma *et al* (2025) reported that 74% of the study participants and users of algorithmic tools across each State complained of the tools' misinterpretation of planting terminologies, farm inputs, and pests in Hausa, Igbo, and Yoruba languages. Asiabaka (2019) contextualized misinterpretation in technology dissemination as distortion, misrepresentation, misguidance, and misapplication of methods/techniques, research recommendations, terms, and indigenous knowledge, which ultimately compromise the quality of information delivered to farmers and weaken trust in digital extension services. Oyinbo, Chamberlin & Maertens (2020) noted that this happens when machine learning algorithms are trained on datasets that do not adequately embed local languages and cultural expressions.

More importantly, despite the critical role of gender and youth groups in agricultural production and knowledge systems in Nigeria, their linguistic expressions, communication styles, and experiential knowledge are not prioritized while building digital datasets in agriculture. For instance, Yahaya *et al* (2019) focused on Text-to-Speech technologies without consideration of gender and the youth perspective. Liakos *et al* (2018) concentrated on Machine learning applications in agriculture without disaggregating gender and youth perspectives. Tzachor *et al* (2023) looked at the potential of integrating Large Language Models in agriculture without addressing gender and youth gaps in the interpretation of agricultural lexicon. This exclusion contributes to biased algorithmic outputs that fail to capture the diversity of agricultural knowledge systems, thereby reinforcing the inequalities that put women and youth in digital agriculture at a disadvantaged position.

Objectives of the study include to:

- i. describe the socio-demographic characteristics of the study participants.
- ii. classify indigenous agricultural terminologies misinterpreted by algorithmic tools as assessed by the participants;
- iii. ascertain the frequency of algorithmic misinterpretation of indigenous agricultural terminologies;
- iv. examine challenges promoting the misinterpretation of indigenous agricultural terminologies.

METHODOLOGY

The study was carried out in Nigeria, a country located within the West African sub-region.

Agricultural extension and advisory services in Nigeria are coordinated through State-wide Agricultural Development Programmes (ADPs), Ministries of Agriculture, Agricultural institutions, Nongovernment agencies, and professional associations. AgriPredict, Apollo Agriculture, FarmCrowdy, and CashtoCrop are the major algorithmic tools used in Nigeria.

The study adopted a quantitative research design. The population comprised members of Agricultural Extension Society of Nigeria (AESON), Nigerian Forum for Agricultural Advisory Services (NIFAAS), Society for Climate Action in Nigeria (SCAN), Agriculture, Nutrition and Health (ANH), Young Innovation Leadership Fellowship (YIL) and members of other agricultural organizations who use algorithmic tools, as well as experts in data science, machine learning, computer programming, and sociolinguistics. Data were collected from 396 participants using a 2stage sampling procedure. First, members of the aforementioned organizations were proportionately distributed at 20% due to the unequal membership composition of the groups. In the second stage, members of the organizations who had experienced misinterpretation of indigenous agricultural terminologies while using algorithmic tools were purposively selected as participants based on their firsthand experience. Table 1 presents a summary of the proportionate sampling. Data analysis was carried out using a frequency distribution table and a percentage count.

Table 1: Proportionate sample distribution by organization

Organization	Population	Sample@20%
AESON	490	98
NIFAAS	170	34
SCAN	60	12
ANH	75	15
YIL	35	7
Total	830	166
Other agricultural organizations	1,150	230
Grand total	1,980	396

RESULTS AND DISCUSSION

Socio-demographics of participants

Table 2 presents the socio-demographic characteristics of respondents disaggregated by age group and gender. Results in Table 2 showed that the male gender constituted the majority of respondents (60.4%), while females accounted for 39.6%. Youths aged 21–40 years represented the largest proportion compared to 40.7% adults aged 41 years and above. Most of the respondents (33.0%) had a Master's degree, followed by 24.3% who had a Bachelor's degree and 22.0% with PhDs degree. Professorial rank accounted for 12.9%. By work experience, most respondents (33.8%) had 5–15 years and 16–26 years (32.5%) of experience.

The results showed a well-represented distribution of youth and gender in the utilization of algorithmic tools in agriculture, in confirmation of the assertion of Osabohlen (2024) that youth with access to ICT participate in agriculture more than those who do not have. This result contrasts the long-held view that electronic agriculture in Nigeria is ineffective and highly encumbered by digital gaps between rural and urban agricultural workforce, low literacy level, unstable power supply, poor access to enabling tools and connectivity. These earlier electronic barriers, according to Okoroma *et al* (2025), have been removed through household members' linkage and involvement in electronic agricultural information sharing, promoting youth and gender representation. Also, the results verified the critique view of ElDidin *et al.* (2020); Solomon (2021), and Fasakin *et al.* (2022), which asserted that the youth and gender gaps in electronic agriculture are not predestined outcomes, but an outcome of unequal access to education experienced by youth and women. They argued that if given considerable opportunities, their male adult counterparts would end the digital gaps amongst the youth and the female gender. Reddy *et al* (2025) warned that insufficient representation of youth and women's experiences within AI-driven agro-advisory platforms contributes to unequal outputs and biased interpretations.

Therefore, to narrow the youth and gender gaps towards achieving inclusive systems that incorporate indigenous knowledge, local languages, and the perspectives of youths, male and female in Nigeria, it may be more plausible to prioritize educational attainment across youth and gender groups than prioritizing power supply, since many users deploy alternative power supply to power their devices; availability of electronic gadgets since evidence from users' statistics shows soaring number; and internet connectivity since most algorithmic tools are offline non-webbased tools.

Table 2: Socio-demographic characteristics of respondents disaggregated by Age group and gender

Socio-demographic Variables		Male		Female	
Age	Group	Frequency	Percentage	Frequency	Percentage
21 – 40 Years	Youth	143	36.10	92	23.20
41 years and above	Adult	96	24.30	65	16.40
Total		239	60.4	157	39.60
Sex		Frequency	Percentage	Frequency	Percentage
	Youth	141	35.60	94	23.70
	Adult	98	24.70	63	15.90
Total		239	60.4	157	39.60
Qualifications		Frequency	Percentage	Frequency	Percentage
Professional Certificate	Youth	10	2.50	7	1.80
	Adult	6	1.50	4	1.00
Total		16	4.00	11	2.8
HND	Youth	2	0.50	1	0.3
	Adult	1	0.30	0	0.0
Total		3	0.80	1	0.30
Bachelor’s Degree	Youth	36	9.10	23	5.8
	Adult	22	5.60	15	3.8
Total		58	14.70	38	9.6
Master’s Degree	Youth	48	12.10	31	7.8
	Adult	33	8.30	19	4.8
Total		81	20.40	50	12.6
PhD	Youth	33	8.3	22	5.6
	Adult	19	4.8	13	3.3
Total		52	13.10	35	8.90
Professor	Youth	4	1.00	3	0.9
	Adult	25	6.31	19	4.8
Total		29	7.31	22	5.7
Work Experience		Frequency	Percentage	Frequency	Percentage
< 5 years	Youth	35	8.80	20	5.10
	Adult	15	3.80	8	2.00
Total		50	12.60	28	7.10
5 – 15 years	Youth	55	13.90	35	8.8
	Adult	28	7.10	16	4.0
Total		83	21.00	51	12.80
16-26 years	Youth	38	9.6	25	6.3
	Adult	39	9.8	27	6.8
Total		77	19.4	52	13.1
27 years and above	Youth	13	3.30	14	3.5
	Adult	16	4.10	12	3.0
Total		29	7.40	26	6.50

Source: Field survey data (2025)

Classification of Misinterpreted Indigenous Agricultural Terminologies

Table 3 shows the distribution of respondents based on the classification of misinterpreted indigenous agricultural terminologies. From the result, the classification varied across different age groups and gender, with 15.7% of youth males, 10.4% of youth females, 11.1% of adult males, and 7.1% of adult females indicating that indigenous practices and cultural beliefs were frequently misinterpreted by algorithmic tools. Similarly, 14.9% of youth males, and 14.4% youth males perceived local tools and farming methods among the misinterpreted terminologies. The findings further showed that 15.2% of youth males agreed that planting methods and patterns were commonly misinterpreted, with 14.9% strongly agreeing that indigenous food names were frequently distorted within algorithmic systems.

The result corroborates the argument of Vidanapathirana (2019) that digital agricultural systems often struggle to adequately capture indigenous knowledge and local agricultural expressions. Similarly, Sharma *et al.* (2021) observed that semantic distortion and misinterpretation are part of the consequences of excluding indigenous knowledge systems in digital agricultural technologies. It is important to note also that while the higher responses among youth males may reflect their greater interaction with algorithmic tools, the lower responses recorded among women and older adults may suggest underrepresentation within Nigeria's digital agricultural ecosystems rather than reduced exposure to misinterpretation.

Table 3: Distribution of Respondents by Classification of Misinterpreted Indigenous Agricultural Terminologies

Statements	Youth Male		Youth Female		Adult Male		Adult Female	
Indigenous practices and cultural beliefs	F	%	F	%	F	%	F	%
Strongly Agree	62	15.7	41	10.4	44	11.1	28	7.1
Agree	50	12.6	34	8.6	36	9.1	24	6.1
No Response	14	3.5	10	2.5	11	2.8	7	1.8
Disagree	12	3.0	8	2.0	9	2.3	6	1.5
Strongly Disagree	7	1.8	5	1.3	6	1.5	3	0.8
	Youth Male		Youth Female		Adult Male		Adult Female	
Local tools and farming methods	F	%	F	%	F	%	F	%
Strongly Agree	59	14.9	39	9.8	41	10.4	27	6.8
Agree	45	11.4	30	7.6	32	8.1	20	5.1
No Response	12	3.0	8	2.0	9	2.3	5	1.3
Disagree	16	4.0	10	2.5	11	2.8	7	1.8
Strongly Disagree	9	2.3	7	1.8	6	1.5	3	0.8
	Youth Male		Youth Female		Adult Male		Adult Female	
Names of local crops and livestock	F	%	F	%	F	%	F	%
Strongly Agree	53	13.4	35	8.8	37	9.3	24	6.1
Agree	57	14.4	38	9.6	40	10.1	25	6.3
No Response	8	2.0	5	1.3	6	1.5	4	1.0
Disagree	7	1.8	5	1.3	5	1.3	3	0.8
Strongly Disagree	16	4.0	10	2.5	11	2.8	7	1.8
	Youth Male		Youth Female		Adult Male		Adult Female	
Planting methods and patterns	F	%	F	%	F	%	F	%
Strongly Agree	48	12.1	32	8.1	34	8.6	22	5.6
Agree	60	15.2	39	9.8	43	10.9	26	6.6
No Response	12	3.0	8	2.0	8	2.0	5	1.3
Disagree	11	2.8	8	2.0	8	2.0	5	1.3
Strongly Disagree	10	2.5	6	1.5	8	2.0	3	0.8

	Youth Male		Youth Female		Adult Male		Adult Female	
Indigenous food names	F	%	F	%	F	%	F	%
Strongly Agree	50	12.6	33	8.3	35	8.8	22	5.6
Agree	59	14.9	39	9.8	41	10.4	26	6.6
No Response	8	2.0	5	1.3	6	1.5	4	1.0
Disagree	12	3.0	8	2.0	9	2.3	5	1.3
Strongly Disagree	12	3.0	8	2.0	9	2.3	5	1.3
	Youth Male		Youth Female		Adult Male		Adult Female	
Local names of improved crop varieties and animal species	F	%	F	%	F	%	F	%
Strongly Agree	51	12.9	34	8.6	36	9.1	23	5.8
Agree	49	12.4	32	8.1	36	9.1	21	5.3
No Response	12	3.0	8	2.0	9	2.3	5	1.3
Disagree	20	5.1	13	3.3	15	3.8	9	2.3
Strongly Disagree	8	2.0	6	1.5	6	1.5	3	0.8

Source: Field survey data (2025)

Frequency of misinterpretation of indigenous agricultural terminologies

The result (Table 4) on the frequency of misinterpretation revealed that 15.9% of youth males and 11.1% of adult males identified indigenous practices and cultural beliefs as frequently misinterpreted, while 16.2% of youth males reported frequent misinterpretation of names of local crops and livestock. Similarly, local tools and farming methods recorded 14.9% frequent misinterpretation among youth males, expressing algorithmic misinterpretation of indigenous agricultural terminologies as persistent occurrences rather than isolated incidents. The result further showed that planting methods and patterns, indigenous food names, local land/management terms, and local names of improved varieties also experienced frequent algorithmic distortion as indicated by an average of 10.3% of the respondents across all age and gender groups. This further demonstrates that misinterpretation of indigenous agricultural terminologies is commonly experienced across all age groups and gender.

The finding aligns with Yin *et al.* (2019), who observed that AI systems often fail to accurately process indigenous linguistic structures because indigenous knowledge systems are poorly represented in training datasets. Similarly, Yu *et al.* (2018) argued that algorithmic bias emerges when AI systems are developed using incomplete or socially skewed datasets that exclude marginalized linguistic groups.

By this finding, it could be implied that while the digital agricultural system is increasingly being mainstreamed in Nigeria's agricultural value chain, its algorithmic development remains insufficiently localised for multilingual and culturally diverse agricultural environments, such as those found in Nigeria. Implicitly, continued exclusion of youth and gender-sensitive linguistic terminologies and expressions may weaken the reliability, inclusiveness, and effectiveness of algorithm-based tools for the Nigerian context.

Table 4: Distribution of Respondents by Frequency of misinterpretation of indigenous agricultural terminologies

Frequency of misinterpretation of indigenous agricultural terminologies	Youth				Adult			
	Male		Female		Male		Female	
	Freq	%	Freq	%	Freq	%	Freq	%
Indigenous practices and cultural beliefs								
Frequently	63	15.9	42	10.6	44	11.1	29	7.3
Occasionally	55	13.9	37	9.3	38	9.6	25	6.3
Rarely	28	7.1	18	4.5	20	5.1	12	3.0
Local tools and farming methods	Freq	%	Freq	%	Freq	%	Freq	%
Frequently	59	14.9	39	9.8	41	10.4	26	6.6
Occasionally	52	13.1	35	8.8	36	9.1	24	6.1
Rarely	30	7.6	20	5.1	21	5.3	13	3.3
Names of local crops and livestock	Freq	%	Freq	%	Freq	%	Freq	%
Frequently	64	16.2	43	10.9	45	11.4	29	7.3
Occasionally	62	15.7	41	10.4	43	10.9	28	7.1
Rarely	15	3.8	10	2.5	10	2.5	6	1.5
Planting methods and patterns	Freq	%	Freq	%	Freq	%	Freq	%
Frequently	58	14.6	39	9.8	41	10.4	27	6.8
Occasionally	50	12.6	34	8.6	36	9.1	23	5.8
Rarely	27	6.8	18	4.5	19	4.8	12	3.0
Indigenous food names	Freq	%	Freq	%	Freq	%	Freq	%
Frequently	60	15.2	40	10.1	42	10.6	28	7.1
Occasionally	52	13.1	35	8.8	36	9.1	24	6.1
Rarely	25	6.3	17	4.3	18	4.5	11	2.8
Local names of improved varieties	Freq	%	Freq	%	Freq	%	Freq	%
Frequently	56	14.1	37	9.3	39	9.8	25	6.3
Occasionally	48	12.1	32	8.1	34	8.6	22	5.6
Rarely	22	5.6	15	3.8	16	4.0	10	2.5

Source: Field survey data (2025)

Challenges promoting the misinterpretation of indigenous agricultural terminologies

The result (Table 5) on challenges promoting the misinterpretation of indigenous agricultural terminologies showed that lack of localized NLP training data is the most prominent constraint across all age and gender groups, with 18.2% of youth males, 12.1% of youth females, and 12.6% of adult males strongly affirming. Similarly, 15.9% youth males strongly identified multiple names for the same concept as a challenge, while dialectal variations were identified by 14.4% of youth males as key challenges, suggesting linguistic complexity as a major barrier to effective digitization. Lack of standardized spelling and code-switching with English further complicates natural language processing and data harmonisation in agricultural communication systems were identified by an average of 11.6% across all age groups and gender. Contextual ambiguity also emerged as a significant challenge, with 13.6% of youth males agreeing that meaning varies depending on usage context.

These findings have reinforced the earlier claims of Parr *et al.* (2020) and Pinguet (2021) that the increasing integration of AI in e-agriculture is creating a new challenge that transcends unstable power supply, internet connectivity, and electronic gadgets. Under the new reality, the challenge of e-agriculture has moved from how to use digital tools in agriculture to how to design and build algorithms to speak, understand, interpret, predict, and supervise agricultural operations. Okoroma *et al.* (2025) added that the paradigm shift has equally moved the place of agricultural extension from utilization to creation. The results imply that without robust localisation of datasets, AI-driven agricultural extension systems risk persistent misinterpretation of indigenous terminologies, thereby limiting their effectiveness and inclusiveness in rural agricultural communication.

Table 5: Youth and Gender Distribution by Challenges promoting the misinterpretation of indigenous agricultural terminologies

Challenges	Youth				Adult			
	Male		Female		Male		Female	
	Freq	%	Freq	%	Freq	%	Freq	%
Lack of localized NLP training data								
Strongly Agree	72	18.2	48	12.1	50	12.6	32	8.1
Agree	25	6.3	17	4.3	18	4.5	11	2.8
No Response	14	3.5	9	2.3	10	2.5	6	1.5
Disagree	11	2.8	7	1.8	7	1.8	5	1.3
Strongly Disagree	19	4.8	13	3.3	13	3.3	9	2.3
Multiple names for same concept	Freq	%	Freq	%	Freq	%	Freq	%
Strongly Agree	63	15.9	42	10.6	44	11.1	29	7.3
Agree	32	8.1	21	5.3	22	5.6	14	3.5
No Response	15	3.8	10	2.5	10	2.5	6	1.5
Disagree	15	3.8	10	2.5	10	2.5	7	1.8
Strongly Disagree	16	4.0	11	2.8	11	2.8	8	2.0
Dialectal variations	Freq	%	Freq	%	Freq	%	Freq	%
Strongly Agree	57	14.4	38	9.6	40	10.1	25	6.3
Agree	38	9.6	25	6.3	26	6.6	17	4.3
No Response	15	3.8	10	2.5	11	2.8	7	1.8
Disagree	16	4.0	10	2.5	11	2.8	7	1.8
Strongly Disagree	15	3.8	10	2.5	10	2.5	7	1.8
Lack of standardized spelling	Freq	%	Freq	%	Freq	%	Freq	%
Strongly Agree	64	16.2	42	10.6	44	11.1	29	7.3
Agree	29	7.3	19	4.8	20	5.1	14	3.5
No Response	16	4.0	10	2.5	11	2.8	7	1.8
Disagree	16	4.0	11	2.8	11	2.8	7	1.8
Strongly Disagree	16	4.0	11	2.8	11	2.8	8	2.0
Code-switching with English	Freq	%	Freq	%	Freq	%	Freq	%
Strongly Agree	67	16.9	45	11.4	47	11.9	30	7.6
Agree	26	6.6	17	4.3	18	4.5	11	2.8
No Response	19	4.8	12	3.0	13	3.3	8	2.0
Disagree	11	2.8	8	2.0	8	2.0	5	1.3
Strongly Agree	18	4.5	12	3.0	13	3.3	8	2.0
Contextual ambiguity	Freq	%	Freq	%	Freq	%	Freq	%
Strongly Agree	41	10.4	27	6.8	29	7.3	19	4.8
Agree	54	13.6	36	9.1	38	9.6	24	6.1
No Response	12	3.0	8	2.0	8	2.0	6	1.5
Disagree	18	4.5	12	3.0	13	3.3	8	2.0
Strongly Agree	15	3.8	10	2.5	11	2.8	7	1.8

Source: Field survey data

CONCLUSION AND RECOMMENDATIONS

The study concluded that indigenous practices and cultural beliefs, local crop and livestock names, local farming tools, planting methods, indigenous food names, and land management terms were indigenous agricultural terminologies frequently misinterpreted by algorithmic systems across age and gender groups. Youth males reported the highest levels of misinterpretation, suggesting their greater interaction with algorithmic tools. Lack of localized natural language processing (NLP) training data, multiple names for the same agricultural concept, dialectal variations, nonstandardized spelling, code-switching between local languages and English, and contextual ambiguity are the major factors promoting algorithmic misinterpretation.

Hence, it is recommended that:

1. Developers of agricultural algorithmic systems should learn to collaborate with agricultural scientists and linguists in their team to provide technical guidance that ensures that algorithms incorporate indigenous agricultural terminologies, local languages, and cultural knowledge into NLP datasets to improve interpretation accuracy.
2. Government and research institutions should develop gender- and youth-responsive localized NLP datasets that capture linguistic variations, indigenous farming practices, and local agricultural expressions across different demographic groups.
3. Agricultural technology developers should collaborate with youth groups, women farmers, extension agents, and indigenous knowledge holders to improve the contextual accuracy of algorithmic systems.

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