Integrated Development Program Discussion Paper 5

Emotion classification and sentiment analysis for sustainable agricultural development:

exploring available tools for analyzing African farmer interviews

Eliot Jones-Garcia, Gideon Kruseman and Brendan Brown

CIMMYT
International Maize and Wheat Improvement Center

CGIAR

Integrated Development Program Discussion Paper 5

Emotion classification and sentiment analysis for sustainable agricultural development:

exploring available tools for analyzing African farmer interviews

Principal Investigator

Eliot Jones-Garcia

(Nottingham University)

Co-Investigators

Gideon Kruseman

Brendan Brown

(CIMMYT)

International Maize and Wheat Improvement Center CIMMYT in collaboration with Nottingham University

The International Maize and Wheat Improvement Center (CIMMYT) is a non-profit international agricultural research and training organization. CIMMYT focuses on sustainable agri-food systems and improved livelihoods through research on maize, wheat and other food crops.

Applying high-quality science and strong partnerships, CIMMYT works for a world with healthier and more prosperous people, free from global food crises and with more resilient agri-food systems. Its research brings enhanced productivity and better profits to farmers, mitigates the effects of the climate crisis, and reduces the environmental impact of agriculture.

CIMMYT is a member of CGIAR, a global research partnership for a food secure future dedicated to reducing poverty, enhancing food and nutrition security, and improving natural resources.

Citation information
Jones-Garcia E, Kruseman G, Brown B. 2021. Emotion classification and sentiment analysis for sustainable agricultural development: exploring available tools for analyzing African farmer interviews. Integrated Development Program Discussion Paper no. 5. El Batan, Texcoco, Mexico: International Maize and Wheat Improvement Center CIMMYT. 32 Pages.

Support

Financial support
This study was supported by CGIAR Research Program on Maize and the CGIAR Platform for Big Data in Agriculture. It is part of the Community of practice on Socio-economic data as part of the activities on enhancing data analytics to accelerate the impact of agricultural research for development using big data analytics.

Declaration of interest statement

The authors declare no conflicts of interest in the publication of this research.

Purpose of the series

CIMMYT's *Integrated Development Program Discussion Paper* series publishes preliminary research results and study protocols prior to finalizing them for submission as peer-reviewed journal articles. The discussion papers are intended to solicit discussion and comments from stakeholders and peers to improve the quality of the research outputs.

The papers contain preliminary material and research results and are circulated in order to stimulate discussion and critical comment. They have not been subject to a formal external review. Any opinions stated herein are those of the author(s) and are not necessarily representative of or endorsed by CIMMYT.

Reports

001 Springmann M. 2021. Dietary adaptation mechanisms to the potential health impacts of climate related changes in micronutrients in wheat and other cereals

002 Mottaleb KA et al. 2021. Wheat Consumption Dynamics in Selected Countries in Asia and Africa: Implications for Wheat Supply by 2030 and 2050

003 Kruseman G et al. 2021. Effects of dietary change - Synthesis across the case studies

004 Amjath-Babu TS et al. 2021. Hard and Soft Climate Smart Investment in Aquaculture: Conditioning factors and decision space in a developing country context

005 Jones-Garcia E et al. 2021. Emotion classification and sentiment analysis for sustainable agricultural development; exploring available tools for analyzing African farmer interviews

006 Chamberlin J and Sumberg J.2021. Do young farmers farm differently? Evidence from sub-Saharan Africa

007 Chamberlin J. 2021. Life satisfaction of rural young people in Tanzania

Contents

Abstract/executive summary

The emerging 4th industrial revolution is having a profound effect on the direction of agrarian development. Big data technologies are becoming embedded within all walks of life, leading to both significant advancements in utility and to critical ethical concerns about the organization of the social world. Academic attention is growing into how such technologies can be employed for farmers; using enriched forms of data collection to account for contextually embedded factors in smallholder decision making. Further, in the context of ongoing COVID-19 restrictions, research is increasingly being conducted remotely. This removes a significant interpersonal dimension from studies, a particular concern for those which deal with sensitive data such as gender empowerment. In this paper we explore emotion classification and sentiment analysis of text and audio data of farmers' interviews in eastern and southern Africa and their evaluation of a set of sustainable agricultural practices. With this relatively benign dataset, which is known not to include any instances of affective behavior beyond normal discussion of farming techniques, we attempt to test the viability of these tools and what steps are necessary to make them reliable and accessible to researchers. Findings indicate additional insight can be made to support qualitative study, in several cases demonstrating a convergence between traditional anthropological assessment and expected emotional reaction. There are also unexpected responses and unforeseen learning for the process of qualitative data collection and processing. For future research and interventions, however, a series of limitations and developments are identified for this methodology to mature.

Preface

The CGIAR Platform for Big data in Agriculture aims at using big data to solve agricultural development problems faster, better and at greater scale. Data has become a valuable global commodity, but it is much more than simply information: in expert hands, it is intelligence.

Already, analysts are finding ways to turn big data — the immense stocks of information collected in computers worldwide — into an invaluable resource for planning and decision-making. It is helping accelerate the development of robust responses to some of the most pressing challenges of our time: climate change/variability, food insecurity and malnutrition, and environmental degradation. The smart and effective use of data will be one of the most important tools for achieving the United Nations' Sustainable Development Goals. Big data represents an unprecedented opportunity to find new ways of reducing hunger and poverty, by applying data-driven solutions to ongoing research for development impact.

The Community of Practice on socio-economic data (SED-CoP), led by CIMMYT, aims at bringing together CGIAR centers, academia, not-for-profit research and development organizations and private sector partners willing to tackle major issues related to socio-economic data.

The community works together on strategies to make the data interoperable, in order to enhance the impact and the use of CGIAR-related socio-economic data for partners in development. The Community also strives to make new and exciting data analytics tools available for improved analysis.

Sieglinde Snapp

Director CIMMYT Integrated Development Program

1. Introduction

The emerging 4th industrial revolution is having a profound effect on the direction of agrarian development. Big data technologies are becoming embedded within all walks of life, leading to both significant advancements in utility and to critical ethical concerns about the organization of the social world. Academic attention is growing into how such technologies can be employed to improve agricultural research for development and innovation; using enriched forms of data collection to account for contextually embedded factors in smallholder decision making.

Agricultural innovation is reliant on high quality data in order to accurately design and implement technologies and interventions. This is particularly salient in the wake of impending ecological crises and the increasingly evident ‘development gap’ between the rich and the poor, the included and the excluded. As such, greater equality and climate justice are top priorities among the United Nations Sustainable Development Goals. More specifically, gender is a strong focus of funding and research. Studies of this nature, however, are notoriously difficult to quantify. The data collected for these purposes are often subject to a series of biases. It is the intention of this study to utilize data acquired in traditional, anthropological studies of farmers, and to employ novel, big data analytics to enrich our current understanding and to question the validity of this as a tool for supporting qualitative analysis.

Qualitative studies currently depend on several levels of data; including the textual content that the respondent relays, and the researcher’s interpretation of the social dynamic (i.e. respondent body language or emotion) either in the field or from a recording, to name just two. Sentiment analysis is a well-established discipline that attempts to systematically identify, extract, quantify and study affective states and subjective information (Chakriswaran et al., 2019). Scientists in this field are increasingly using Natural Language Processing (NLP); a branch of machine learning which deals with textual and audio data. By modeling a computer program to automate the time-consuming process of qualitative data analysis, NLP algorithms may assist in overcoming many of the barriers that have curtailed the impact of anthropological work in the past. NLP incorporates a number of other tasks but in this case we will be investigating usage of automated sentiment analysis and emotion recognition as part of the emerging field known as affective computing (Uluocak, 2019).

By standardizing and quantifying what has come to be described as ‘thick data’, NLP algorithms can harness the tools often used in big data, supplementing qualitative datasets, at little extra cost. This has become popular within customer service improvement or in analyzing social media, where extensive datasets exist and are constantly growing. In agriculture, there is also an abundance of data with which to experiment and train new techniques. This is of particular significance as travel restrictions hinder in person research and telephone surveys play a larger role in socio-economic research. With the help of these tools, designers and developers may more easily implement targeted data driven interventions.

Further, the introduction of computers can assist in overcoming fundamental flaws in anthropological studies. For example, when dealing with sensitive themes such as gender empowerment, certain elements of the interviews can be obscured by the participant or go unnoticed by the researcher. This is particularly true for those working only from textual data. Employing NLP with audio data can measure and standardize elements of speech and intonation, enriching findings with an affective understanding of the participants demeanor. Equally, this may become an additional tool for anthropologists to maintain consistency in their analysis, which can be easily skewed based on political bias or lack of objectivity when processing data. Many of these can still, however, be carried over into the algorithm.

It must be recognized that computational analyses are not inherently objective and that they are only as unbiased as their creators and the data upon which their models are trained (Dourish and Gómez Cruz, 2018). For example, language and intonation are of great concern, which are 'systematically different for different socio-cultural groups' (Mohammad, 2020). Audio emotion recognition remains novel in our field of study and, therefore, few training datasets exist that can be considered ideal for this kind of analysis. There are further considerations regarding quality of recording, translation and transcription, as we will explore later in this paper. We hope our study can contribute to the literature by introducing these tools to the field of agricultural socio-economics and development anthropology, and drawing attention to some of the limitations to be overcome if this methodology is to mature. We envision this discussion paper as the first step in outlining a robust methodology for dealing with issues of gender in impoverished rural communities and, in recognising the sensitivity of such data and the necessity for scientific rigour, going forward we hope to motivate a long body of work harnessing the power of these technologies for farmers.

In light of the above, the following research questions have been formulated:

- **Can these tools for emotion and sentiment analysis be applied to qualitative farmer interview data and what comparisons and connections can be drawn between traditional, text and audio analysis?**
- **What limitations must be considered for future traditional, text and audio analyses and interventions?**

The following sections of this paper will first explore existing literature in affective computing, its definition and relationship with agriculture. Then, the methodological approach is explained, including training, and testing data. The results section visualizes the different approaches taken and finally, the discussion and conclusions reflect on the potential ethical biases and practical implications of the study and future research.

2. Affective computing

According to Taverner et al., (2019), affective computing is 'the area of computing related to the recognition, processing and simulation of different affective characteristics including emotions, personality or mood' (Poria et al., 2018). Each sound has its own 'language and structure' (Chaudhuri, 2011) which digital analytic tools are increasingly effective at reading. The discipline attempts to draw out information from a range of data sources, be it visual, textual or audio. Data can be extracted anywhere from traditional interviews to internet blogs. Sentiment analysis is particularly popular, with frequency of articles being published rapidly increasing over the last ten years (Kucher et al., 2018).

Sentiment is concerned with detecting specifically attitudes at the level of words, utterances and complete documents (Kucher et al., 2018). It is generally measured by a value between -1 and 1, indicating negative to neutral to positive sentiment. Sentiment analysis is said to determine the exactness of the underlying emotion in the context which enables machines to understand these emotions more accurately (Chakriswaran et al., 2019). Sentiment analysis, according to Wang et al., (2018), is focused on 'people's opinions, sentiments, evaluation, appraisals, attitudes, and emotions towards entities such as products, services, organizations, individuals, issues, events, topics, and their attributes'. As such, it is frequently used in areas such as marketing. In such circumstances documents, users, videos can be assigned a sentimental weight, statistically compared and categorized (Parmar et al., 2018).

Emotion, in contrast, is considerably more expansive in definition and measurement. Emotion is considered the most difficult concept to define in psychology (Kerkeni et al., 2019). While there is little consensus within the scientific community, Kerkeni et al., (2019) state that studies generally draw toward 'temperament, mood, personality, motivation, and disposition'. Taverner et al., (2019) argue an emotion can be defined as a rapid response to a given stimulus. The significance of context is evident here, showing how emotions are motivational states with the specific role of adapting to situational conditions (Nnamso et al., 2019). Significantly, emotions depend on language and culture (Taverner et al., 2019) although there are few papers that take this into account.

Emotions convey considerable information about the mental state of an individual (Kerkeni et al., 2019). Several challenges have been to extract emotions by examining explicit (linguistic) and implicit messages (paralinguistic) (Kaur and Kautish, 2019) from human subjects. Kerkeni et al., (2019) argue that feature extraction is the most difficult part of speech emotion recognition with the variety of methodologies on offer; 'emotion information, such as energy, pitch, formant frequency, Linear Prediction Cepstrum Coefficients, Mel-frequency cepstrum coefficients, and modulation spectral features' (Poria et al., 2017). Nnamso et al., (2019) argue that speech features, when applied appropriately, can be good enough to recognize emotion and even discriminate between languages accurately. Furthermore, multimodal streams are recommended, triangulating text with audio cues.

Despite these discrepancies, most studies tend to draw toward the same model of emotion classification (Kerkeni et al., 2019; López-Gil and Garay-Vitoria, 2019). Ekman (1997) in the 1970s found evidence that humans share six basic emotions: happiness, sadness, fear, anger, disgust, and surprise with the additional neutral state. The theory states that each event that can be detected by a human being produces an associated emotion, each of which have a universal meaning, irrespective of language. Each emotion acts as a discrete category rather than an individual emotional state. While there are alternative, constructivist theories of emotion, which take a contextual approach rooted in language and culture (Mourad and Darwish, 2013; Taverner et al., 2019), Ekman's model is among the most widely practiced. Several start-ups and industry specialists offer a variety of business services regarding emotion and sentiment built on this model (Kolog et al., 2018; Oord et al., 2016).

Aside from feature selection, Kerkeni et al., (2019) argue there are two more key actions to understand these classifications and sentiments; choice of a good emotional database and designing reliable classifiers using machine learning algorithms. Poria et al., (2017) present the breadth of available databases for textual, visual and audio emotion recognition and sentiment analysis. Two types of datasets are utilized for preparing the classifier: subjective information and unbiased information (Chakriswaran et al., 2019). Unbiased representations of emotional states are performed by actors which are used to train models to be applied on a chosen real-world dataset.

Choice of machine learning algorithm is broad, with a wealth of literature presenting different possibilities. Noteworthy mentions include fuzzy logic, a classifier known for appreciating 'vagueness', that is adapted to the cultural environment in which the agent is located and can be easily adapted to other languages (Taverner et al., 2021). Many papers employ convolutional neural network as an ideal methodology (Anand, 2015; Cai et al., 2019; Kansizoglou et al., 2019; Sukanya and Sunny, 2019; Xu et al., 2019). Figure 1 below show an 'extreme learning machine' based on a deep neural network from Han et al., (2014). The images clearly demonstrate an approach to algorithm building for speech emotion recognition, from input to output. Authors claim this is the most easily accessible, affectively rich and accurate form of input data (Kerkeni et al., 2019; Poria et al., 2018).

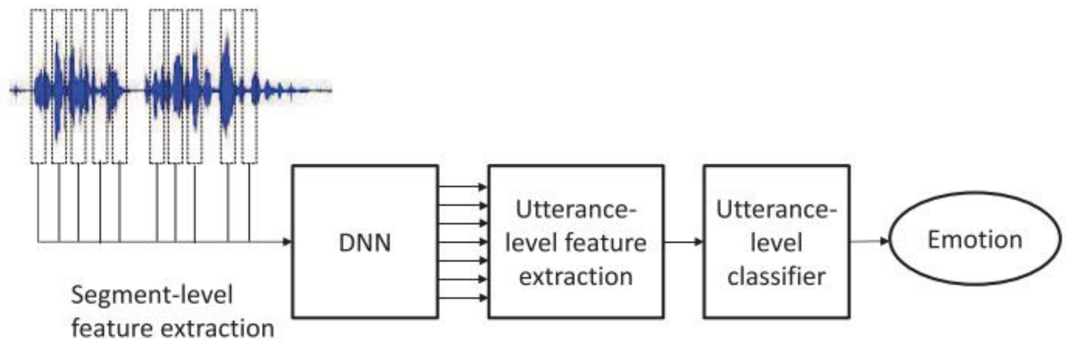

Figure 1: Deep Neural Network Data Analysis Framework (Han et al.,2014)

In this novel field most of the literature remains methodological in its' contributions but this is beginning to change (Issa et al., 2020). Some studies seek to take advantage of the increasing number of farmers with access to telecommunications. They have collected data (Godambe and Samudravijaya, 2011) and developed tools (Mohan et al., 2014) for recognising agricultural words in speech to respond to farmers queries in real time. This offers great benefit, where farmers indicate the majority of their support either comes from peers or the television / radio (Ali et al., 2016). Yadava and Jayanna(2017) and then Pai et al., (2019) trained to the Kannada language of India, designing a personalised tool for an isolated region that was able to identify farmer queries. Xu et al., (2018) developed a model for collecting agricultural price information in Mandarin. In each case, automated information provision on demand is a potentially revolutionary tool for smallholders (Imran and Kopparapu, 2011; Mantena et al., 2011; Shrishrimal, 2014).

In regard to emotion recognition, Pengnate and Riggins (2020) perform an analysis of peer to peer microfinance loan applications in online environments. Where previous studies have focused on quantitative aspects, machine learning has allowed observation of affective notions of funding success, including spelling, grammar, cognitive complexity and coherence. Kumar and Sharma (2020) propose a 'socio-sentic framework for sustainable agricultural governance', using opinion mining from twitter to assist in developing policy and transparency in India. They were able to harvest and accurately classify tweets in real time. Rulong and Min (2020) have used emotion recognition in price appraisal of agricultural commodities. Gender researchers have used such analyses to reveal how female science interpreters are received in YouTube, generating more comments with higher levels of 'hostile, critical/negative and sexist/sexual commentary', leading to fewer women taking part in this environment (Amarasekara and Grant, 2019).

The study of affect in agriculture is varied and profound and their influence is only just beginning to be felt. In their study of Irish farmers, Hayden, Mattimoe, & Jack (2021) revealed a deep identity-driven, emotional facet to farmer motivations. Many from their sample made decisions based on their love of farming, succession planning, pride, status and ‘access or right of way’. Glover & Touboulic (2020) emphasize this affective dimension, demonstrating how emotional reactions reflect the agency of a subject, ‘rehumanizing’ their role in processes of organizational change. The study of affect reveals modes by which actors come to understand and embed change into their lived experience. Where conventional analysis of farmers has envisioned a passive subject (Jones-Garcia and Krishna, 2021), emotion accounts for how farmers can assert their own influence and adapt a given narrative.

This study is an exploration into the application of affective computing on an existing analysis of qualitative data, to test its accuracy and to determine what additional conclusions can be made. It is envisioned that by combining these fields of study, future qualitative studies of smallholder farmers can be supported by automated sentiment analysis and emotion recognition, overcoming certain research biases, and centralizing a human-emotional dimension in research.

3. Methodology

3.1. Sample

The data to be examined in this document is taken from the Sustainable Intensification of Maize Legume systems in Eastern and South Africa (SIMLESA) project, led by the International Maize and Wheat Research Center (CIMMYT).

325 qualitative semi-structured interviews were conducted in 85 communities across 20 case study locations in 6 countries (Ethiopia, Kenya, Uganda, Malawi, Zambia and Mozambique). There were 179 interviews with farmers, 7 of which were also community leaders but for the sake of this analysis will be treated as farmers as their primary identity, and 146 with other stakeholders. Case study locations were purposely selected due to the importance of conservation agriculture (CA) systems for farmer livelihoods and subsequent high potential for impact, as well as for having promotional activities currently active in the district. CA is a farming approach generally consisting of crop rotations, minimum tillage and crop residue, in this case focused around maize-legume intercropping (Brown et al., 2017a). Adoption of agricultural practice is frequently criticized for reducing decisions to a binary variable. To mitigate this the process of agricultural utilization framework (Brown et al., 2017b) was used. As such, it should be noted that this work is not intended to provide a representative sample of communities, but specifically seeks a diversity of stakeholder perspectives. Farmers were categorized into 4 types:

1. "Negative evaluation" (35) were farmers with a negative opinion toward CA. These were both dis-interested and dis-adopter farmers. That is they have trialed the technology and are closed to further experimentation, the first having received sufficient training and the second simply choosing to cease practice on all plots (see Brown, 2017).
2. "Unexposed" (29) were farmers who had not yet experimented with CA (see Brown et al., 2018a).
3. "Progression" (58) farmers were those with positive experiences, looking to increase their use of CA (see Brown et al., 2019a).
4. "Toward Full" (57) were farmers that used CA on the majority of their land (see Brown et al., 2019b).

Other stakeholders were:

1. “Extension workers” (29), respondents involved in provision of agricultural extension in the explored communities (see Brown et al., 2018c)
2. “Community leaders” (49), elected or culturally appointed leaders with the communities investigated (see Brown et al., 2018d)
3. “Local researchers” (28), scientists in charge of research activities through state and national and international research institutions (see Brown et al., 2018b)

3.2. Data Analysis - Text

All interviews were conducted by a single interviewer and where local languages were used, there was a different translator dependent on location and language needs. The same person transcribed all English interviews, reducing bias of multiple translators and transcribers. In total, a further 17 transcribers were used. English transcripts were standardized, cleaned and structured with questions written in bold font for easy recognition by the computer model. The analysis was completed using R and the “Syuzhet” package, produced by Jockers (2020). This software is capable of recognizing the unique text necessary for analysis and then, using the NRC Emotion Lexicon, classify the proportion of words and phrases that indicate certain emotions and sentiments. The scores were gathered for each interview and then comparisons were made with the socio-economic characteristics of each farmer and the categories generated from the original research.

The NRC Emotion Lexicon is a list of English words and their associations with two sentiments (negative and positive) and eight basic emotions (anger, fear, anticipation, trust, surprise, sadness, joy, and disgust), Ekman's (1970) original six plus an additional two emotions identified by Plutchik (1991). The annotations were manually done by crowdsourcing via Amazon's Mechanical Turk service. Through a series of questions, annotators assigned an emotion to words and phrases identified with the Macquarie Thesaurus (Bernard, 1986), the General Inquirer (Stone, Philip J., Dunphi Dexter C., Smith S. Marshall, 1966) and the WordNet Affect Lexicon (Strapparava and Valitutti, n.d.). In total, 10170 words and phrases were iteratively identified. All words have an additional sentiment score between 1 and 0 (Mohammad and Turney, 2013). The lexicon was the first for word-emotion association and is now available in several languages. While earlier lexicons focused on words that denotate emotion, this work included the larger set of words that are associated with or connotate an emotion. Careful attention was paid to ensure appropriate annotations, including the use of separate word choice questions to make sure annotators knew the word and to guide them to the desired sense of the word for which annotations were solicited.

3.3. Data Analysis - Audio

For audio analysis, while there is a wealth of training data to be used, there is still no standard package in R or Python which provides an approach to emotion recognition. Therefore, for this analysis, a model was trained on separate datasets, based on the work of several GitHub users (Baram, 2021; Chu, 2019; De Pinto et al., 2020; Delta, 2020; Giannakopoulos, 2015; Han et al., n.d.; Nikhil, 2019; Rockikz, 2020). As such, all tools are open source and are accompanied with instructions on how to use them. The choice to use open source tools was deliberate in order to demonstrate the accessibility and support offered by the online research community.

The 3 training datasets are listed below. We want to point out the western nature of these training sets. Using these training sets is a possible limitation of the study that needs further exploration.

- RAVDESS: The Ryson Audio-Visual Database of Emotional Speech and Song that contains 24 actors (12 male, 12 female), vocalizing two lexically-matched statements in a neutral North American accent (Livingstone and Russo, 2018).
- TESS: Toronto Emotional Speech Set that was modeled on the Northwestern University Auditory Test No. 6 (NU-6; Tillman & Carhart, 1966). A set of 200 target words were spoken in the carrier phrase "Say the word _____' by two actresses (aged 26 and 64 years).
- EMO-DB: As a part of the DFG funded research project SE462/3-1 in 1997 and 1999 a database of emotional utterances spoken by actors was recorded. The recordings took place in the anechoic chamber of the Technical University Berlin, department of Technical Acoustics.

Feature extraction was completed via the 'Librosa' Python package (McFee et al., 2015), converting speech wave form into a form of parametric data with a lesser rate, employing MFCC and Chroma as speech features.

- Mel Spectrogram: remaps the values in hertz to the mel scale. It logarithmically renders frequencies above a certain threshold (the corner frequency) and computes its output by multiplying frequency-domain values by a filter bank.
- MFCC: Mel-frequency cepstral coefficients, a representation of the

short-term power spectrum of a sound, based on a linear cosine transform of a log power spectrum on a nonlinear mel-scale of frequency.

- Chroma: class profiles for categorized pitch.

In order to balance accuracy with output data, 6 emotions of the available 8 emotions were selected. Those were anger, sadness, happiness, disgust, surprise and fear so that comparisons could be drawn with the textual analysis. Other available emotions, neutral and calm, were not selected as they do not run parallel with the emotions in the text analysis. The model was a recurrent, deep neural network, with 2 layers that contains 128 units, batch size of 64 and 100 epochs (Rockikz, 2020). The trained model achieved an accuracy of over 75% classifying emotion on the validation test set. Raw interview files were formatted for use in Python, reducing the hertz level and number of channels, then the model was applied to each to achieve the results found below.

4. Results

4.1. Text

The text analysis is presented first. The use of words corresponding to emotions is consistent across farmer categories, with anticipation followed by trust, joy, fear, sadness, anger and surprise. This was also consistent for all other comparisons made (see Appendix) with the exception of trust and anticipation. For each category, more than 20% of the words are related to anticipation or trust. An ANOVA of Anticipation was significantly different in distribution across farmer type, with progressive farmers ahead of others

.

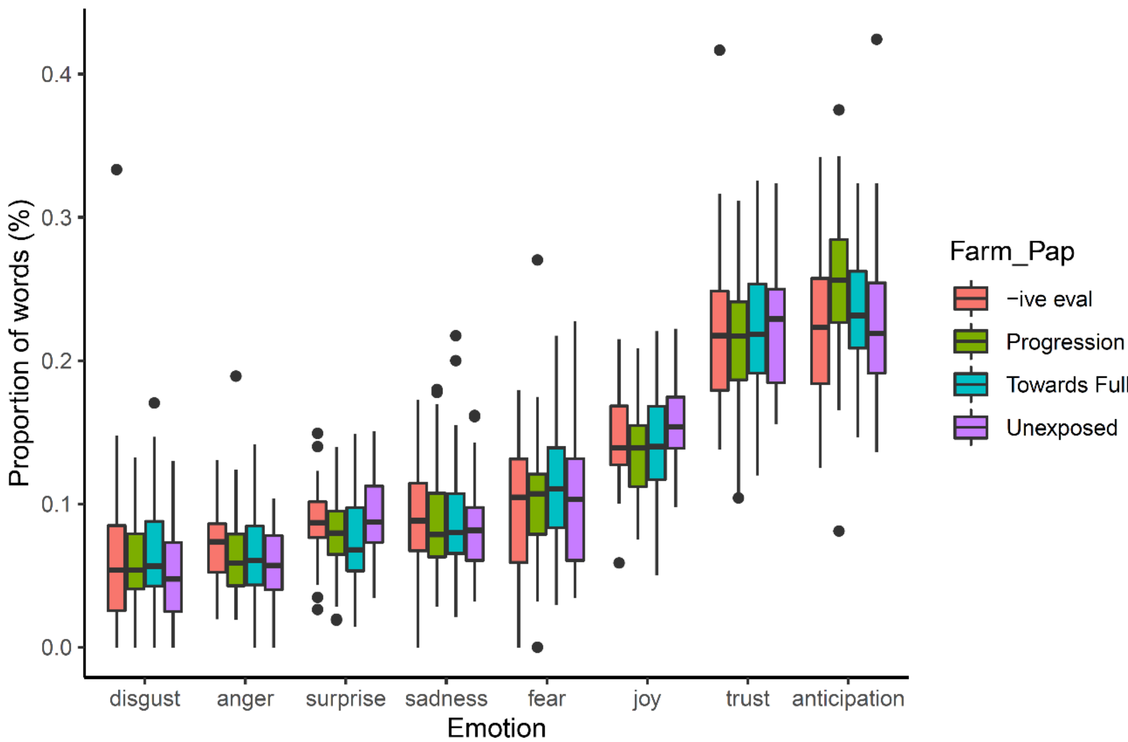

Figure 2: Farmer group and emotional response text analysis. Note: "-ive" stands for "negative evaluation".

Table 1: ANOVA of emotion by category text analysis

variable	DFd	F	p	p<.05
anger	175	1.230	0.300	
anticipation	175	4.083	0.008	*
disgust	175	0.882	0.452	
fear	175	1.012	0.389	
joy	175	2.220	0.088	
sadness	175	0.097	0.962	
surprise	175	2.332	0.076	
trust	175	0.368	0.776	

Sentiment was positive in all cases, with an average split of 67% positive and 33% negative words. Countries are the most diverse in terms of sentiment and emotion, as in Figure 3, with Mozambique showing a much higher rate of positive responses and Ethiopia the reverse. As mentioned above, this may be due to distribution of categories, with 60% of farmers interviewed in Mozambique expressing a progressive approach to technology, and 40% of Ethiopians negative.

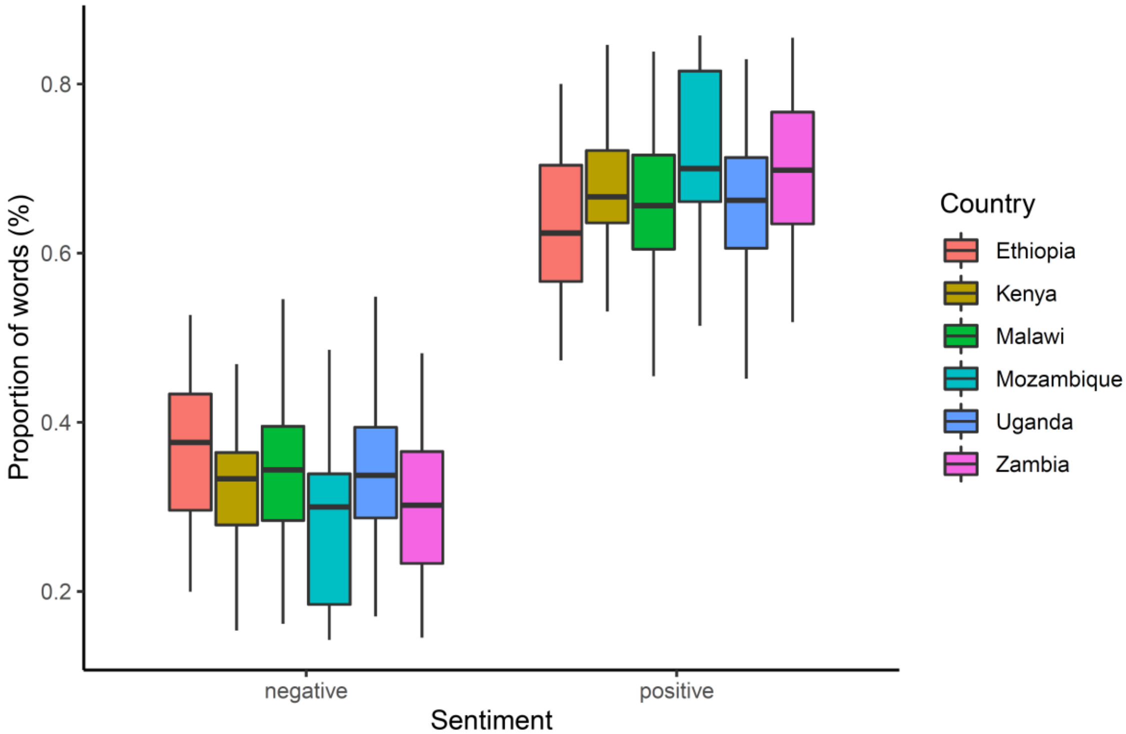

Figure 3: Country and sentiment text analysis

Table 2: Distribution of farmer category per country

	-ive eval	Progression	Towards Full	Unexposed
Ethiopia	0.41	0.36	0.14	0.09
Kenya	0.17	0.30	0.37	0.17
Malawi	0.17	0.33	0.35	0.15
Mozambique	0.05	0.63	0.26	0.05
Uganda	0.21	0.17	0.17	0.46
Zambia	0.21	0.21	0.54	0.04

4.2. Audio

The order in which the emotions are distributed is significantly different between text and audio analyses. In Figure 4 fear and disgust are the highest emotions whereas in text happiness/joy is higher. Despite this the actual distribution within emotions is very similar, for example, surprise, happiness/joy and sadness.

Figures 4 and 5 are a comparison between all farmers in the sample and those who are English speakers. This is intended to demonstrate and mitigate the potential biases that can occur when using data trained on English speakers. In Figure 4 the results meet expectations, for example, unexposed farmers are estimated as expressing greater surprise and fully adopted farmers the least. In Figure 5 these differences are more distinct, with the addition of a much lower mean value for negative evaluators.

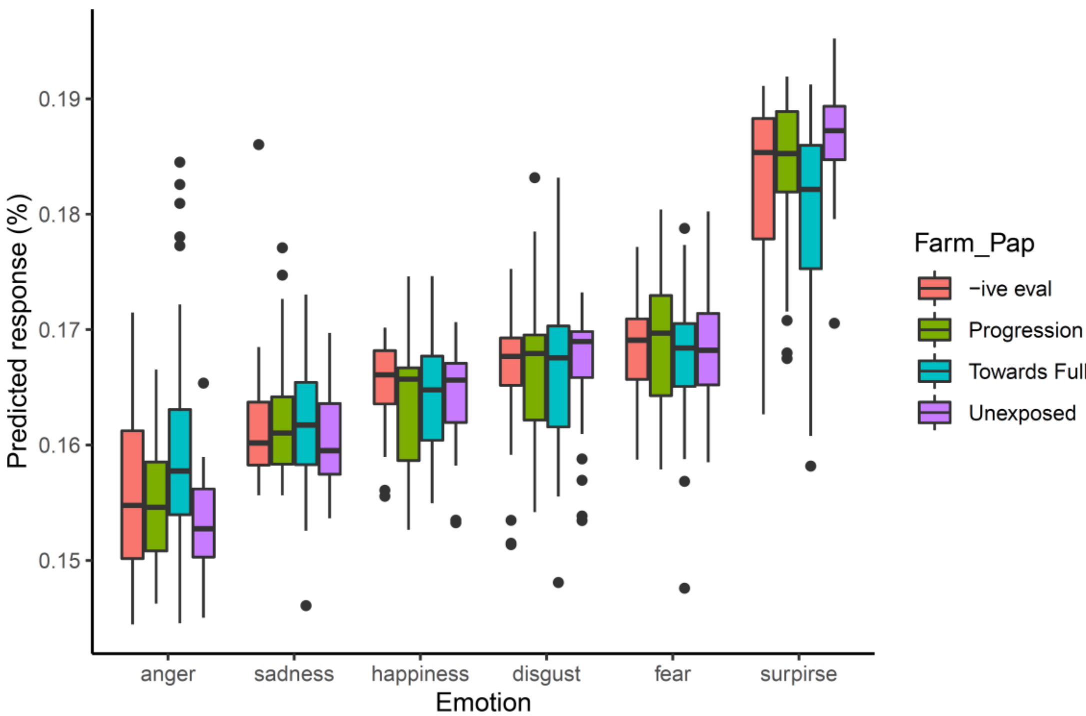

Figure 4: Farmer group and emotional response audio analysis. Note: “-ive” stands for “negative evaluation”.

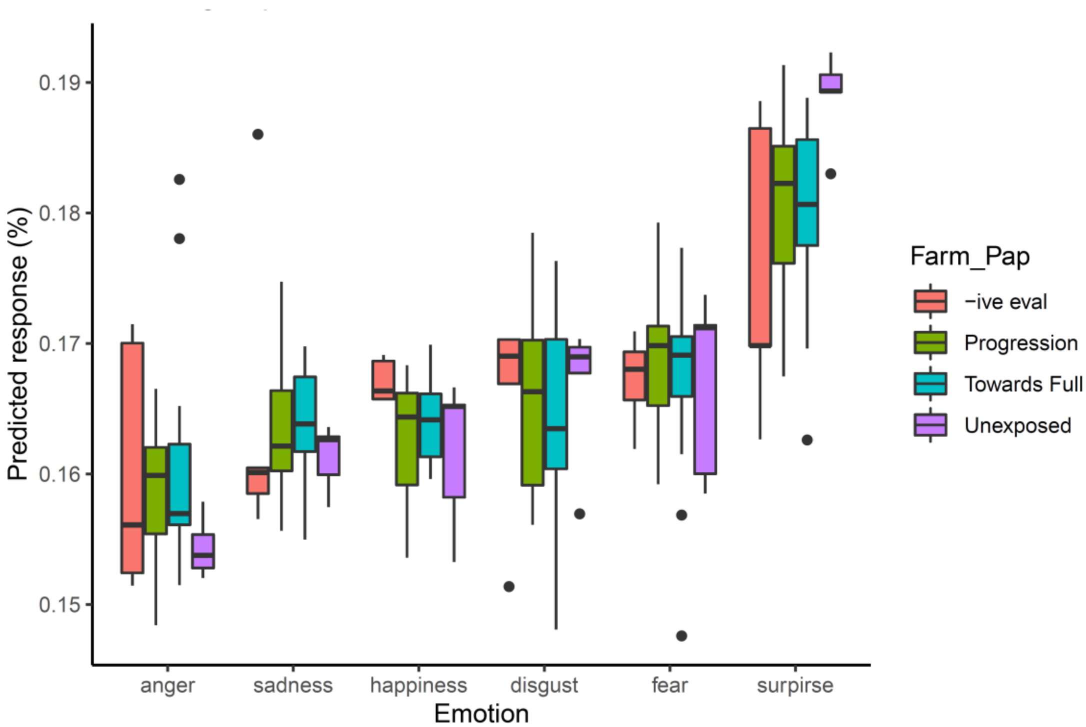

Figure 5: English speaking, farmer group and emotional response audio analysis Note: "-ive" stands for "negative evaluation".

Figure 6 shows the difference in predicted audio emotion response between English speaking male and female farmers. Male farmers express greater anger whereas female farmers are estimated to express greater surprise and sadness. These results are consistent with the text analysis and non-English speakers, with particular reference to the high distribution with the lower quartile of fear in female farmers.

Finally, Figure 7 displays correlations between audio and text output for each interview. Anger has a positive correlation, indicating similar results, whereas, Joy/happiness is negative.

In the appendix additional Figures with results from the analysis are presented without further narrative.

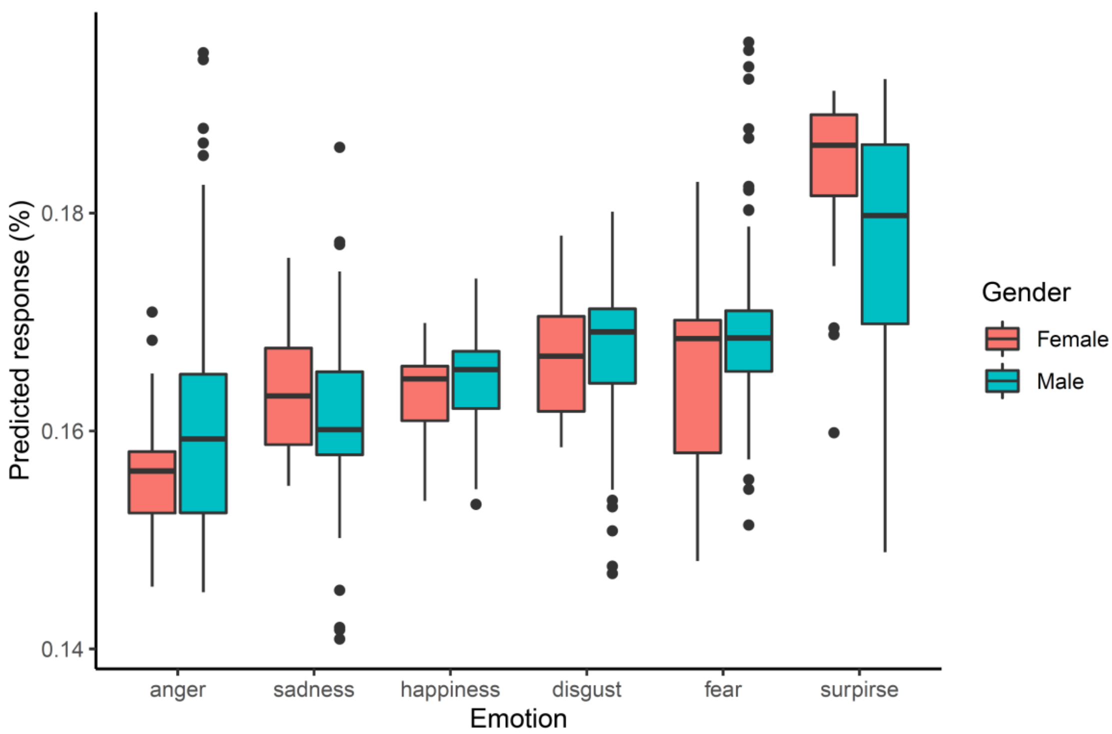

Figure 6: English speaking, farmer gender and emotional response audio analysis

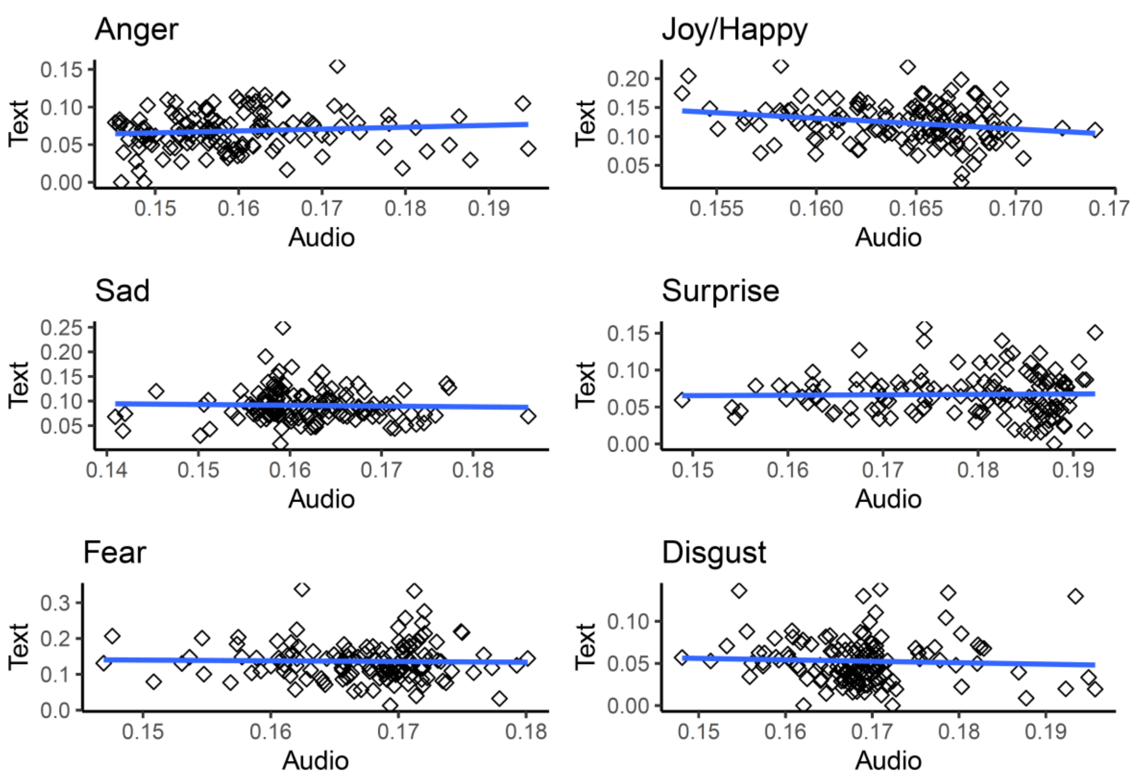

Figure 7: Audio and text analysis

5. Discussion

In the application of text and audio emotion classification and sentiment analysis, this paper has set out to test the viability of these tools in farmer interviews and what steps are necessary to make these tools reliable and accessible to researchers. The results section presents certain points where the traditional, text and audio analysis converge, which are exacerbated by biases within the sampling data. For example, in Figure 3, where Ethiopia, the country with the most negative evaluators has the most negative sentiment, and the opposite for Mozambique. While this reveals a limitation in the dataset, which was acknowledged to be unbalanced, it does speak to the accuracy of the tool. Similar expectations were met in category and emotional reaction, for example, progressive farmers using the greatest amount of anticipation words in Figure 2, and Unexposed farmers showing the greatest amount of surprise in Figures 2, 4 and 5. Unexpected but interesting results include the lower level of fear among female farmers throughout each analysis.

There is, however, little correlation between the different outputs as seen in Figure 7. In terms of drawing further insight from this data and identifying potential biases, we can already see that results are different between audio and text. These differences do not necessarily speak to the audio analysis being incorrect, these inconsistencies could equally be due to the unreliability of determining emotion from raw text when it can be more obvious in speech and intonation. For example, the participant could be describing something very sad in an ironic or joyful way, which is culturally defined. This is evidenced in the similarities between emotions according to dependent variable, for example, the distribution of joy, sadness and surprise between farmer category is very similar, however, the text and audio analyses read these in different magnitudes.

This difference could be related to the metrics used, for example, having fewer emotions to test for and leading to varying distributions, however, it is equally valid that certain emotions are more easily or better represented in intonation and speech than words chosen. In this regard, while surprise, joy and sadness remain similar, the audio might be more sensitive to anger, disgust and fear. Figure 5 evidences this by meeting expectations in the anger held by negative evaluating farmers and the breadth of fear in unexposed farmers.

The analysis indicates that certain emotions do not come across in text as they do in audio, which makes it even more important for offering new information. There are several biases, however, that need to be overcome in order to put this methodology into practice. To begin, the text lexicon alone has been critiqued for giving words meaning by aggregate and, therefore, lesser-known interpretations which are not necessarily wrong are nonetheless excluded. Alternatively, certain characteristics are overly attributed to certain demographics (Mohammad, 2020). In this case, the transcriptions and translations for each interview were conducted by different individuals and it is possible that certain terms were open to interpretation. Translators potentially introduced their own cultural biases, for example, writing words they associated with women and different words for men.

As mentioned previously, a sampling bias meant that selection of farmer categories is more concentrated in certain countries. We have attempted to balance this by reflecting on various levels of aggregation, for example, community and language group. As can be seen in the appendices, this revealed much greater diversity within regions that did not reflect the country level analysis.

In terms of audio analysis, the model for recognizing emotion in speech is trained on

North American English language speakers. It is likely the accuracy of prediction will be limited by this on diverse language groups. We have included an analysis of just English speakers to attempt to manage this and found few differences within the aggregated outcomes. To combat this, models must be trained on local languages and labelled by those who understand the local culture. Heldert (2021) recognises this challenge, with smallholder communities in the global south frequently being multilingual, with several official, native and trade languages. The success of NLP in agriculture, however, hinges on investment to build models robust enough to deal with this linguistic diversity.

The large volume of transcribers and translators reflects the regional investigation across six countries and multiple language groups. On the one hand, this might be considered a gap in methodological approach that could be reduced though these methods. The biases of translation and transcription are difficult to determine and often are overlooked in qualitative studies. These tools can be used to unpack them but also the audio may act to standardize that data and make overarching conclusions beyond human interpretation. On the other, the critique can be extended further in to the choice of emotion frameworks (Ekman, 1970; Plutchik, 1991). We have attempted to engage with the ongoing debate between universal, basic and culturally defined emotional states by comparing English and non-English speakers, however, for many this will not go far enough, and it should be considered whether a bottom-up, constructivist approach might be applied. For example, not only might an emotion be expressed in a certain way, it may also be interpreted differently, and hence be described as something else (Mohammad and Turney, 2013).

Finally, the audio data contains speech from translators and enumerators alongside interviews, as well as background interference. Therefore, results may be less reliable than text, although these interferences are standard across all recordings. For future studies, recordings must be made with a level of quality and clarity to better suit this form of analysis.

Despite these limitations, this paper has managed to draw some insight and ambition for further research. We purposefully opted for a benign dataset in order to explore the possibilities of analysis and to identify what research is necessary to make this methodology to mature within socio-economics studies. We have uncovered useful information which is difficult to attain through traditional data collection techniques. Particularly for structured surveys but also, as shown here, for interview data. This comes at a critical time when phone surveys are becoming the standard form of data collection due to the ongoing effects of the COVID-19 pandemic. Surveys in this context are generally recorded and would not need additional review and may be able to enrich this impersonal form of collection with additional unexpected insights.

Looking ahead, automatic emotion classification and sentiment analysis may be able to support qualitative agricultural research and development in a number of ways. We have already mentioned speed of analysis, reduction of biases and aggregation of data for new and diverse insights, however, it also presents new avenues and opportunities for study. The added value of emotion for evaluation of technologies seen in this study not only gives an average indication of affective states produced in farmers' relationship with CA, it offers new and insightful research question, for example, how instrumental is emotion in determining a farmers' decision making? What intervening factors might undermine this? How might future interventions appeal to affective states and context to generate greater impact?

In particular, there are opportunities for experimenting with more sensitive data. As mentioned above, issues with gender and equality are currently considered top of the agenda in development circles. The data we have produced indicates a distinction between men and women in their affective response to technology evaluation. Therefore, how does this reflect the current assumptions of decision making in relation to gender equality? How might this reveal methods for empowering female farmers and better engaging them in extension activities? Further, how can the use of affective data be used to detect those things that may get left unsaid in the presence of a power imbalance? In these circumstances, this methodology might be able to reveal the most vulnerable farmers and, as such, those most in demand. NLP may be the next step in incorporating an affective sense of identity and agency in research, allowing for greater dynamism in targeted interventions.

6. Conclusions

In this discussion paper we have introduced the possibility of using affective computing methodologies, namely sentiment analysis and emotion recognition, into the field of agricultural socioeconomics and qualitative data analysis. We took a sample of 325 interviews from farmers and relevant stakeholders in Easter and Southern Africa and compared and contrasted the findings from traditional, text and audio analysis. Despite a series of limitations, we were able to show that each layer of analysis builds a greater understanding of the data and, by avoiding these in future research, studies may be able to incorporate these insights, particularly as remote research becomes standard practice during the COVID-19 pandemic. There is a need within international agricultural research for development to consider creating labeled audio emotion datasets to meet the demand for affective data with accurate and unbiased findings, to keep up with the surge forward in terms of big data driven research across the sciences and to strive to build interventions based on the best available data.

References

Ali, S., Durrani, H., Naeem, M., Riaz, W., & Shahid, S. (2016). Supporting Pakistani farmers through digital means: An exploratory study. Conference on Human Factors in Computing Systems - Proceedings, 07-12-May-, 2299–2305. https://doi.org/10.1145/2851581.2892527

Amarasekara, I., & Grant, W. J. (2019). Exploring the YouTube science communication gender gap: A sentiment analysis. Public Understanding of Science, 28(1), 68–84. https://doi.org/10.1177/0963662518786654

Anand, N. (2015). Convoluted Feelings Convolutional and recurrent nets for detecting emotion from audio data. 2–7. Retrieved from http://cs231n.stanford.edu/reports/2015/pdfs/Cs_231n_paper.pdf

Baram, T. (2021). GitHub - talbaram3192/Emotion_Recognition_project. Retrieved September 2, 2021, from Github website: https://github.com/talbaram3192/Emotion_Recognition_project

Bernard, J. R. L. (1986). The Macquarie thesaurus. 900.

Brown, B., Llewellyn, R., & Nuberg, I. (2018). Why do information gaps persist in African smallholder agriculture? Perspectives from farmers lacking exposure to conservation agriculture. Journal of Agricultural Education and Extension, 24(2), 191–208. https://doi.org/10.1080/1389224X.2018.1429283

Brown, B., Nuberg, I., & Llewellyn, R. (2017a). Negative evaluation of conservation agriculture: perspectives from African smallholder farmers. International Journal of Agricultural Sustainability, 15(4), 467–481. https://doi.org/10.1080/14735903.2017.1336051

Brown, B., Nuberg, I., & Llewellyn, R. (2017b). Stepwise frameworks for understanding the utilisation of Conservation agriculture in Africa. Agricultural Systems, 153, 11–22. https://doi.org/10.1016/j.agsy.2017.01.012

Brown, B., Nuberg, I., & Llewellyn, R. (2018a). Constraints to the utilisation of conservation agriculture in Africa as perceived by agricultural extension service providers. Land Use Policy, 73, 331–340. https://doi.org/10.1016/J.LANDUSEPOL.2018.02.009

Brown, B., Nuberg, I., & Llewellyn, R. (2018b). Further participatory adaptation is required for community leaders to champion conservation agriculture in Africa. International Journal of Agricultural Sustainabiltity, 16(3), 286–296. https://doi.org/10.1080/14735903.2018.1472410

Brown, B., Nuberg, I., & Llewellyn, R. (2019a). From interest to implementation: exploring farmer progression of conservation agriculture in Eastern and Southern Africa. Environment, Development and Sustainability 2019 22:4, 22(4), 3159–3177. https://doi.org/10.1007/S10668-019-00340-5

Brown, B., Nuberg, I., & Llewellyn, R. (2019b). Pathways to intensify the utilization of conservation agriculture by African smallholder farmers. Renewable Agriculture and Food Systems, 34(6), 558–570. https://doi.org/10.1017/S1742170518000108

Cai, L., Hu, Y., Dong, J., & Zhou, S. (2019). Audio-Textual Emotion Recognition Based on Improved Neural Networks. Mathematical Problems in Engineering, 2019. https://doi.org/10.1155/2019/2593036

Chakriswaran, P., Vincent, D. R., Srinivasan, K., Sharma, V., Chang, C. Y., & Reina, D. G. (2019). Emotion AI-driven sentiment analysis: A survey, future research directions, and open issues. Applied Sciences (Switzerland), 9(24). https://doi.org/10.3390/app9245462

Chaudhuri, S. (2011). Structured Models for Audio Content Analysis. Analysis. Retrieved from http://errico.srv.cs.cmu.edu/research/thesis/2013/cmulti13005.pdf

Chu, R. (2019). GitHub - rezachu/emotion_recognition_cnn. Retrieved September 2, 2021, from Github website: https://github.com/rezachu/emotion_recognition_cnn

De Pinto, M. G., Polignano, M., Lops, P., & Semeraro, G. (2020). Emotions Understanding Model from Spoken Language using Deep Neural Networks and Mel-Frequency Cepstral Coefficients. IEEE Conference on Evolving and Adaptive Intelligent Systems. https://doi.org/10.1109/EAIS48028.2020.9122698

Delta. (2020). GitHub - Delta-ML/delta: DELTA is a deep learning based natural language and speech processing platform. Retrieved September 2, 2021, from Github website: https://github.com/Delta-ML/delta#install-from-source-code

Dourish, P., & Gómez Cruz, E. (2018). Datafication and data fiction: Narrating data and narrating with data. Big Data and Society, 5(2), 1–10. https://doi.org/10.1177/2053951718784083

Ekman, P. (1997). Universal Facial Expressions of Emotion: An Old Controversy and New Findings. Nonverbal Communication: Where Nature Meets Culture, pp. 27–46. Retrieved from http://www.paulekman.com/wp-content/uploads/2009/02/Universal-Facial-Expressions-of-Emotions1.pdf

Ekman, Paul. (1970). Universal facial expressions of emotion. California Mental Health, Vol. 8, pp. 151–158.

Giannakopoulos, T. (2015). PyAudioAnalysis: An open-source python library for audio signal analysis. PLoS ONE, 10(12), 1–17. https://doi.org/10.1371/journal.pone.0144610

Glover, J., & Touboulic, A. (2020). Tales from the countryside: Unpacking “passing the environmental buck” as hypocritical practice in the food supply chain. Journal of Business Research, 121, 33–46. https://doi.org/10.1016/j.jbusres.2020.06.066

Godambe, T., & Samudravijaya, K. (2011). Speech Data Acquisition for Voice based Agricultural Information Retrieval. In Proceeding of 39th All India DLA Conference,Punjabi University,Patiala, India.

Han, K., Chen, J., Zhang, H., Xu, H., Peng, Y., Wang, Y., … Chuxing, D. (2019). DELTA A DEep learning based Language Technology plAtform. Retrieved from https://github.com/fxsjy/jieba

Han, K., Yu, D., & Tashev, I. (2014). Speech emotion recognition using deep neural network and extreme learning machine. Proceedings of the Annual Conference of the International Speech Communication Association, INTERSPEECH, (September), 223–227.

Hayden, M. T., Mattimoe, R., & Jack, L. (2021). Sensemaking and the influencing factors on farmer decision-making. Journal of Rural Studies, 84(February), 31–44. https://doi.org/10.1016/j.jrurstud.2021.03.007

Heldert, C. (2021). What Does AI mean for Smallholder farmers? A Proposal for Farmer-centred ai research. Angewandte Chemie International Edition, 6(11), 951–952.

Huang, Z., Dong, M., Mao, Q., & Zan, Y. (2014). Speech emotion recognition using CNN. MM ’14: Proceedings of the 22nd ACM International Conference on Multimedia. https://doi.org/https://doi.org/10.1145/2647868.2654984

Imran, A., & Kopparapu, S. K. (2011). Building a natural language Hindi speech interface to access market information. Proceedings - 2011 3rd National Conference on Computer Vision, Pattern Recognition, Image Processing and Graphics, NCVPRIPG 2011, 58–61. https://doi.org/10.1109/NCVPRIPG.2011.20

Issa, D., Fatih Demirci, M., & Yazici, A. (2020). Speech emotion recognition with deep convolutional neural networks. Biomedical Signal Processing and Control, 59, 101894. https://doi.org/10.1016/j.bspc.2020.101894

Jockers, M. (2020). Introduction to the Syuzhet Package. Retrieved September 2, 2021, from cran-r-project website: https://cran.r-project.org/web/packages/syuzhet/vignettes/syuzhet-vignette.html

Jones-Garcia, E., & Krishna, V. V. (2021). Farmer adoption of sustainable intensification technologies in the maize systems of the Global South. A review. Agronomy for Sustainable Development, 41(1), 8. https://doi.org/10.1007/s13593-020-00658-9

Kansizoglou, I., Bampis, L., & Gasteratos, A. (2019). An Active Learning Paradigm for Online Audio-Visual Emotion Recognition. IEEE Transactions on Affective Computing. https://doi.org/10.1109/TAFFC.2019.2961089

Kaur, R., & Kautish, S. (2019). Multimodal sentiment analysis: A survey and comparison. International Journal of Service Science, Management, Engineering, and Technology, 10(2), 38–58. https://doi.org/10.4018/IJSSMET.2019040103

Kerkeni, L., Serrestou, Y., Mbarki, M., Raoof, K., Mahjoub, M. A., & Cleder, C. (2019). Automatic Speech Emotion Recognition Using Machine Learning. Social Media and Machine Learning, 32, 137–144. Retrieved from http://www.intechopen.com/books/trends-in-telecommunications-technologies/gps-total-electron-content-tec- prediction-at-ionosphere-layer-over-the-equatorial-region%0AInTec

Kolog, E. A., Montero, C. S., & Tukiainen, M. (2018). Development and Evaluation of an Automated e-Counselling System for Emotion and Sentiment Analysis. The Electronic Journal Information Systems Evaluation, 21(1), 1–19. Retrieved from www.ejise.com

Kucher, K., Paradis, C., & Kerren, A. (2018). The state of the art in sentiment visualization. Computer Graphics Forum, 37(1), 71–96. https://doi.org/10.1111/cgf.13217

Kumar, A., & Sharma, A. (2020). Socio-Sentic framework for sustainable agricultural governance. Sustainable Computing: Informatics and Systems, 28, 100274. https://doi.org/10.1016/j.suscom.2018.08.006

Livingstone, S. R., & Russo, F. A. (2018). The Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS): A dynamic, multimodal set of facial and vocal expressions in North American English. PLoS ONE, 5(13). https://doi.org/https://doi.org/10.1371/journal. pone.0196391 Editor:

López-Gil, J. M., & Garay-Vitoria, N. (2019). Emotion recognition in video and audio through the use of Artificial Intelligence techniques. ACM International Conference Proceeding Series. https://doi.org/10.1145/3335595.3335619

Mantena, G. V., Rajendran, S., Rambabu, B., Gangashetty, S. V., Yegnanarayana, B., & Prahallad, K. (2011). A speech-based conversation system for accessing agriculture commodity prices in Indian languages. 2011 Joint Workshop on Hands-Free Speech Communication and Microphone Arrays, HSCMA’11, 153–154. https://doi.org/10.1109/HSCMA.2011.5942384

McFee, B., Raffel, C., Liang, D., Ellis, D., McVicar, M., Battenburg, E., & Nieto, O. (2015). librosa: Audio and music signal analysis in python. Retrieved September 2, 2021, from Proceedings of the 14th python in science conference website: https://librosa.org/doc/latest/index.html

Mohammad, S. M. (2020). Practical and Ethical Considerations in the Effective use of Emotion and Sentiment Lexicons. Retrieved from http://arxiv.org/abs/2011.03492

Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word-emotion association lexicon. Computational Intelligence, 29(3), 436–465. https://doi.org/10.1111/j.1467-8640.2012.00460.x

Mohan, A., Rose, R., Ghalehjegh, S. H., & Umesh, S. (2014). Acoustic modelling for speech recognition in Indian languages in an agricultural commodities task domain. Speech Communication, 56(1), 167–180. https://doi.org/10.1016/j.specom.2013.07.005

Mourad, A., & Darwish, K. (2013). Subjectivity and Sentiment Analysis of Modern Standard Arabic and Arabic Microblogs. Proceedings of the 4th Workshop on Computational Approaches to Subjectivity, Sentiment and Social Media Analysis, (3), 55–64.

Nikhil, M. (2019). GitHub - maheshwari-nikhil/emotion-recognition. Retrieved September 2, 2021, from Github website: https://github.com/maheshwari-nikhil/emotion-recognition

Nnamso, U. M., Nwokoro, C., Oyong, S. B., Ejodamen, P., Asuquo, S. L., Ekong, E. E., & Ekpenyong, M. E. (2019). Speech Emotion Classification of African Tone Languages. (November 2017).

Oord, A. van den, Dieleman, S., Zen, H., Simonyan, K., Vinyals, O., Graves, A., … Kavukcuoglu, K. (2016). WaveNet: A Generative Model for Raw Audio. 1–15. Retrieved from http://arxiv.org/abs/1609.03499

Pai, A., Of, D., & Hegde, S. (2019). Study on Machine Learning for Identification of Farmer's Query in Kannada Language. International Journal of Computer Applications, 178(19), 40–47. https://doi.org/10.5120/ijca2019919017

Parmar, M., Maturi, B., Dutt, J. M., & Phate, H. (2018). Sentiment Analysis on Interview Transcripts: An application of NLP for Quantitative Analysis. 2018 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2018, 1063–1068. https://doi.org/10.1109/ICACCI.2018.8554498

Pengnate, S. (Fone), & Riggins, F. J. (2020). The role of emotion in P2P microfinance funding: A sentiment analysis approach. International Journal of Information Management, 54. https://doi.org/10.1016/j.ijinfomgt.2020.102138

Plutchik, R. (1991). The Emotions, Revised Edition. 216. Retrieved from https://books.google.com/books/about/The_Emotions.html?id=JaQauznPoiEC

Poria, S., Cambria, E., Bajpai, R., & Hussain, A. (2017). A review of affective computing: From unimodal analysis to multimodal fusion. Information Fusion, 37, 98–125. https://doi.org/10.1016/j.inffus.2017.02.003

Poria, S., Majumder, N., Hazarika, D., Cambria, E., Gelbukh, A., & Hussain, A. (2018). Multimodal Sentiment Analysis: Addressing Key Issues and Setting Up the Baselines. IEEE Intelligent Systems, 33(6), 17–25. https://doi.org/10.1109/MIS.2018.2882362

Rockikz, A. (2020). pythoncode-tutorials/machine-learning/speech-emotion-recognition at master · x4nth055/pythoncode-tutorials · GitHub. Retrieved September 2, 2021, from Github website:

https://github.com/x4nth055/pythoncode-tutorials/tree/master/machine-learning/speech-emotion-recognition

Rulong, C., & Min, L. (2020). Agricultural Commodity Recommendation based on Emotion Analysis. 2020 International Conference on Internet of Things and Intelligent Applications, ITIA 2020, 10–13. https://doi.org/10.1109/ITIA50152.2020.9312324

Shrishrimal, P. P. (2014). Marathi Isolated Words Speech Database for Agriculture Purpose. 3(3). https://doi.org/https://www.researchgate.net/publication/262793622 Marathi

Stone, P. J., Dunphi, D. C., Smith, S. M., & Olgilvie, D. M. (1966). General Inquirer: A Computer Approach to Content Analsis. In The MIT Press.

Strapparava, C., & Valitutti, A. (2004). WordNet-Affect: an Affective Extension of WordNet. Retrieved from http://openmind.media.mit.edu

Taverner, Joaquin, Vivancos, E., & Botti, V. (2021). A fuzzy appraisal model for affective agents adapted to cultural environments using the pleasure and arousal dimensions. Information Sciences, 546, 74–86. https://doi.org/10.1016/j.ins.2020.08.006

Taverner, Joaquín, Vivancos, E., & Botti, V. (2019). Towards a computational approach to emotion elicitation in affective agents. ICAART 2019 - Proceedings of the 11th International Conference on Agents and Artificial Intelligence, 1(Icaart), 275–280. https://doi.org/10.5220/0007579302750280

Uluocak, A. (2019). Speech Emotion Recognition in Continuous Space by Using Machine Learning. Retrieved from http://arno.uvt.nl/show.cgi?fid=149448

Wang, Y., Rao, Y., & Wu, L. (2018). A Review of Sentiment Semantic Analysis Technology and Progress. Proceedings - 13th International Conference on Computational Intelligence and Security, CIS 2017, 2018-Janua, 452–455. https://doi.org/10.1109/CIS.2017.00105

Xu, Jiahao, Zhang, B., Wang, Z., Wang, Y., Chen, F., Gao, J., & Feng, D. D. (2019). Affective Audio Annotation of Public Speeches with Convolutional Clustering Neural Network. IEEE Transactions on Affective Computing, X(XX), 1–1. https://doi.org/10.1109/taffc.2019.2937028

Xu, Jinpu, Zhu, Y., Xu, P., & Ma, D. (2018). Agricultural price information acquisition using noise-robust Mandarin auto speech recognition. International Journal of Speech Technology, 21(3), 681–688. https://doi.org/10.1007/S10772-018-9532-7

Yadava, T. G., & Jayanna, H. S. (2017). A spoken query system for the agricultural commodity prices and weather information access in Kannada language. International Journal of Speech Technology, 20(3), 635–644. https://doi.org/10.1007/S10772-017-9428-Y

Appendix

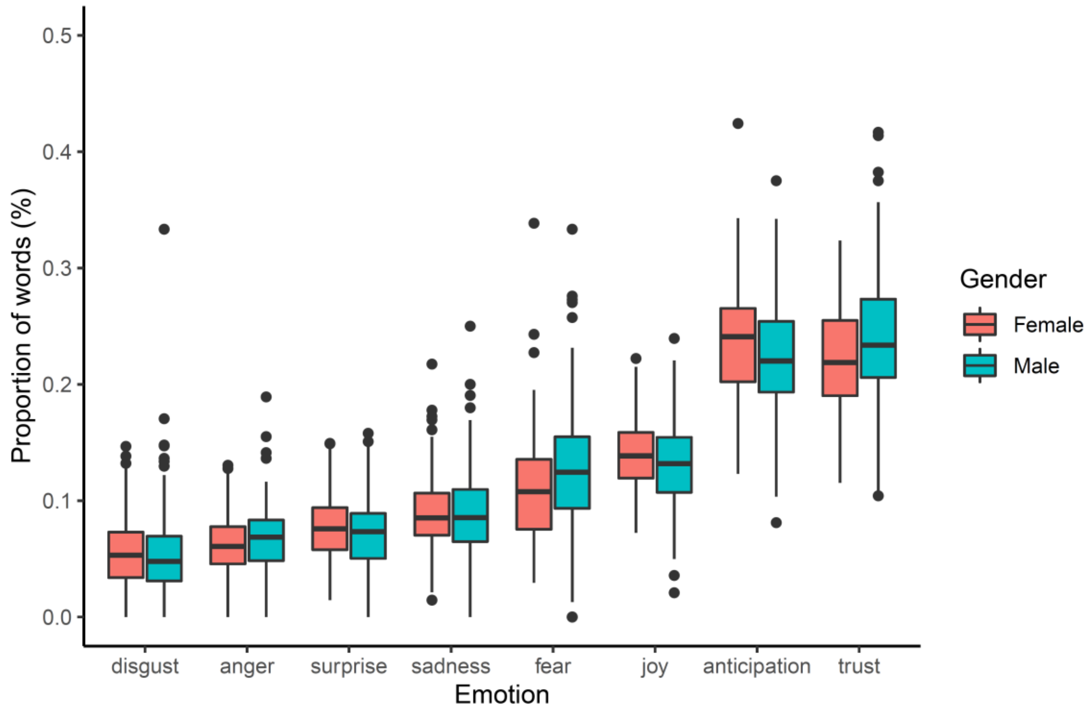

Figure 8 Text analysis of gender and emotional response

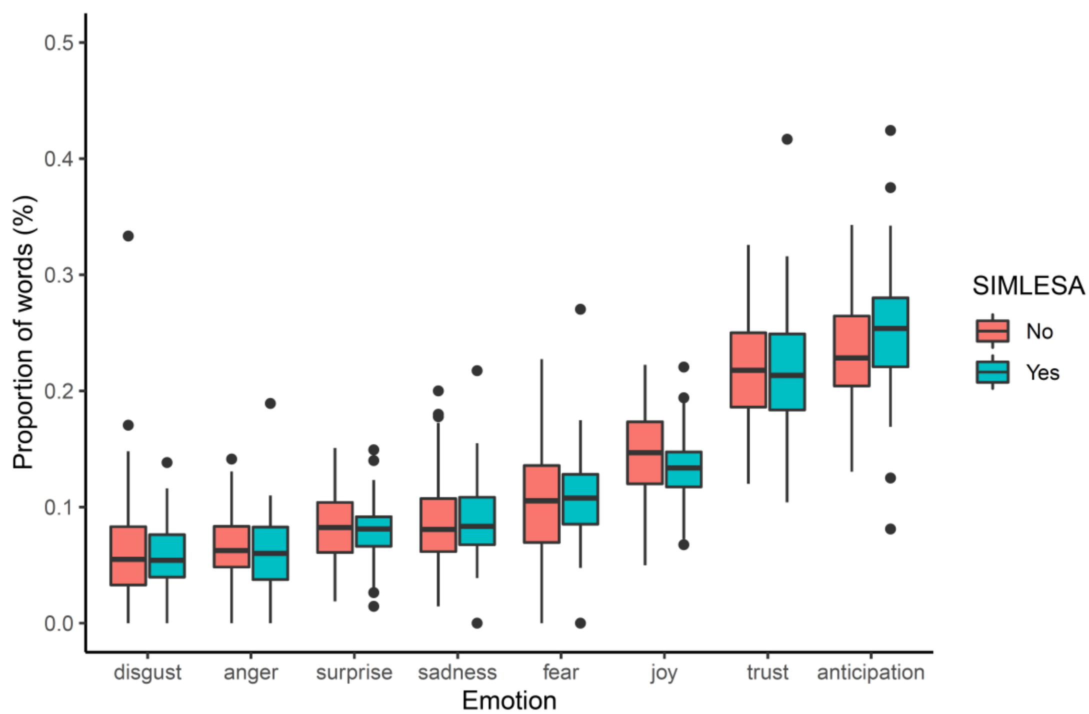

Figure 9 Text analysis of SIMLESA project membership and emotional response

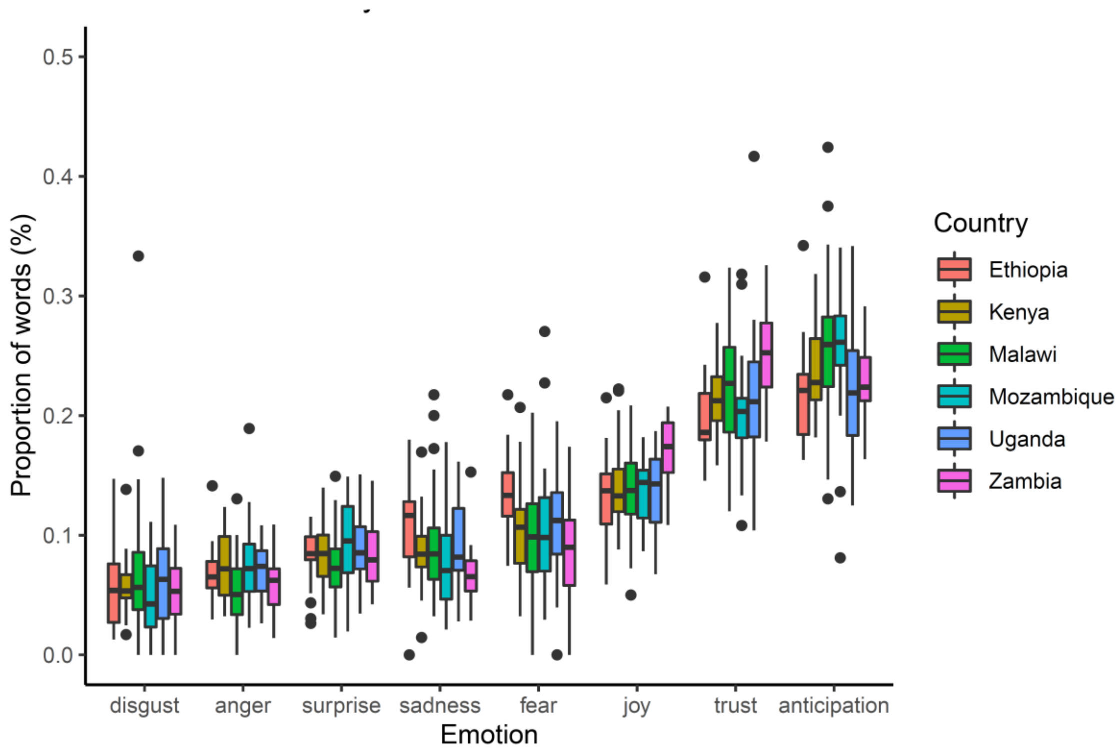

Figure 10 Text analysis of country and emotional response

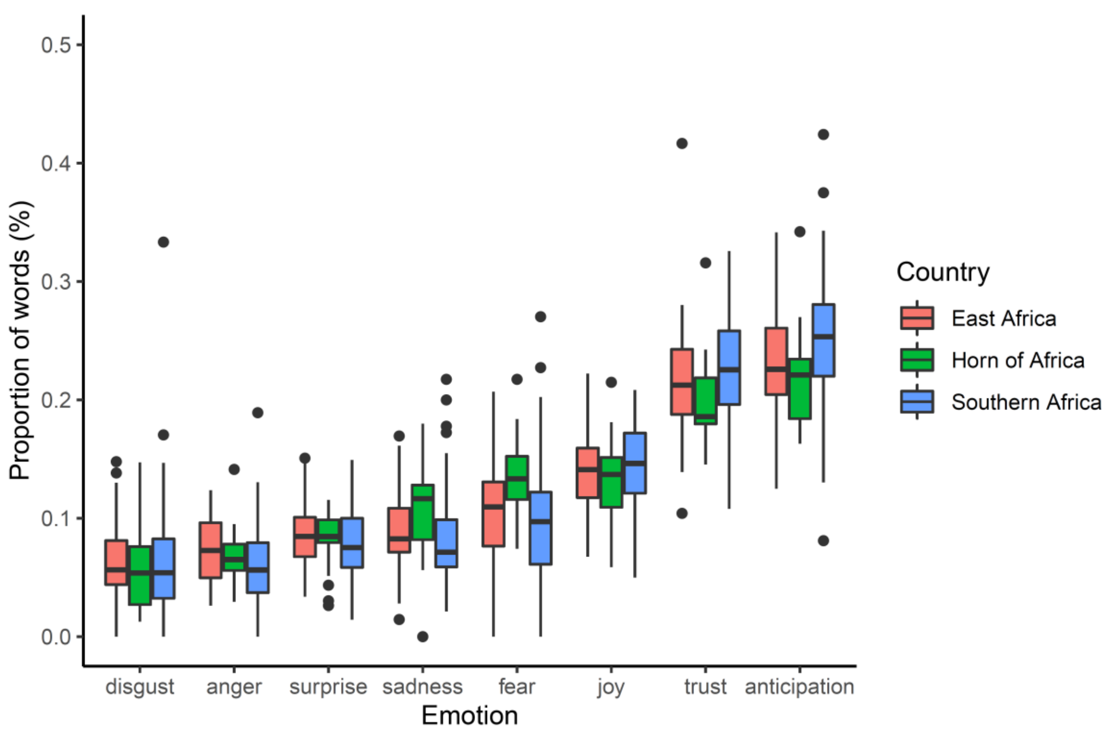

Figure 11 Text analysis of language/cultural group and emotional response

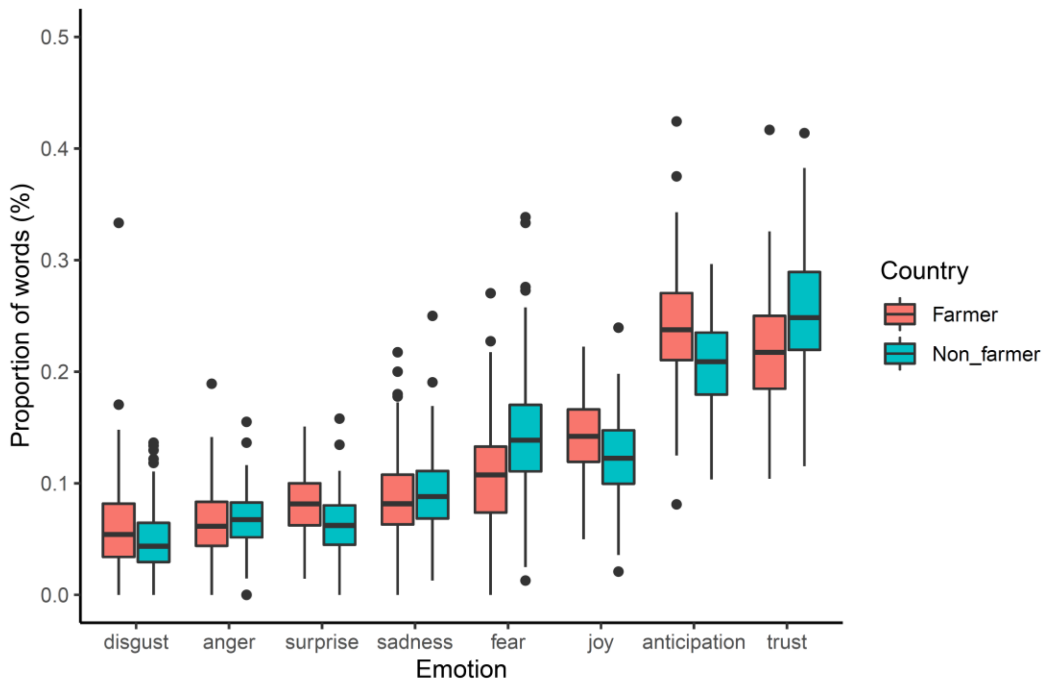

Figure 12 Text analysis of farmer and non-farmer emotional response

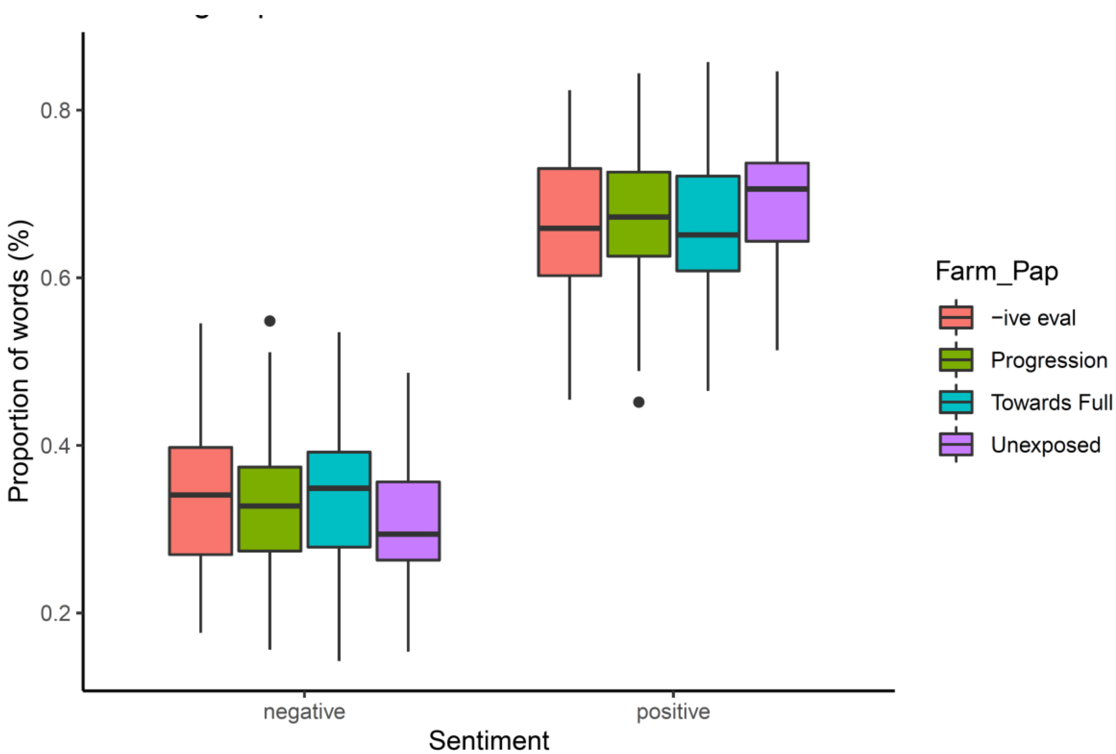

Figure 13 Text analysis of farmer typology and sentiment

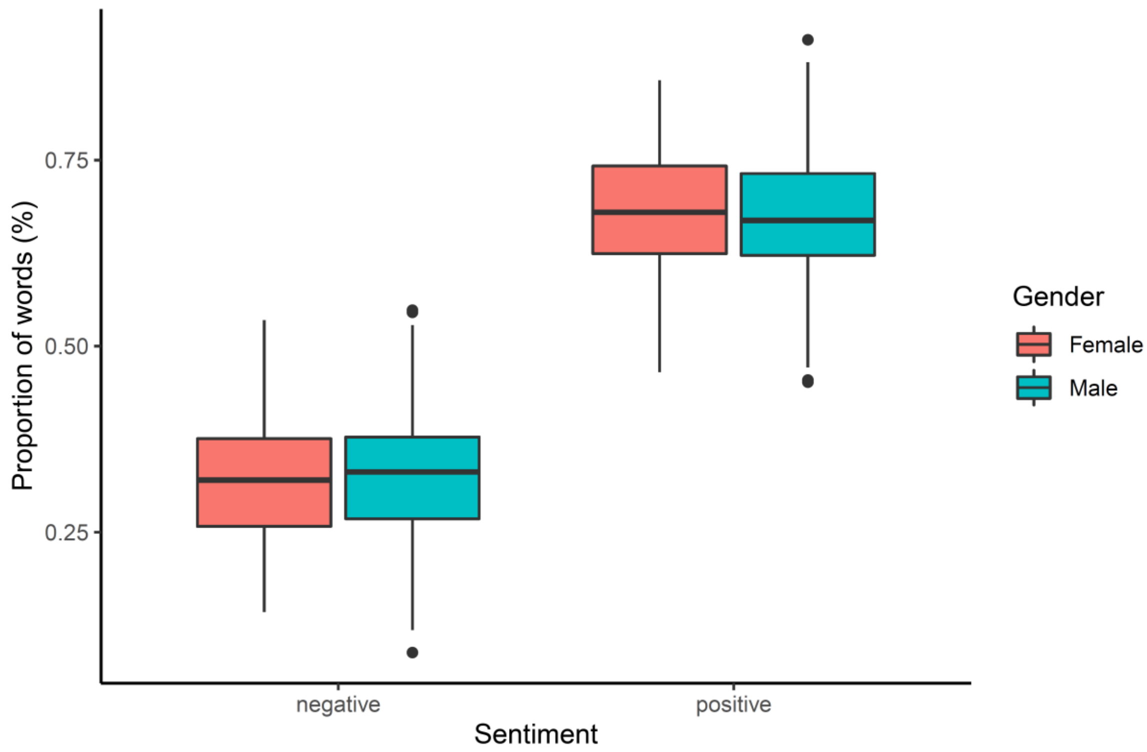

Figure 14 Text analysis of gender and sentiment

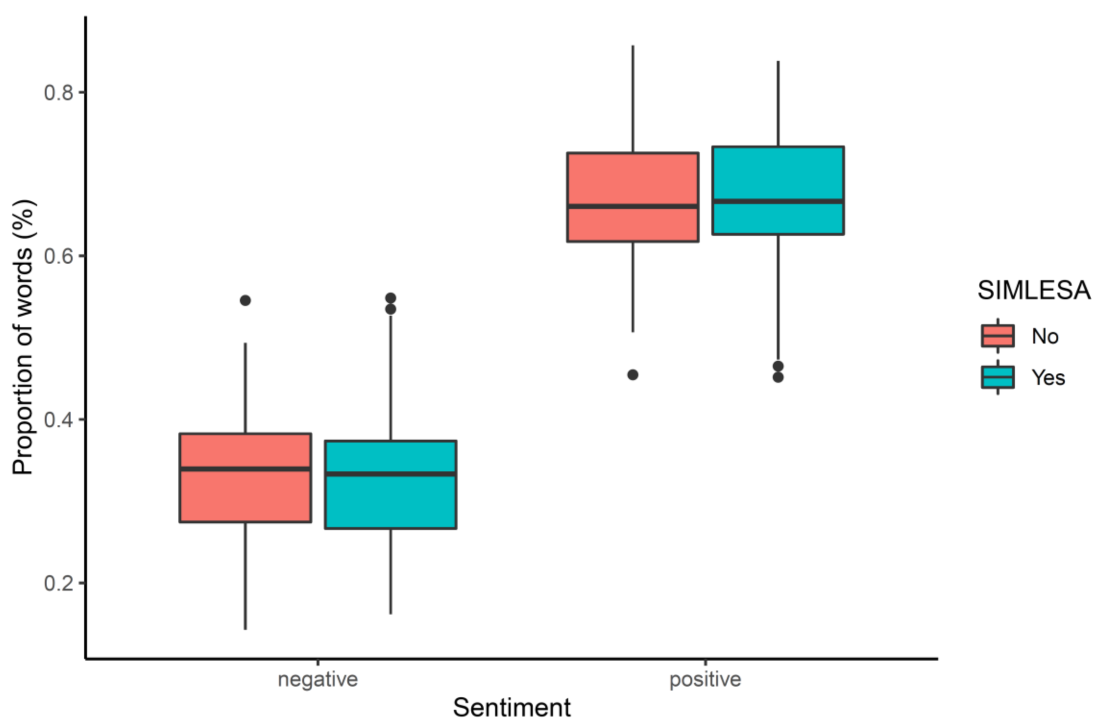

Figure 15 Text analysis of SIMLESA project membership and sentiment

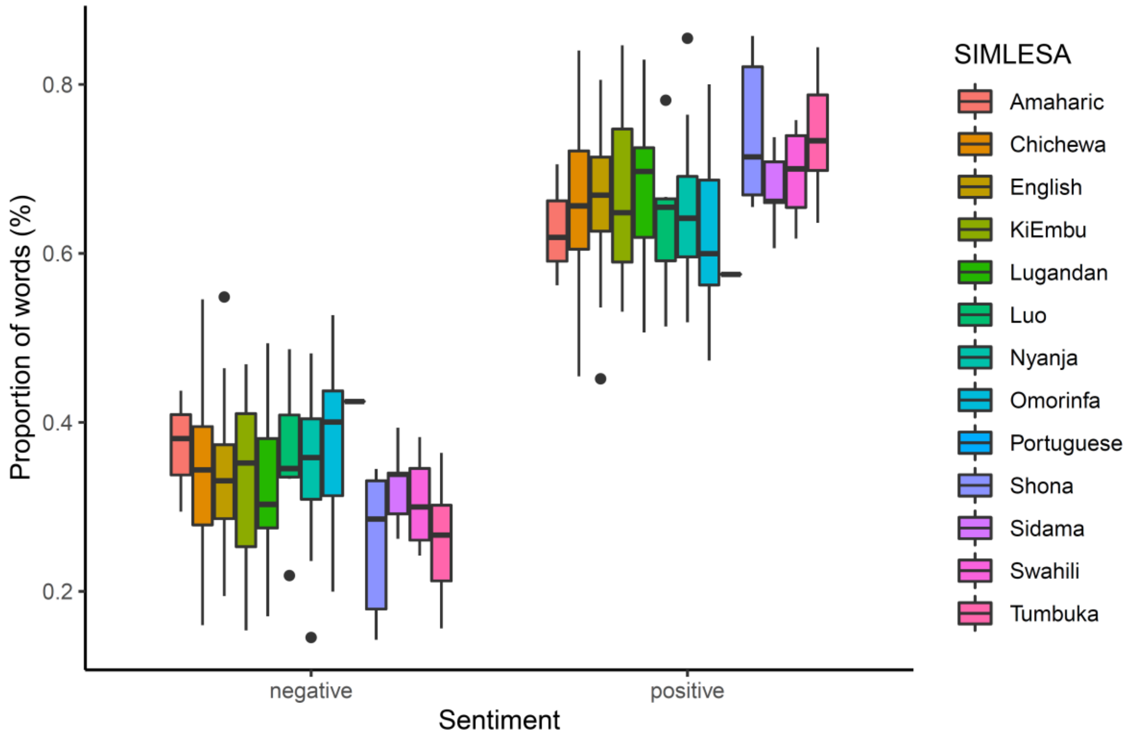

Figure 16 Text analysis of language group and sentiment

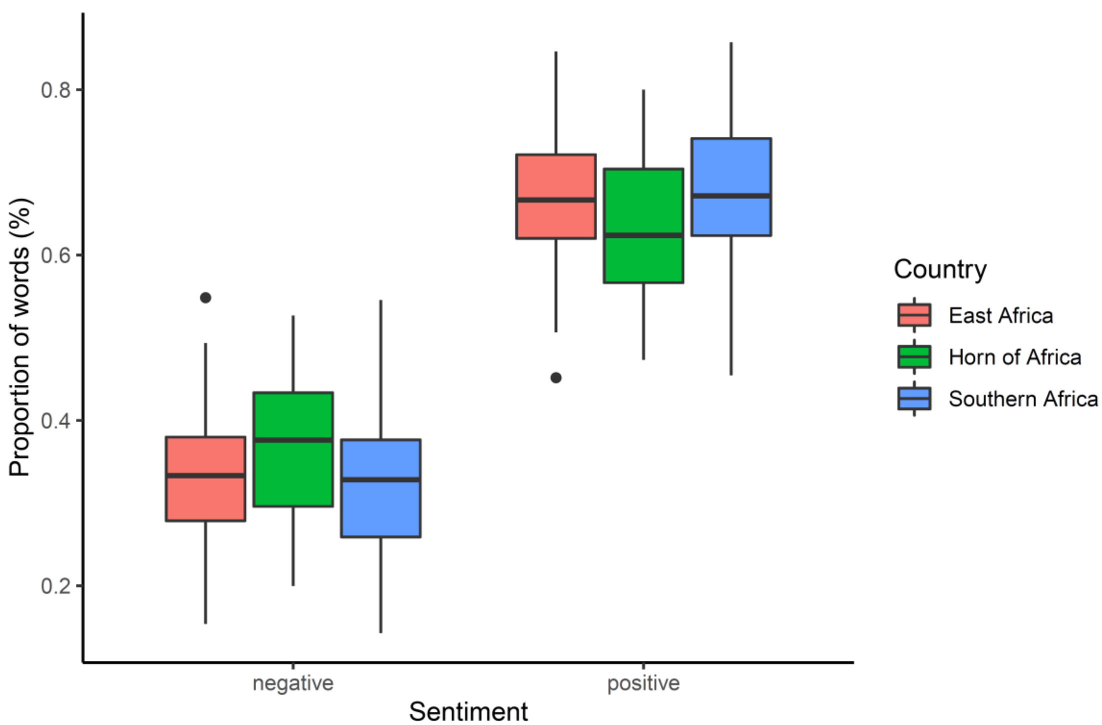

Figure 17 Text analysis of language/cultural group and sentiment

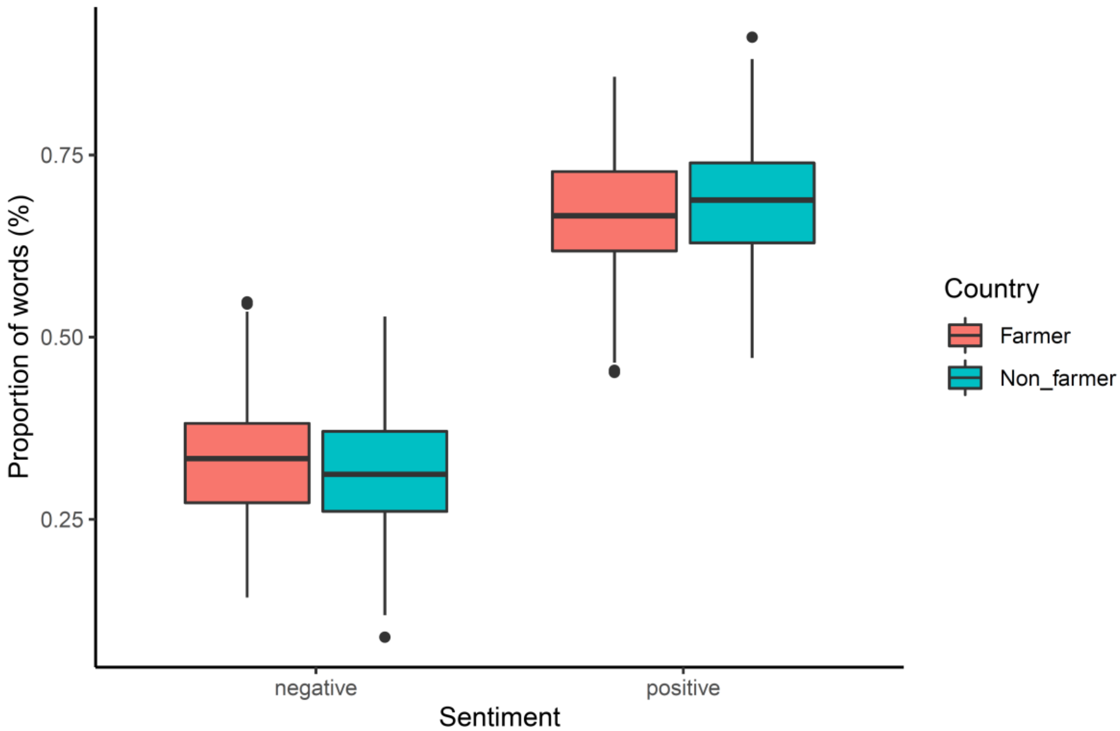

Figure 18 Text analysis of farmer and non-farmer sentiment

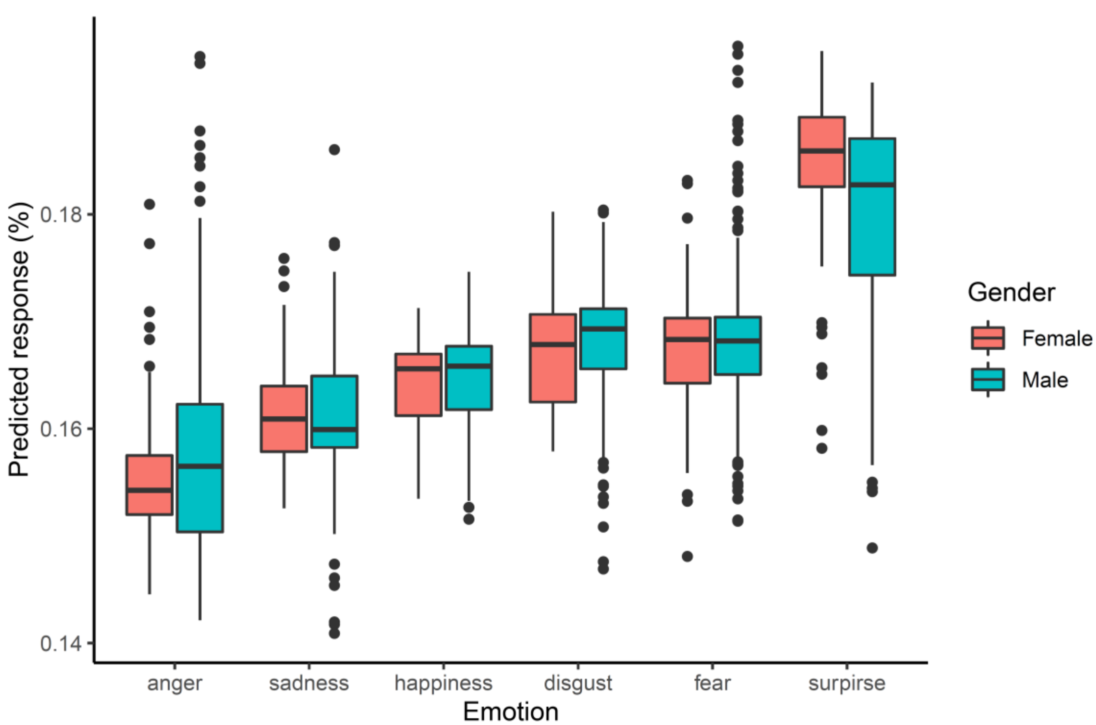

Figure 19 Audio analysis of gender and emotional response

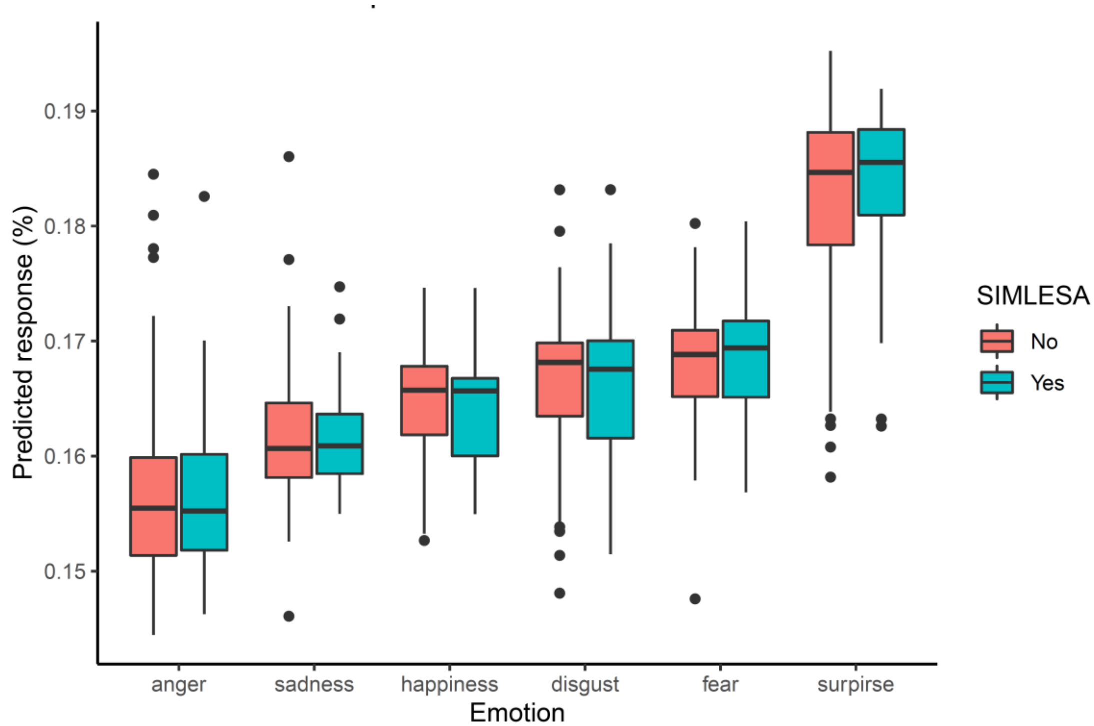

Figure 20 Audio analysis of SIMLESA project membership and emotional response

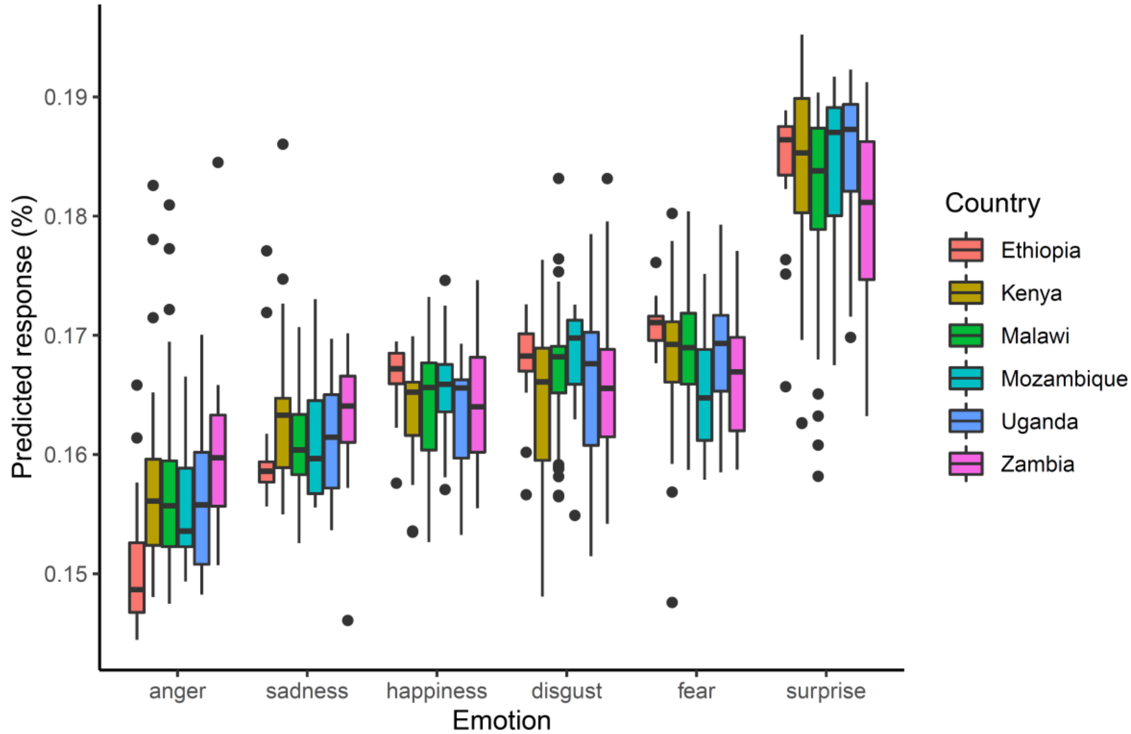

Figure 21 Audio analysis of country and emotional response

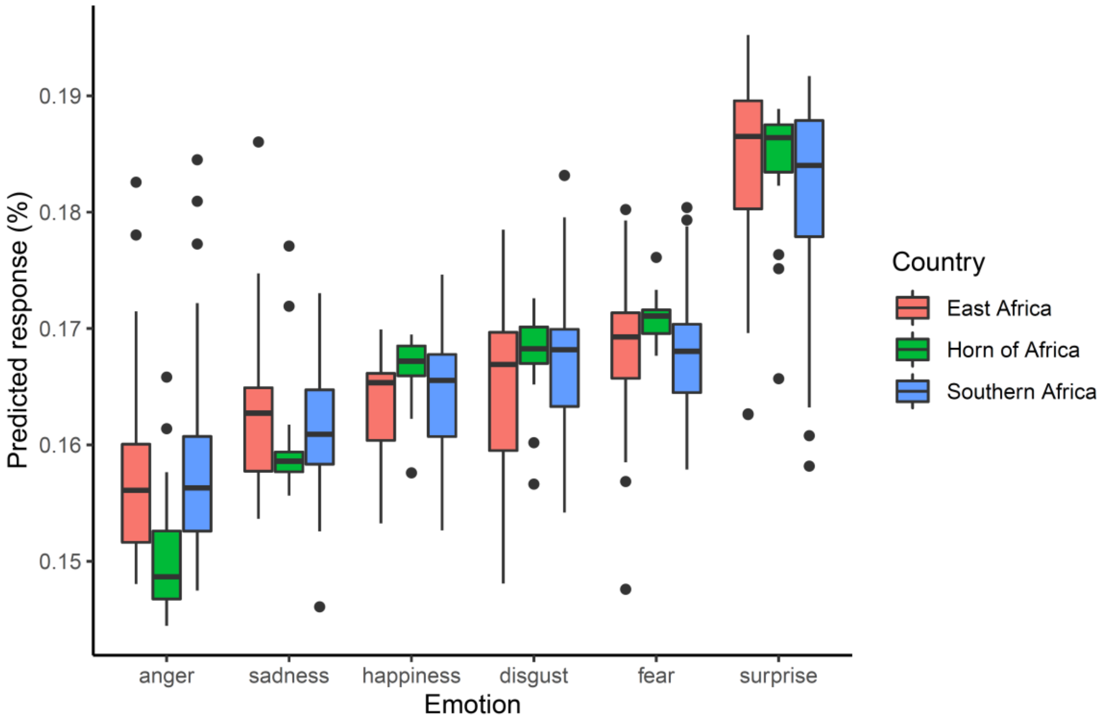

Figure 22 Audio analysis of language/cultural group and emotional response

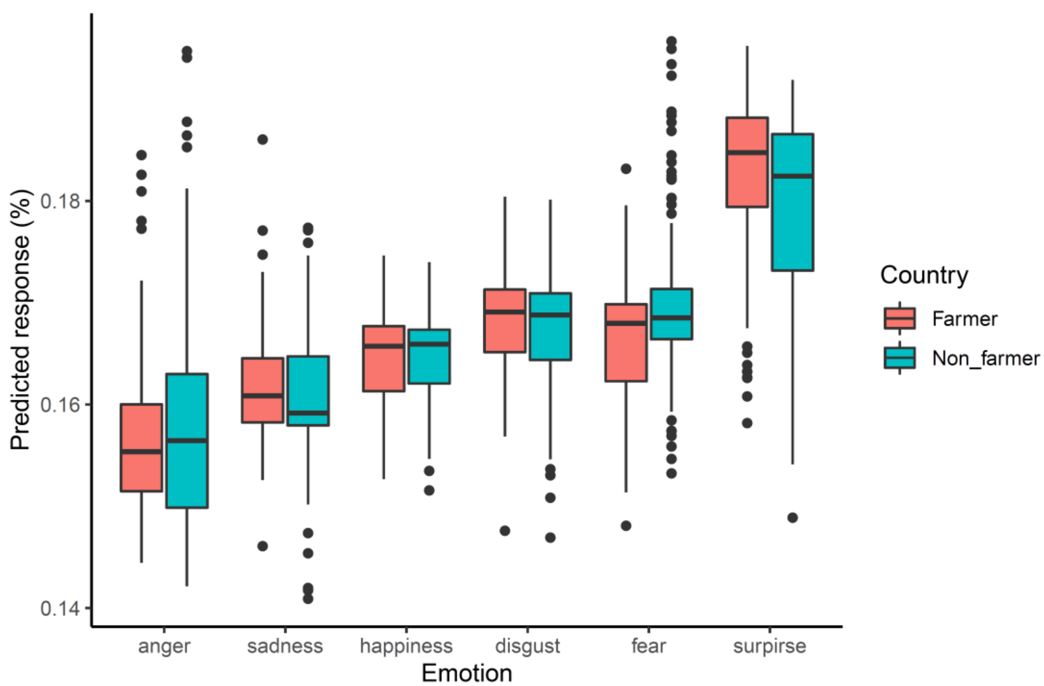

Figure 23 Audio analysis of farmer and non-farmer emotional response

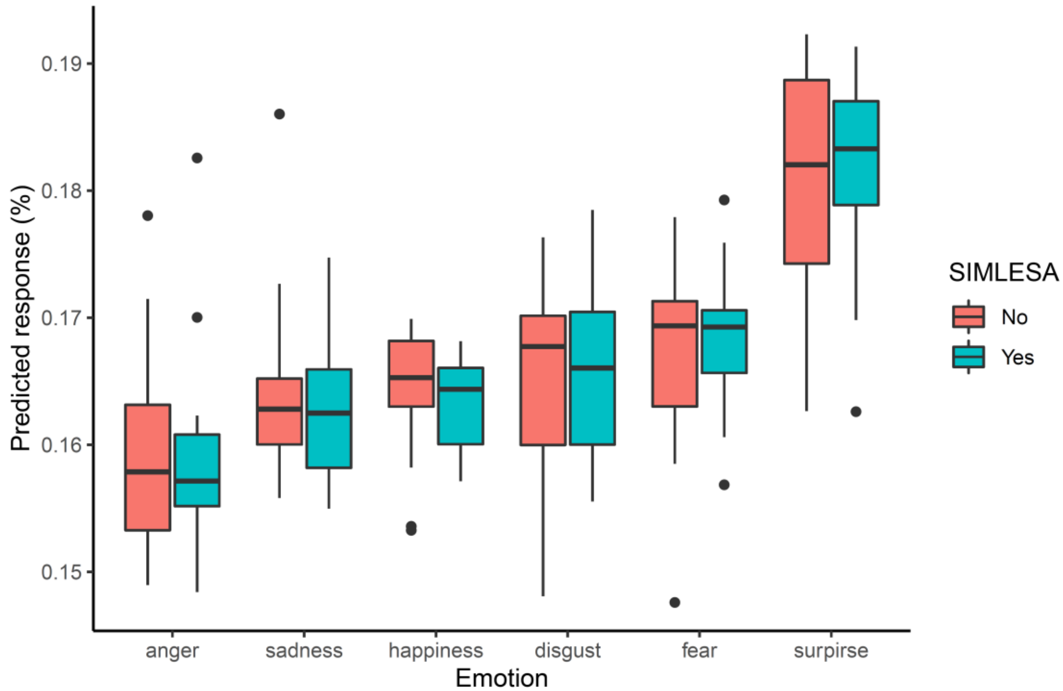

Figure 24 Audio analysis of English-speaking SIMLESA project membership and emotional response

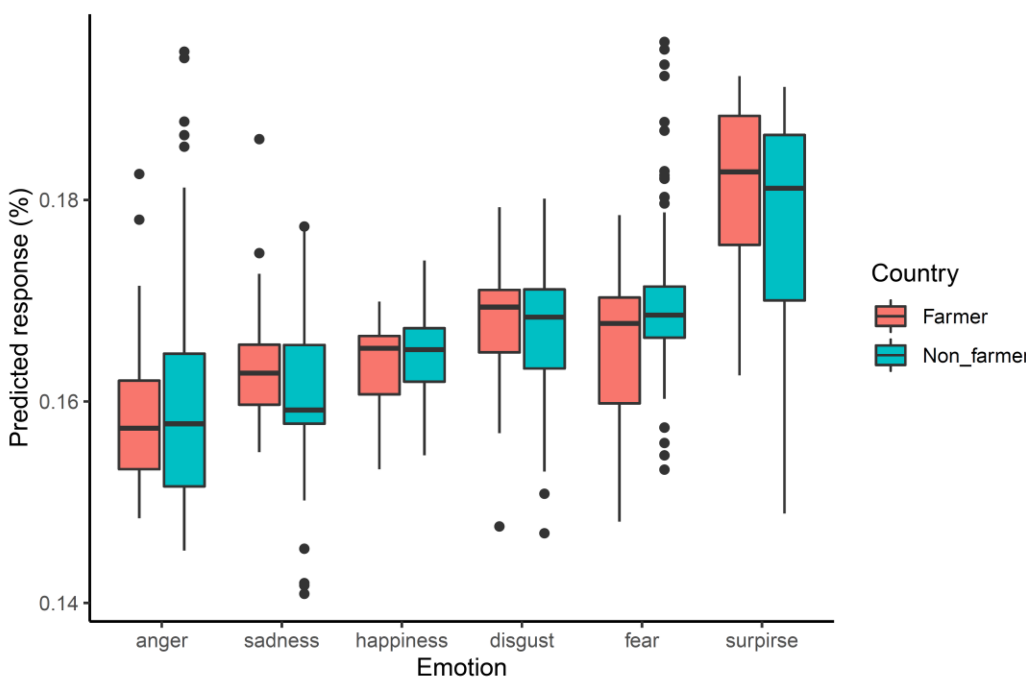

Figure 25 Audio analysis of English-speaking farmer and non-farmer emotional response

Notes

CIMMYT Headquarters:
Apdo. Postal 041, C.A.P. Plaza Galerías,
Col. Verónica Anzures, 11305 CDMX, México
Email: cimmyt@cgiar.org
www.cimmyt.org