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Speaking Their Language: Language Inclusion and YouTube Agricultural Content Engagement in Africa

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ABSTRACT

Efficiently educating farmers in effective agricultural practices is critical in resource-limited developing countries. YouTube, with its broad accessibility and built-in viewership tracking, presents a potential scalable platform for agricultural education. This study assesses how language inclusion policies affect engagement with agricultural YouTube content. We conducted a case study using a video campaign to address post-harvest loss in Africa, featuring an educational animation translated into 14 Ghanaian, 35 Kenyan, and 16 Nigerian languages. The campaign was distributed through paid YouTube ads. Two inclusion policies were evaluated through computational simulations using real-world data: equal opportunity (i.e., equal spending across languages) and equal outcome (i.e., adjusted spending to equalize viewership across languages). We also estimated viewership under two additional scenarios: using only the official language and using the most cost-effective language for each country. The most cost-effective campaigns coincided with the official language of English in Ghana (8.9 viewers per USD) and Nigeria (3.1 viewers per USD), but not in Kenya, where the most effective language campaign was Kikuyu (16.2 viewers/USD). Overall, the equal spending policy reduced viewership by 43%, while the equal outcome policy reduced viewership by 66% compared to campaigns in official languages. However, results show country-specific trends. Differences in viewership between inclusion policies were minimal in Ghana and Nigeria. Conversely, in Kenya, the discrepancy in inclusion policy impact was more pronounced, suggesting that in certain regions, more inclusive policies are likely to significantly influence viewership levels. These findings highlight the importance of localized evaluations of inclusion policies in digital agricultural education.

1 | Introduction

Democratization of education entails increasing accessibility to all members of society, breaking down barriers hindering access, and promoting inclusion, especially for underserved demographic groups (Carrington 2023). In developing countries, where agriculture profoundly impacts both population health (Hawkes and Ruel 2006) and economic growth (Berthelemy and Thuilliez 2013; Dethier and Effenberger 2012), democratizing agricultural education is crucial. Despite an ever-growing wealth of agricultural knowledge (Fuglie et al. 2019), transferring it to farmers with low literacy levels and non-English speakers remains a significant challenge (FAO 2017).

A promising solution to tackle the challenges posed by literacy and language barriers involves harnessing information and communication technologies, such as computer-generated training animations tailored for low-literacy, non-English-speaking audiences (Bello-Bravo 2020; Bello-Bravo, Lutomia, et al. 2020). These multilingual training animations have demonstrated their efficacy in expanding access to food production education (Akpabio et al. 2007; Strong et al. 2014; Tata and McNamara 2016, 2018) and promoting the adoption of innovative agricultural practices (Bello-Bravo et al. 2018, 2019; Bello-Bravo, Abbott, et al. 2020). Importantly, animations can be shared via digital platforms like YouTube, allowing for the measurement of campaign viewership reach. Such measurements then facilitate data-driven approaches to optimize educational investments and can be tailored to account for inclusion policies.

This study aims to assess the influence of inclusion policies on YouTube agricultural content engagement, particularly concerning language diversity. It uses agricultural education focused on reducing post-harvest loss as a case study, addressing the critical global problem of food wastage (FAO 2010; Prusky 2011) in developing countries primarily attributed to spoilage (Hodges et al. 2011). Consequently, education campaigns promoting techniques to reduce post-harvest loss are expected to be impactful (Sheahan and Barrett 2017), especially when conducted at scale through digital platforms.

Our primary objective is to evaluate the impact of different language inclusion policies on YouTube agricultural content engagement and determine whether these effects vary across countries. A secondary aim is to demonstrate how data-driven approaches can guide stakeholders in making informed decisions about educational funding and language inclusion strategies, ultimately supporting more effective and inclusive agricultural education initiatives in developing nations.

2 | Methods

Data for this study were collected as part of a United States Agency for International Development (USAID) supported project to address food insecurity in Africa during the COVID-19 pandemic. Michigan State University's Biomedical and Health Institutional Review Board (IRB number 202101087) deemed the study exempt. The study is not considered human subject research since it uses existing data not specifically collected for research purposes and uses de-identified information. Daily YouTube reports obtained for the study supply aggregated data, recorded in a manner that individual information cannot be identified. Given that individuals cannot be identified, obtaining informed consent was not required nor would be possible.

2.1 | Key Elements of Study Design

There were three phases to the study: (1) retrospective real-world data collection from YouTube campaigns, (2) language model development using these data, and (3) model simulations to assess the impact of inclusion policies using these language models. Unlike other observational studies that compare population cohorts, this study creates synthetic cohorts (i.e., a group of individuals generated from real-world data but constructed using simulations) to compare campaign viewership reach between inclusion policies.

2.2 | Digital Education Intervention

A digital education intervention was implemented via a YouTube animation designed to educate farmers on the storage of beans using sanitized, hermetically-sealed jerrycans (or other readily available household containers) to prevent insect-related spoilage (see the following link to view the training video https://rapid.sawbo-animations.org/video/1445). For Ghana, 14 language variants of the jerrycan animation were produced, with 35 for Kenya, and 16 for Nigeria. Between July 19 and November 18, 2021, YouTube campaigns were conducted to disseminate the jerrycan storage technique across the three African countries. These campaigns were specifically directed at USAID identified "zones of influence" (ZOIs), corresponding to economically disadvantaged agricultural regions that included bean production suitable for jerrycan storage. The selection of these zones was determined by the corresponding USAID Missions in each country and recommendations of in-country experts. Languages were chosen based on those that are commonly spoken within the geographical areas identified as ZOIs (Tables S1-1–S1-3 in the Supporting Information S1).

2.3 | Study Population

The study population consisted of individuals who had direct exposure to the jerrycan storage technique through YouTube advertisements. It does not include individuals exposed to the taught technique through organic reach such as unpaid video sharing.

2.4 | Data Collection

The study obtained data from daily YouTube reports for each language campaign, which included metrics such as daily money spent, total number of views (defined as viewers watching at least 30 s of the animation (Google 2022), and percentage of viewers who watched 25%, 50%, 75%, and 100% of the video. One of the limitations of online educational approaches is the inability to directly observe learning or behavior changes without direct observation and questioning (Guo et al. 2014). Direct observation and questioning across the number of regions and languages would be challenging. Therefore, we used exposure to the educational content as a proxy. Prior research shows a linear relationship between the number of views and subsequent adoption of content (Singh et al. 2023), suggesting that viewership can serve as a reasonable proxy. It is important to note that 100% of the video includes credits and disclaimers and 75% is approximately the extent of the informational content contained in the video. For estimating exposure to the jerrycan storage technique, the study utilized the percentage of viewers who watched at least 75% of the video and determined the number of viewers by multiplying it by the total number of views. Data for the study is publicly available (DOI: 10.4231/TJK7-YD07).

2.5 | Model Development

Models were developed for each language campaign to predict the expected number of viewers per USD spent (Figure 1). This

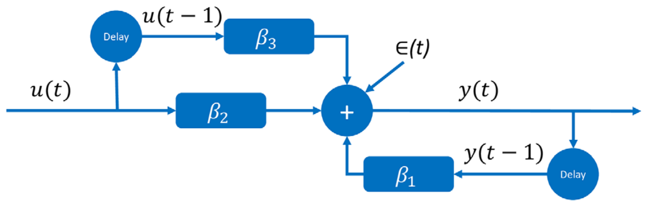

FIGURE 1 | Schematic drawing of YouTube Ad campaign model. The model estimates the number of viewers reached, denoted as $y(t)$ on day t. Note that the model can use historical data, such as previous number of viewers, $y(t-1)$, and previous money spent, $u(t-1)$, to enhance the accuracy of viewer estimations. The time delay, $(t-1)$, signifies a one-day delay, and the error term, $\epsilon(t)$, accounts for unexplained variations in the data for day t.

was accomplished using an autoregressive distributed lag linear model, which characterized the relationship between spending and the number of viewers. The regression coefficients of these linear models provide a direct insight into temporal dependencies, making it easier to explain and compare simulation outcomes across policy types and countries. Preliminary modeling analysis using Durbin–Watson tests revealed autocorrelations between daily observations for several language campaigns. To account for this autocorrelation and to improve model prediction accuracy, four mathematical models with different numbers of input variables were considered: first, current daily money spent (Equation (1)); second, current and previous daily money spent (Equation (2)); third, previous number of viewers and current daily money spent (Equation (3)); and finally, previous and current daily money spent and previous number of viewers (Equation (4)).

$$y(t) = \beta_2 u(t) + \epsilon(t) \tag{1}$$

$$y(t) = \beta_2 u(t) + \beta_3 u(t-1) + \epsilon(t) \tag{2}$$

$$y(t) = \beta_1 y(t-1) + \beta_2 u(t) + \epsilon(t) \tag{3}$$

$$y(t) = \beta_1 y(t-1) + \beta_2 u(t) + \beta_3 u(t-1) + \epsilon(t) \tag{4}$$

where $y(t)$ represents the observed number of viewers on day t. β_1 reflects the change in the expected number of viewers following a one viewer increment in the previous day, $y(t-1)$. β_2 reflects the immediate change in the expected number of viewers following a one dollar increment in campaign investment in the current day, $u(t)$. β_3 reflects the change in the expected number of viewers following a one dollar increment in investment in the previous day, $u(t-1)$. $\epsilon(t)$ denotes the time series error term.

To select the model type reflected in Equations (1–4), an Akaike Information Criterion (AIC) statistic was used. The model with the lowest AIC was selected and the estimated model parameters were used for simulations. Model parameters β_1, β_2, and β_3 were estimated for each language model by adjusting these parameters to minimize the error between the model estimated viewership and viewership observed in real-world data. A least square errors method was used to converge on model parameters.

2.6 | Model Simulations

Once the model type was selected and associated model parameters defined for each language campaign, these models were then used to simulate two inclusion policies: (1) equal spending across all languages (i.e., equal opportunity policy), and (2) equal viewers across all languages (i.e., equal outcomes policy). As a reference, simulations were also performed to estimate the number of viewers reached for campaigns conducted exclusively in each country's official language (i.e., official language campaigns), as well as the most cost-effective language campaign for each respective country (i.e., max viewership campaigns). For Kenya, which had two official languages (Swahili and English), the most cost effective language campaign of the two was used as the reference.

Simulations used the following constraints: \$10,000 per country budget spent over a 100-day period with a maximal daily expenditure of \$200. The \$200 and 100-day constraints were used to avoid extrapolating models beyond the expenditure range and period in the real-world data.

To optimize spending over the 100-day period, a closed form model was developed:

$$\begin{bmatrix} y(1) \\ y(2) \\ y(3) \\ \vdots \\ y(n) \end{bmatrix} = \begin{bmatrix} \beta_2 & 0 & \cdots & 0 \\ (\beta_1\beta_2+\beta_3) & \beta_2 & \cdots & 0 \\ \beta_1(\beta_1\beta_2+\beta_3) & (\beta_1\beta_2+\beta_3) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ \beta_1^{n-2}(\beta_1\beta_2+\beta_3) & \beta_1^{n-3}(\beta_1\beta_2+\beta_3) & \cdots & \beta_2 \end{bmatrix} \begin{bmatrix} u(1) \\ u(2) \\ u(3) \\ \vdots \\ u(n) \end{bmatrix}$$

where $\beta_2+\beta_3>0$ and $\beta_2>0$, with a fixed constraint $u(t)\leq 200$ with $n\leq 100$. For language models that omitted previous number of viewers, β_1 was set to zero. Similarly, for language models that omitted previous spending, β_3 was set to zero.

The following objective function was optimized for each language model:

$$\max \sum_{n=1,\ldots,100} y(t)$$

This optimization routine was used to determine the daily spending trajectory over the 100-day period with the goal to maximize viewership for each language model. Once the daily spending trajectory was established, it was applied to estimate the total number of viewers for the language model based on a campaign budget for that language.

For *official language campaigns*, the total viewership for the English campaigns in Ghana and Nigeria, as well as the English and Swahili campaigns in Kenya, were estimated using a \$10,000 country budget.

For *max viewership campaigns*, the language projected to yield the highest number of viewers in each country was chosen, and the total viewership was estimated using a \$10,000 country budget.

For *equal opportunity campaigns*, the $10,000 country budget was distributed evenly across all languages. Viewership for each language was estimated separately and then combined to predict the total audience for this policy.

For *equal outcome campaigns*, we applied an iterative process. First, using the equal opportunity results, spending was proportionally adjusted according to the share of viewers each language generated. For example, in a hypothetical country with two language campaigns, if one campaign attracted twice as many viewers as the other under equal spending, the budget would be divided 2/3 and 1/3, respectively. This provided a starting point for allocation. Next, optimization determined daily spending across 100 days for each language campaign. Adjusting spending to inversely correlate with viewership in each language campaign resulted in a more balanced viewership across languages, which further improved with each iteration. Once viewership was balanced across all languages, the expected number of viewers from each language was summed to determine overall viewership for the equal outcome policy.

To quantify the impact of different campaign strategies, the percentage reduction/increase in viewership expected for each campaign strategy was calculated. This calculation was achieved by subtracting the total number of viewers for the various campaign policies (i.e., max viewership, equal opportunity, equal outcome) by the total viewership in the official language campaign, dividing it by the total viewership in the official language campaign and then multiplying by 100%. These percentages provide estimates of the expected reduction/increase in viewership for each campaign strategy.

All model development and simulations were completed using MATLAB R2021b (MathWorks, Natick, MA). For more model details refer to the Supporting Information S2.

3 | Results

The observed total number of viewers for all campaigns was 63,564, with 24.3% from Ghana, 70.3% from Kenya, and 5.4% from Nigeria (Table 1). The observed mean daily amount of campaign spending for each language was $9.0 in Ghana, $18.4 in Kenya, and $8.6 in Nigeria, with the mean daily viewership for each language being 10 for Ghana, 10 for Kenya, and 2 for Nigeria. When evaluating cost-effectiveness, Ghanaian campaigns were the most efficient, reaching 1.1 viewers per USD spent. Kenya followed with 0.5 viewers per USD spent, while Nigerian campaigns were the least cost-effective, reaching only 0.2 viewers per USD spent.

In terms of modeling, 56 out of 65 campaigns (86.2%) were represented by the full model that included previous and current money spent and previous viewer terms. One campaign had no previous viewers term, six had no previous money spent term, and two had no previous viewers and money spent terms in the model. For those full models, β_1 coefficients tended to be positive with a mean β_1 value of 0.5. Note that there was one campaign, Ijaw in Nigeria, with a negative value of −0.48; all other campaigns had positive β_1 values ranging from 0.17 to 0.96. The positive β_1 suggests that the previous viewer term can be regarded as a priming effect (i.e., higher viewership on the previous day positively influences the number of viewers on the current day). While not observed in this study, a value of $\beta_1 > 1$ would indicate conditions in which a video would become "viral." As expected, the β_2 coefficients were also positive ranging from 0.08 to 1.56 with a mean value of 0.34, with greater values indicating that more viewers are expected to be reached per dollar spent. The β_3 coefficients tended to be negative with a mean of −0.20 and a range of −1.13 to 0.02. A negative β_3 value suggests that the previous money spent term can be interpreted as a saturation effect (i.e., higher spending on the previous day results in fewer viewers on the current day). This could occur if the same audience is repeatedly targeted on consecutive days, and those viewers are less inclined to watch the animation again. These models were able to fit the observed viewership data with an average adjusted R^2 of 0.93 (range 0.65–0.98) (see Figure 2 for an example of model fitting). Moreover, the simulated results demonstrated robustness to variability in model parameters. For further details, please refer to the sensitivity analysis provided in Supporting Information S3.

In terms of the cost-effectiveness of various policies, simulations suggest that the most effective language campaigns coincided with the official language of English in Ghana (8.9 viewers per USD) and Nigeria (3.1 viewers per USD), but not in Kenya, where English and Swahili are the official languages, but the most effective language campaign was Kikuyu (16.2 viewers per USD). Between the two official languages in Kenya, Swahili was the most cost-effective, reaching 4.5 viewers per USD, compared to English, which reached 2.9 viewers per USD. Therefore, Swahili was used as the reference official language for Kenya. When compared to the official language campaign as a reference point, the equal spending policy resulted in a 58% reduction in

TABLE 1 | Observed total number of campaigns and viewers for Ghana, Kenya, and Nigeria.

Country	Total number of viewers[a]	Daily money spent per campaign (USD) mean (Interquartile, range)	Daily number of viewers per campaign mean (Interquartile, range)
Ghana	15,448	9.0 (1.1–7.3; 0.0–159.9)	10 (1–6; 0–747)
Kenya	44,711	18.4 (1.3–21.6; 0.0–446.3)	10 (1–8; 0–376)
Nigeria	3,406	8.6 (0.9–7.3; 0.0–158.2)	2 (0–1; 0–90)
Combined	63,565	14.3 (1.1–21.5; 0.0–446.3)	8 (1–6; 0–747)

[a]Viewers represent the number of YouTube viewers who watched 75% or more of the video.

viewership in Ghana, a 13% reduction in viewership in Kenya, and a 58% reduction in viewership in Nigeria. In comparison, the equal outcome policy led to a 77% reduction in viewership in Ghana, a 53% reduction in viewership in Kenya, and a 68% reduction in viewership in Nigeria (Figure 3).

4 | Discussion

This study aimed to evaluate the impact of language inclusion policies on YouTube agricultural content engagement and to assess whether these effects vary by country. Using the official

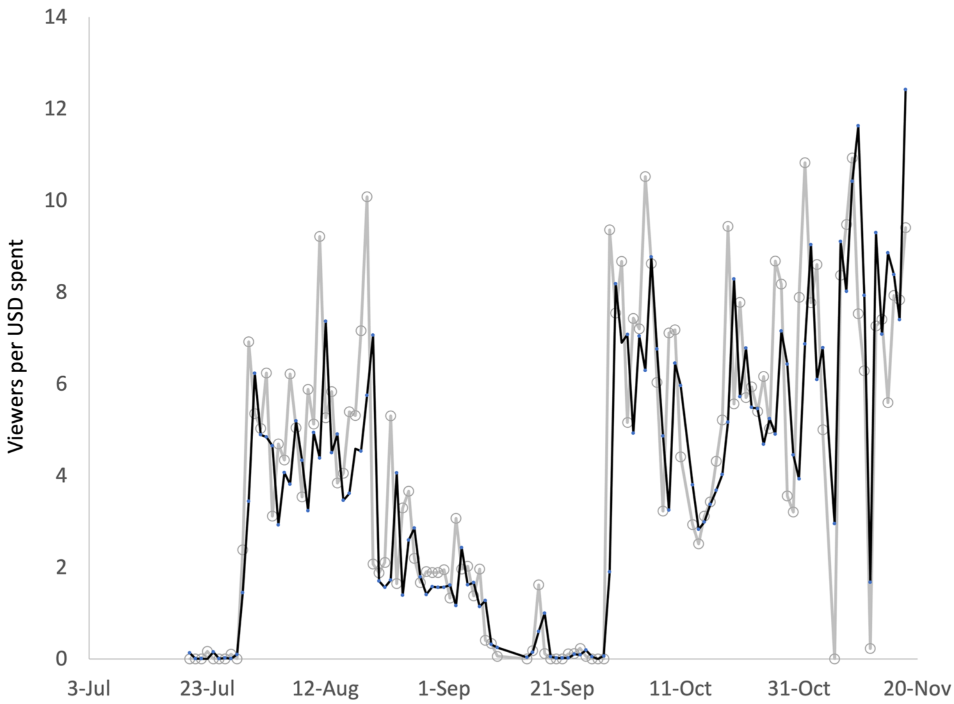

FIGURE 2 | Model fitting of real-world data. Model predicted (black line) versus observed (gray line) time series data of viewership for Swahili campaigns in Kenya.

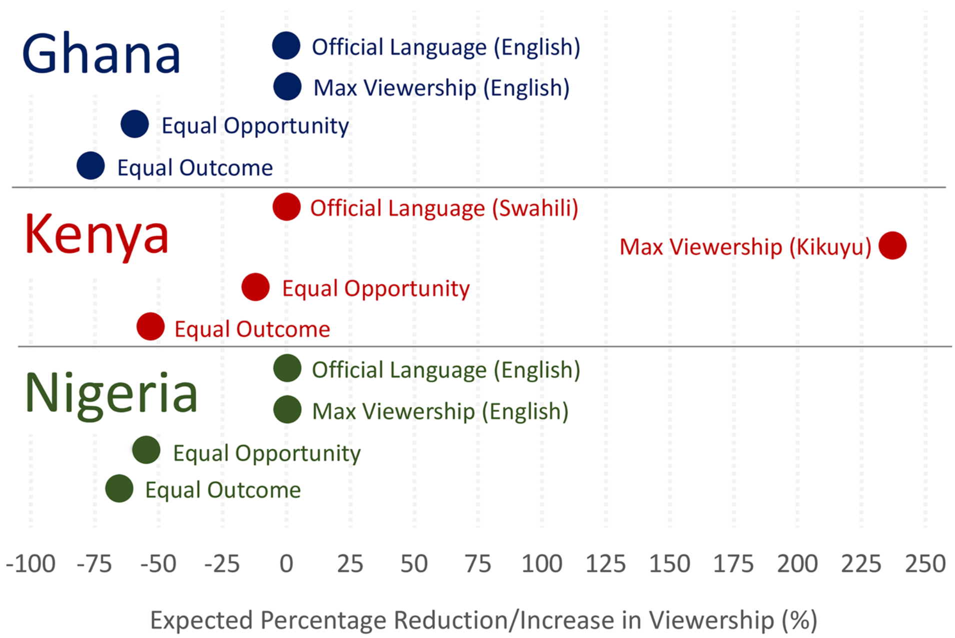

FIGURE 3 | Campaign policy impact on viewership. Expected reduction/increase in viewership for various campaigns, using the official language campaign as a reference. In Ghana and Nigeria, English campaigns were the most cost-effective, while Kikuyu was the most cost-effective in Kenya. As expected, the stricter inclusion policy of equal number of viewers across all languages (i.e., equal outcomes) resulted in fewer expected viewers (mean 66% reduction) than the equal opportunity policy (mean 43% reduction), in which campaign funds were equally dispersed across all languages. However, the differences between the two inclusion policies were small, particularly in Ghana and Nigeria.

language campaign as a benchmark, simulations showed that inclusion policies led to decreased viewership. The equal opportunity policy (i.e., equal spending across languages) resulted in an average reduction of 43% in viewership across all countries, while the equal outcomes policy (i.e., spending adjusted to equalize viewership) led to a larger average reduction of 66%. These findings highlight a central ethical dilemma for policymakers: whether to prioritize maximizing overall educational reach, to pursue inclusivity, or to find an appropriate balance between the two.

Despite these overall decreases, the impact of inclusion policies was not consistent across regions. For instance, the difference in effectiveness between the two inclusion policies was minimal in Ghana and Nigeria, indicating that stricter equity-focused policies may not significantly reduce reach in these regions. However, in Kenya, the gap between the two policies was more pronounced, suggesting policy trends are not consistent across Africa. Kenya also differed from the other two countries in that the official language was not the most cost-effective for campaign delivery. Instead, a local language yielded the highest viewership per dollar spent, highlighting the importance of localized evaluation in digital agricultural learning initiatives.

To our knowledge, there have not been any studies investigating language inclusion policies in African agricultural education. Most of the work in the area has focused on gender-inclusive agriculture, highlighting the need to address barriers to women's access to resources in agriculture, particularly in the context of climate change (Nyasimi and Huyer 2017; Paudyal et al. 2019). One study conducted in India showed that information delivered through mobile phones reduced information asymmetry between female and male farmers and that this information helped make informed decisions, leading to savings on irrigation and reducing the cost of other inputs such as pesticides and fertilizers (Mittal 2016). Using real-world data from agricultural in-person training in Bangladesh, computer simulations predicted that female participation could be significantly increased by selecting when and where training should take place and by selecting the gender of the trainer to lead extension services events (Reeves et al. 2023). This work also predicted a reduction in overall attendance with a strict inclusion policy to balance male and female attendance. Simulations also demonstrated that a strategy involving the selection of half of the training events to emphasize total attendance and the remaining half to prioritize female participation (akin to an equal opportunity policy) can increase female participation by over 82% while at the same time increasing total turnout by 14%. These findings indicate that devising thoughtful inclusion policies via computational methods has the potential to significantly enhance both the overall reach and inclusivity of agricultural education.

The current study showcases the potential of employing computational analysis driven by real-world data to evaluate various inclusion policies, enabling policymakers to make well-informed decisions. The narrow focus was intentional, designed to clearly showcase the methodology and its interpretability. While the primary focus of this research centered on language diversity, a similar methodology could be applied to formulate inclusion policies for other demographic characteristics, including gender and age. Furthermore, these computational approaches could be expanded to optimize inclusive educational programs across multiple criteria simultaneously, a task that would prove challenging without the aid of machine learning and optimization techniques.

Aside from the computational insights, information and communication technologies used in the current study, specifically the use of multilingual YouTube animations, offer several other benefits. The ability to scale educational programs through digital platforms has tremendous potential for government sponsored programs, especially in Sub-Saharan Africa where the ratio of agricultural extension agents to farmers averages around 1 to 5000, and can have ratios as high as 1 to 22,000 (Speranza et al. 2018). Mobile internet access due to a lack of electricity/networks remains a barrier in Africa (Houngbonon et al. 2021; Richard 2019) but is gradually becoming less of an impediment, with an estimated 40% of the adult population now being connected and an additional 100 million new users expected by 2025 (GSMA 2022). Finally, digital education could emerge as an effective tool to enhance system resilience, particularly when in-person training is not feasible due to external shocks like health outbreaks or regional conflicts (Osumah 2013) or government corruption (Payumo et al. 2021).

In terms of future research, the tangible real-world impact of online agricultural education remains an open question, warranting further exploration. The next logical step involves investigating whether this channel of information dissemination promotes the adoption of agricultural techniques and, subsequently, leads to measurable enhancements in agricultural productivity. Prior research suggests that in-person education using ICTs including linguistically-localized animations leads to learning and the adoption of techniques taught in the animations (Bello-Bravo et al. 2018, 2019; Bello-Bravo, Abbott, et al. 2020; Ghandi et al. 2009), although it is not clear if online training will yield similar results. Additionally, it is recommended to expand the project's scope to include the integration of other inclusive policies, encompassing aspects such as gender and age.

Future research should also address the issue of language group overlap, particularly in regions where dialect continua and multilingualism are common. The current analysis assumes distinct, non-overlapping language audiences, which may introduce estimation bias in areas with high linguistic diversity. Incorporating more nuanced linguistic data through surveys could help improve targeting strategies and better estimate the marginal impact of language inclusion policies.

Finally, the current modeling approach assumes a time-invariant digital ad marketplace and does not account for potential system changes such as bidding volatility. Despite this simplification, the fitted models appear to capture observed behavior reasonably well (average adjusted R^2 of 0.93). Nonetheless, future work should consider time-varying modeling approaches in which parameters are allowed to evolve over time to better reflect shifts in the digital advertising environment.

5 | Conclusion

This study demonstrates that language inclusion policies can influence the reach of digital agricultural education campaigns, with effects varying by country. While more strict language inclusion policies may slightly reduce viewership in some contexts, such as Ghana and Nigeria, the trade-off appears minimal, suggesting that efficiency and inclusion are not mutually exclusive. However, as demonstrated in Kenya, policy choice plays a greater role. Taken together, these findings highlight the limited generalizability of policy impacts and reinforce the need for localized, data-driven strategies in designing digital agricultural education initiatives.

As online platforms become increasingly central to knowledge dissemination, striking the right balance between maximizing reach and ensuring inclusivity will be essential for advancing both agricultural productivity and equity in developing nations. Policymakers must weigh short-term viewership gains against potential longer-term benefits of equity, trust, and sustained engagement.

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Conflicts of Interest

N. Peter Reeves reports financial support was provided by Purdue University. Ahmed Ramadan reports financial support was provided by Purdue University. Victor Giancarlo Sal Y Rosas Celi reports financial support was provided by Purdue University. N. Peter Reeves reports a relationship with Sumaq Life LLC that includes: equity or stocks. The other authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **File S1:** Links to YubeTube multilingual animations and geographical locations targeted in YouTube Ad campaigns. **File S2:** Model development and results with additional description of modeling and policy results. **File S3:** Simulated results sensitivity to model parameter variability.