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Abstract:

Social networking sites provide a new means of communication for disseminating cutting-edge agricultural technologies. These are unmediated interaction channels that enable a user to communicate their experience with technology and generate negative or positive attitudes that impact technology adoption decisions. We employ a machine learning approach to analyse users' existing semantic predisposition for technology adoption in agriculture at various operational levels. While developing attitudes toward technology adoption, these semantic tendencies become an important aspect of users' cognitive decision making. The study scrapes user comments and conversations about agritech on Twitter through data mining. The research also explains the important characteristics that enhance attitude building on Twitter and are responsible for reinforcing decision making among information seekers using four machine learning models. Based on the results, the research recommends strategies to managers for better communication with agriculturists and enhancement of users' decision making.

Keywords: Agriculture Technology, Attitude Formation, Machine Learning, Predictive Modelling, Social Media, Technology Adoption.

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1 Introduction

Agriculture technology (or Agritech) refers to the use of advanced technologies in agriculture for the enhancement of productivity and profitability. The market value of smart agriculture was recorded to be 14.69 billion US dollars and is expected to increase to 34.1 billion US dollars by 2026 (Shahbandeh, 2022). In agriculture, the primary technologies used include biotechnology, satellite imaging, drones, sensors focused on IoT, big data, artificial intelligence, and blockchain (Ginige et al., 2020; Mangla et al., 2018). These new technologies have helped agriculture industries face the challenges concerning climate change, biodiversity loss, resource depletion, and land management. Ironically, in developing countries such as India, younger generations have stated their disinterest in farming, and the prime reason for the agro brain drain is the low profitability of existing agriculture practices (Erath, 2020; Mahapatra, 2019). Though the majority of agriculturists have a positive inclination towards the use of technology for agriculture, their search for relevant technological consulting is limited to traditional information sources that have led to the slow adoption of smart farming technologies (Das et al., 2019; Elly & Silayo, 2013).

Literature from the United States, Canada, Australia, and the UK has shown a surge in the usage of social media in the agricultural industry (Chowdhury & Odame, 2013; Mills et al., 2019). Although social media has been useful for agricultural marketing and lobbying in the past, it has even greater promise as a worldwide platform for connection, learning, and information sharing (Kaushik et al., 2018; Phillips et al., 2018). Blogs, Facebook, LinkedIn, Twitter, and YouTube are just a handful of the many social media sites accessible, each serving a distinct function. In this study, we look at Twitter, a kind of social media that has been acclaimed as a beneficial resource for collaborative learning and information exchange (Chowdhury & Odame, 2013). Twitter users identify themselves by using a "handle," which is often followed by the '@' sign. A user may refer to another person directly by using their handle, or they can participate in a larger topic by using an indexing phrase denoted by a hashtag "#" (Kumar et al., 2022). Some prominent rising hashtags include the #Agchat discussion forums, which were developed in the United States and are now available in Australia (as #AgChatOZ), the UK (as #Agrichat), and New Zealand (as #AgChatNZ). Furthermore, several farmer communities are growing; for example, in the UK, a Twitter discussion amongst farmers about arable farming resulted in in-person get-togethers under the hashtag #clubhectare.

Twitter also enables you to "follow" the updates of certain people. This feature allows Twitter users to customize their interactions inside the site based on their engagement in certain organizations or networks. Connecting to other Internet-based media is another function of the system, and it is a common practice for Twitter users to do so in order to guide followers to more comprehensive or diverse types of material. Users may use Twitter to post creative compositions or links to websites, photos, videos, or audio files (Mills et al., 2019). Except for those from private accounts, all tweets are available to the whole public. Users indicate their wants to engage in a discussion by retweeting and commenting on tweets. Increased retweeting is seen as an indication of increased active engagement and interaction within the Twitter ecosystem, as opposed to passive information absorption (Boulet & Lebraty, 2018; Lim & Lee-Won, 2017).

Agriculturists may communicate with global clientele and agribusinesses through Facebook, Twitter, and Instagram (Jijina & Raju, 2016; Tao et al., 2020). It allows agriculturists who work in the same area or cultivate the same plants in different parts of the country to exchange expertise via digital networks. Younger farmers utilize social media for both personal and business reasons. Social media is used for operations such as information gathering, customer evaluations, and pricing comparison among agriculturists aged between 34 and 45 years (Nelson, 2019; USDA, 2019). Agriculturists may benefit from social media in understanding the technical advancement of agritech solutions and selecting the best available product. Farmers may obtain feedback and the finest goods at the greatest pricing (Bajaj, 2021). They may also engage with professionals, those in positions of power, and get a wealth of knowledge, information, and guidance from them. Such social media platforms might be a fantastic opportunity for agriculturists, even for traditional farms such as irrigation, pesticide and herbicide application, and harvesting (Anderson & Feder, 2004; Yusuf et al., 2021).

Many prior studies (Di Falco & Chavas, 2009; Foster & Rosenzweig, 2010; Rogers et al., 2019) on agriculturist technology adoption have used traditional methods such as survey methods, which make it difficult to see causal social interactions and their effect on actual learning because of the existence of incidental relationships between the agriculturist's characteristics and behavior induced due to social pressure. Agriculturists to industry networking, consumer involvement, and crisis communication are all critical components of agricultural social media communication (Carr & Hayes, 2015; Platania et al., 2022). Agriculture businesses have never had more opportunities to connect with customers via social media. Social media networks such as Facebook, Twitter, and WhatsApp promote high levels of user engagement, which benefits everyone. Individuals who are not agriculturists are becoming increasingly interested in agriculture, as shown by the huge numbers of page likes, group members, account followers, and channel subscribers that have accumulated on social media.

A recent study conducted by Ofori & El-Gayar (2021) analyses public opinion on precision agriculture (PA) by employing a social media analytics tool based on machine learning, which was trained to identify and classify posts based on lexicons, emoticons, and emojis to capture the sentiments and emotions of social media users towards PA. The purpose of this exploratory project is to collect, evaluate, and interpret social media postings across several platforms and situate them within the context of precision agricultural literature using a mixed-method content analysis methodology. The study provides a descriptive analysis of the most popular themes, including their semantic and emotional orientation and the country of origin. The narrative that PA will be useful for climate control and food sustainability is supported by the study's findings from sentiment and emotion analysis of online debate about PA. In addition, Ofori & El-Gayar (2021) encourage further study into how information disseminated through social media channels affects causal beliefs that manifest as choices about agricultural practices or the incorporation of new technologies.

As a result, it is critical to investigate the attitudes expressed by social media users regarding the adoption of technology in agriculture, as well as the factors that contribute to the formation of such attitudes, and thus we seek to answer the following research objectives:

RO1: Explore the sentimental inclination of the users towards Agritech postings on Twitter.

RO2: Explore the key Twitter attributes leading to users' commenting attitude formation.

Academics exploring social media as a communication medium for agriculturists and other stakeholders can benefit from this study. The insight will help firms construct social media messages and identify significant information disseminators. The research also aims to predict how people will tweet about new agricultural technology. The findings of this study are the first to describe the features and empirical evidence of the transformation of user's attitudes in the agricultural industry through a digital social platform, in this case, Twitter. The findings enable scholars to evaluate how social media-based behaviour patterns evolve as a result of technological advancements in online groups. Based on the results, the study recommends ways that businesses may be used to convert negatively polarised customers into favourable ones. This is the first study of its kind in the agricultural industry that is also exploratory in nature.

The remaining sections of the paper are structured as follows: Section 2 provides detail on the state of literature in the domain. Section 3 elaborates on the methodology adopted for the study and the results have been presented in Section 4. The findings of the study are discussed along with suggestions for theoretical and practical implications in Section 5. Finally, Section 6 provides the concluding remarks.

2 Literature Review

2.1 Decision Making of Agriculturists for a New Technology

Most economic models assume that agriculturists optimize the current value of discounted future profits when deciding to adopt a new technology (Chavas & Nauges, 2020; Findlater et al., 2019). Important factors in this decision-making process include uncertainty and risk associated with adopting new technology, as well as information gained through educational opportunities. Agriculturists are often Bayesian learners, learning from their own or peer group experience (Chavas & Nauges, 2020). Aversion to risk and careful cost-benefit analysis are important factors for agriculturists (Binswanger, 1980; Chavas & Nauges, 2020). Few researchers have found that risk-averse agriculturists are more likely to adopt risk-reducing technologies, with ambiguity aversion having a minor impact on adoption behavior (Emerick et al., 2016; Ward & Singh, 2015). Thus, spreading useful knowledge reduces the uncertainty caused by innovation.

2.2 Contemporary Agricultural Technology

Agricultural production and marketing methods must be modified to meet the demands of sustainability and global markets. Agriculture is becoming an information-intensive sector (Ginige et al., 2020; Miller et al., 2019). The economy's total factor productivity determines its ability to contribute to national growth (Haile et al., 2019). Agriculture's potential for innovation depends on agriculturists' ability to combine inputs, knowledge, and territory management techniques to maximize production (Beza et al., 2018). Increasing productivity necessitates new technologies (Griffith et al., 2004). As a result, access to new technology and information is critical for global growth and agricultural welfare (Khan et al., 2020). Agriculturists' technology adoption behavior has been described across studies (e.g., Laxmi & Mishra, 2007; Mendola, 2007; Villano et al., 2015). The utilization of contemporary agricultural technology is becoming increasingly essential as the world's population grows and there is a greater need for more food (Diiro & Sam, 2015; Fróna et al., 2019).

Through the use of information and communication technologies, agricultural extension services are able to provide farmers with both technical advice on agriculture as well as the products and services they need to increase their crop yields (Barakabitze et al., 2015). Improved crop varieties, better livestock control, enhanced water management, and the elimination of noxious weeds, pests, or diseases are just a few of the many areas that may be addressed by agricultural extension programmes. Building local farmer associations that can make use of extension programmes is another possible outcome of agricultural extension. Therefore, agricultural extension equips farmers with the essential resources they need to raise agricultural output. So far, the debate has been about whether or not extension services could help farmers use new technology, which would lead to increased production and more profit (Anderson & Feder, 2004; Evenson, 2001).

2.3 Appraisal Theory in Adopting New Technologies

Theory of reasoned action (Fishbein & Ajzen, 1975), technology acceptance model (Davis, 1989), theory of planned behaviour (Ajzen, 1991), and the unified theory of acceptance and use of technology (Venkatesh et al., 2003) are all illustrations of cognitive aspects of technology adoption; however, emotions can influence one's use and adoption of technology as well (Brown et al., 2004; Venkatesh, 2000). Although positive emotions such as enthusiasm, arousal, and pleasure have been demonstrated to impact technology adoption (Elliott et al., 2021; Pappas et al., 2014), negative emotions such as fear and concern may have the opposite effect (Hornung & Smolnik, 2022; Venkatesh & Brown, 2001). The adoption of technology may be impacted favourably or adversely by how people feel about it, which can alter their reasonable appraisals of the advantages and disadvantages of adopting it (Carvalho et al., 2019; Pappas et al., 2013).

The accompanying discussion exemplifies the vast range of theoretical "lenses" used to explore how technology usage influences user emotions. Appraisal theory was chosen for our study because it may provide a useful lens for analysing the effect of technology on attitudes (both positive and negative) not only during the early stages of technology adoption, but also later when technology use in agriculture has become more structured and strategic. Appraisal theory has been used in multiple studies to investigate participants' emotional reactions to diverse stimuli. Appraisal theory states that an individual's emotional reaction to a particular circumstance is affected by how that event is seen, evaluated, and appraised (Ellsworth, 2013; Roseman, 2013; Scherer, 2009). Several research papers on the effect of sentiments on technology adoption have utilized appraisal theory as a theoretical framework to dive into the subtle ways in which people's emotions may affect technological adoption (Apostolidis et al., 2022; Soo - Guan Khoo et al., 2012; Zheng & Montargot, 2022).

Appraisal theory describes how individuals communicate their interest in and connection with others via language (Read & Carroll, 2012). As a fundamental explanation, appraisal theory has distinct characteristics, such as how it revises our understanding of how emotions are classified by taking into account the appraisal expression, the language unit through which an opinion is transmitted (Korenek & Šimko, 2014). Some characteristics are as follows: [1] A person's attitude expresses his or her emotional state at the moment the piece was written. It is broken into numerous smaller groups: emotion, or affect, which might be joyful, sad, or neutral depending on the individual. [2] Appreciation, which expresses one's sentiments about an object (ugly, attractive, timid, etc.), and judgment, which expresses one's feelings against another person in a social setting (heroic, feebleminded, etc.). [3] A user's degree of involvement impacts where a text suggestion appears. It generally denotes the likelihood or possibility, as in it may possibly appear.

2.4 Social Media in the Agriculture Sector

The advent of social networking sites has opened new channels of communication for spreading innovative farming techniques. These are user-to-user communication methods where positive or negative feelings about a product may be shared and have an effect on the likelihood of that technology being adopted (Choudrie et al., 2021; Hofmann & Pappas, 2021; Leftheriotis et al., 2016; Pappas et al., 2020). Social media has attracted agricultural extension scholars and practitioners alike (Andres & Woodward, 2013; Bhattacharjee & Raj, 2016). Facebook, Twitter, YouTube, and blogs all have extensions (Kinsey, 2010; Parsons, 2015) that include real-time contact with target groups, mobile access to extension resources, and reaching new audiences (Cornelisse et al., 2011). While social media is frequently used for communicating information, its acceptance in agriculture as a knowledge sharing platform among users is in the nascent stage. A search of subjects on the Web of Science for the phrase “Agriculture AND Social Media” yielded 354 papers. This corpus of papers was segregated into three fields (author country, keywords plus, and source) and their connectedness has been visualized in Figure 1.

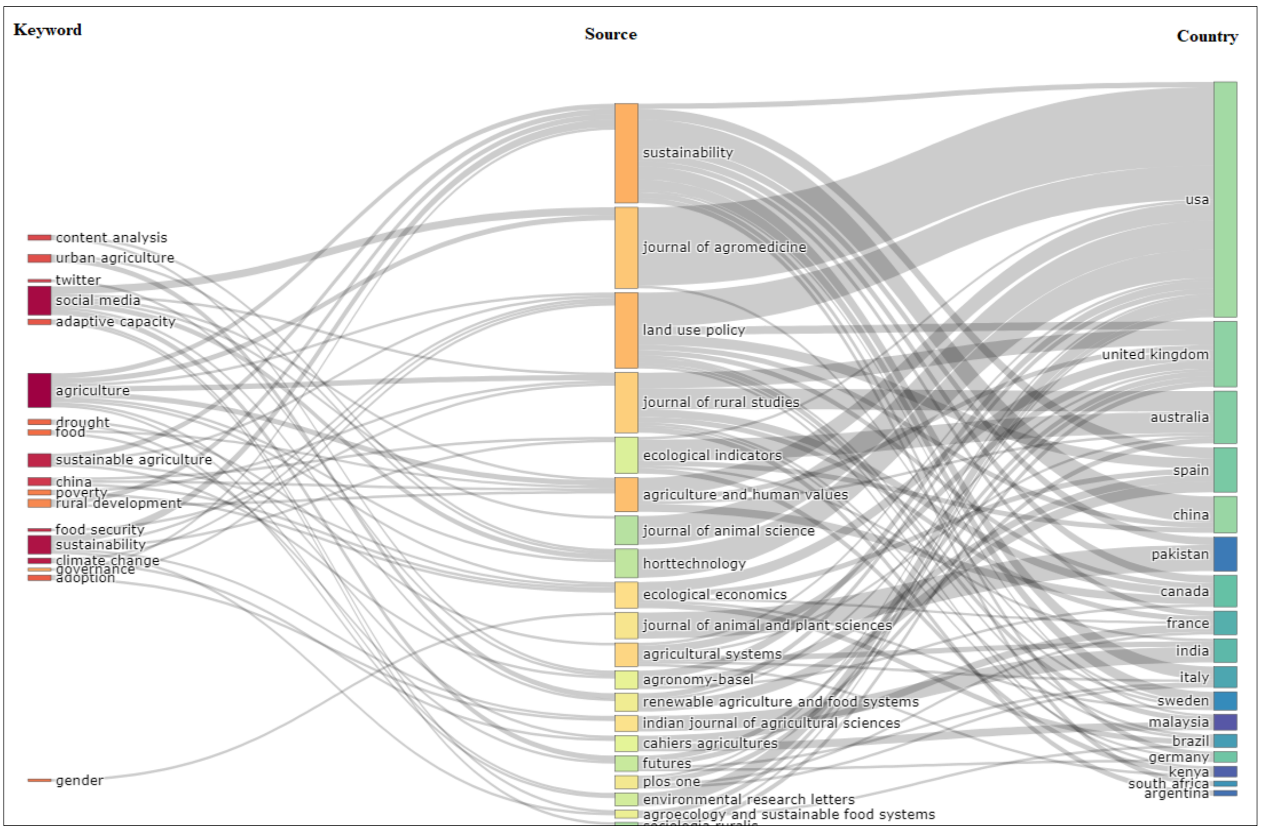

Figure 1. State of Literature on Web of Science

The visualization clearly depicts that the majority of the studies in the agriculture sector have been conducted by developed countries with an emphasis on food safety (Donaghy et al., 2021; Martindale, 2021; Reed & Keech, 2019), land use (Blackman & Villalobos, 2019; Reed & Keech, 2019), welfare (Adams, 2021; Buddle et al., 2018), agroforestry (Heredia-R et al., 2020; Taïbi et al., 2019), and supply chain (Mangla et al., 2018; Yadav et al., 2020a, 2020b). Very limited literature is available that captures the use of social media by agriculturists to share their knowledge and experience with other agriculturists (Chowdhury et al., 2011; Modirwa, 2019; Nyareza & Dick, 2012).

These studies, using traditional research approaches (such as survey, conceptual, or case study research), have outlined the need for an increase in social media-based agriculturist-to-agriculturist communications and/or an increase in more informative social media posting from reliable sources. This study, through non-traditional research, aims to unearth the sentimental inclination of the users concerning agriculture-related information posted and discussed across Twitter communities. The study also explores the key factors contributing to sentiment generation and attitude formation on Twitter.

3 Methodology

Research on technology adoption in agriculture has previously used qualitative, quantitative, or hybrid approaches to develop and strengthen connections (Chowdhury et al., 2011; Modirwa, 2019; Nyareza & Dick, 2012). A huge database of human activity can be found on social media, providing fresh perspectives on individuals, organizations, and society at large (Brooker et al., 2016). For this study, researchers used social media analytics to get a better understanding of current trends in the agricultural community and to verify the characteristics of online commenting behavior. The study used four machine-learning-based classification and regression models, using the suggested approach (Yadav, Misra, & Singh, 2022; Yadav, Misra, Rana, & Singh, 2022; Yadav, Misra, Rana, Singh, et al., 2022) to evaluate the effect of social aspects and characteristics on attitude development and the use intentions of new agricultural technology. The flowchart depicting the methodology adopted for the analysis has been shown in Figure 2.

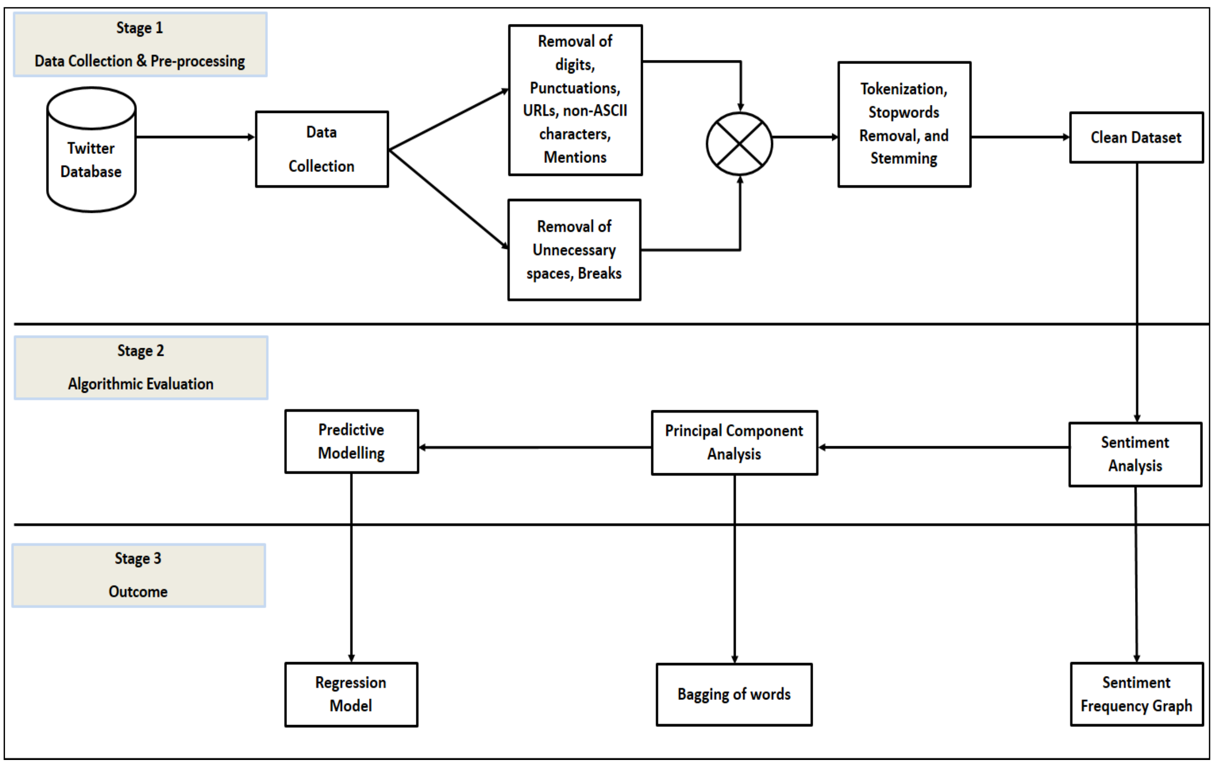

Figure 2. Process Flowchart

3.1 Data Collection

Twitter is a microblogging service that allows users to communicate through tweets and retweets about their views and/or information about current occurrences related to personal, social, or technical issues. By using Twitter, academics may get information on the experiences and opinions of users while also gaining access to user profile details. Using the RStudio (Version 1.3.1093) package twitteR, the research extracts tweets containing the phrase "Agriculture AND Technology" (Gentry, 2016) in order to cover all kinds of technologies that are being discussed by Twitter users. A total dataset of 5,752 tweets was collected from Twitter between October 2020 and November 2020. After removing the retweets from the dataset, the final study included 1193 unique tweets generated by governments, organizations, and users interested in agriculture technologies.

3.2 Pre-processing of Data

Before proceeding with the analysis, data has been cleaned using the suggested approach (Yadav, Misra, & Singh, 2022; Yadav, Misra, Rana, & Singh, 2022; Yadav, Misra, Rana, Singh, et al., 2022), thus eliminating digits, punctuations, URLs, non-ASCII characters, mentions, stopwords, and unnecessary spaces.

3.3 Algorithmic Evaluation

Initially, sentiment analysis was done using a lexicon-based method that relied on a pre-classified list of words with a particular sentiment polarity and emotion categorization. A lexicon-based approach relies on a set of terms with pre-determined semantic orientations. This list of words has either been categorized as positive or negative, or a score indicating whether they are positive or negative has been assigned to them. The NRC Word-Emotion Association Lexicon repository (Mohammad, 2015) was utilized in this research for sentiment evaluations of each word included in user comments using a rule-based method. Based on the individual word frequency and sentiment score, each word has been bagged together as an independent component, these are known as principal components.

To identify relevant tweets in the research, principal component analysis (PCA) was used. PCA is used to reduce dimensionality by dividing a large dataset into smaller groups that better reflect the data's content (Abdi & Williams, 2010; Ringnér, 2008). Based on the similarity of the observations, the important information is extracted from the dataset and aggregated into distinct documents known as main components. Following a preliminary review of the words used in each major component, we discovered that all principal components include tweets on agricultural technology adoption (see Table 1). Therefore, we selected the third principal component at random for further analysis as it contains the most relevant terms (such as market, trend, analysis, growth, size, share, forecast, player, intelligent, and global) that indicate agriculture, technology, and business relations. The contents of the third principal component have been used for predictive modeling to explore the contributing factors leading to users' attitude formation over social media towards the adoption of technologies in agriculture. Four machine learning models are used in classification and predictive analytics: regression tree, generalised linear equation, glmnet, and random forest (Breiman, 2001; Friedman et al., 2010; Kuhn, 2019).

4 Results

4.1 Textual Analysis and Semantic Orientation

Twitter data has been scrapped for the keyword "Agriculture AND Technology" to analyze the communications taking place among agriculturalists. The frequently used terms in the conversations have been shown as wordcloud in Figure 3.

Figure 3. Wordcloud of frequently occurring terms

The wordcloud clearly states that agriculturists are tweeting more about “market” along with the terms “farm”, “agriculture”, “innovation”, “robot”, “farmer”, “development”, and many more related terms, indicating the probable areas that will be influenced by agritech. After cleansing the data, sentiment analysis was performed. Sentiment analysis was performed using the R package Syuzhet (Jockers, 2017), which classifies tweets into eight emotion categories: anger, anticipation, contempt, fear, joy, sadness, surprise, and trust, and two polarities: negative or positive, by comparing terms with the words contained in the NRC Emotion Lexicon repository (Mohammad, 2015). Figure 4 depicts the classification of tweets based on eight different emotions. Most tweets expressed trust and anticipation, while the number of tweets expressing negative emotions was minimal.

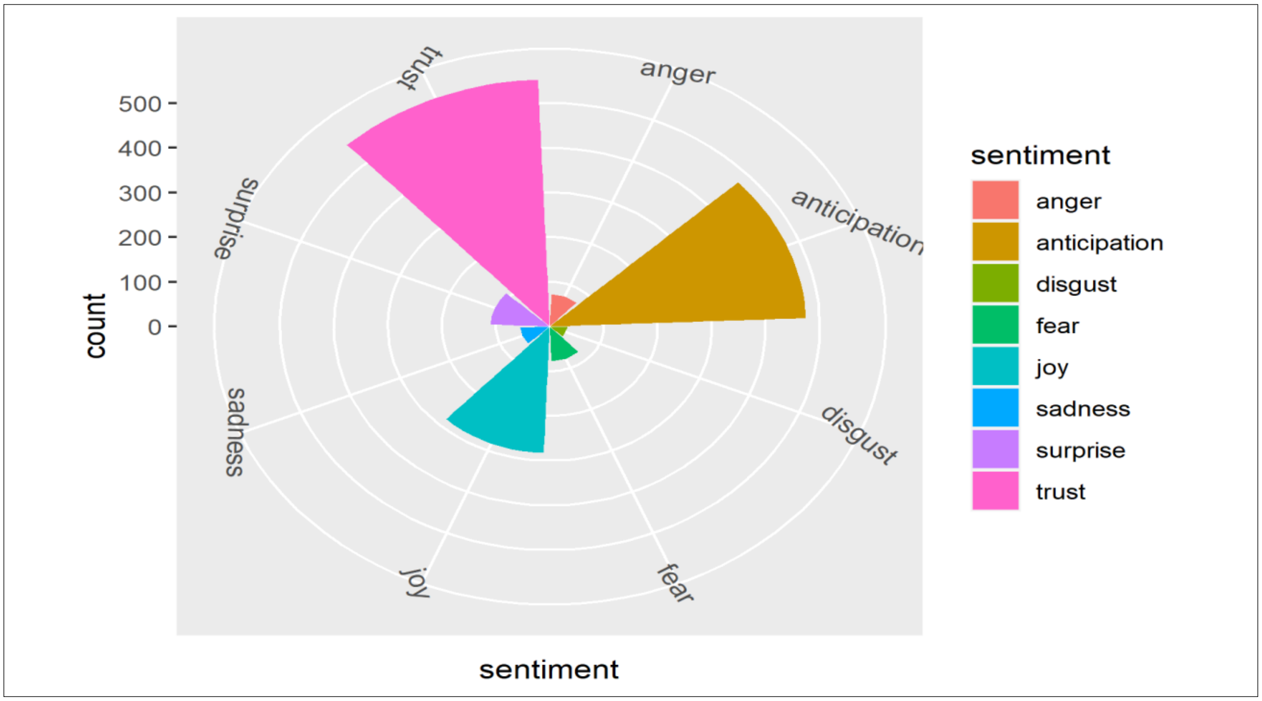

Figure 4. Sentiment Intensity

4.2 Principal Component Analysis and Predictive Modeling

The method of analyzing sentiment compares the words in each phrase to preset terms that have been assigned a sentiment polarity and an emotion category. Each term's emotional polarities are added along with the likelihood of its recurrence in the word bag giving its weight. To summarize, these weighted words are used to create the main components, which are then used in the underlying topic modeling method to group phrases that form a common phrase. For the first five major components, the top ten research words of interest are shown in Table 1.

Table 1. Top 10 Terms in First Five PCA

TERM	PC1	TERM	PC2	TERM	PC3	TERM	PC4	TERM	PC5
eat	0.13	isobus	0.17	market	0.11	advantag	0.19	communic	0.15
nomad	0.13	roboticfarmea	0.17	trend	0.08	inclus	0.18	establish	0.15
stemepeopl	0.13	canbus	0.17	analysi	0.06	further	0.18	inea	0.15
often	0.12	electrohydraul	0.16	growth	0.05	financi	0.17	mobil	0.14
feasibl	0.12	autonom	0.12	size	0.05	narendramodi	0.10	fund	0.13
life	0.11	system	0.07	share	0.05	ofea	0.01	access	0.11
area	0.10	robot	0.05	forecast	0.05	market	0.01	improv	0.07
theea	0.09	farm	0.02	player	0.03	trend	0.01	jomo	0.01
live	0.07	market	0.01	intellig	0.03	live	0.01	kenyatta	0.01
market	0.00	trend	0.00	global	0.03	communic	0.01	jkuat	0.00

The most appropriate component for the study is PC3. The axial locations and the distribution of tweets in PC3 have been shown in Table 2.

Table 2. Top 20 PC3 Axial Locations and Tweet

PC_Val	Text
(-2.12, -1.55]	Two Jomo Kenyatta University of Agriculture and Technology students Anthony Mwangi, 21, and Ann Wambui, 23 were Monâ\200¦ https://t.co/qpUfYNy76r
(-1.55, -0.98]	Join the Panel: Precision Water Management: An Information and Technology Based Agriculture at 10:30am\ Expert Panelâ\200¦ https://t.co/7GnKL7UBDF
(-0.98, -0.42]	Hand in hand to transform agri-food systems in Europe, Central Asia and beyond: FAO - https://t.co/btYoDHV8hbâ\200 ¦ https://t.co/Hstsf3BwkU
(-0.42,0.14]	The advancement in technology has created a significant impact in how farms handle their operations.â\200¦ https://t.co/lfF77lk1RR
(0.14,0.71]	Weeding robot to save you cost of herbicides - The Standard https://t.co/pWAyXKSvnB #futureofag #agriculture #technology
(0.71,1.27]	Using data analysis to improve sweet potatoes - https://t.co/ScYRaylLPT https://t.co/xUKtGvXUMd #futureofag #agriculture #technology
(1.27,1.83]	AGRICULTURAL PRODUCT TRACEABILITY: https://t.co/YMFeEYdYk5 | Using blockchain to prove product quality can commandâ\200¦ https://t.co/llJU4Oi2Mw
(1.83,2.4]	Global economy is not out of the woods yet: QNB Analysis - https://t.co/JTWvqtTYz2 https://t.co/CGbwUofxmKâ\200 ¦ https://t.co/8iBGG7H8CF
(2.4,2.96]	Global Smart Agriculture Market Projected to Garner $25.6 billion by 2027 despite the Covid-19 Chaos - Zenit Newsâ\200¦ https://t.co/P2ckf9XkkX
(2.96,3.52]	Agricultural Robots and Drones Market 2020-2028 | Worldwide Opportunities, Driving Forces, Future Potential 2028 wiâ\200¦ https://t.co/yTDiO8huCB
(3.52,4.09]	Agricultural Drones & Robots Market 2020 Emergent Technology Advancement in upComing Years - Stock Market Vistaâ\200¦ https://t.co/wQGQmL9DTv
(4.09,4.65]	Agricultural Robots Market Is Estimated to Grow at the Highest Growth Rate Till 2027 by Top Players Topcon, AgEagleâ\200¦ https://t.co/YFkOhsYBBT
(4.65,5.21]	Impact of COVID-19 on Articulated Robots Market to Record Significant Revenue Growth During the Forecast Period 202â\200¦ https://t.co/mnEk220QrU
(5.21,5.78]	Worldwide AI in Agriculture Industry Market Boosting the Growth, Dynamics Trends, Efficiencies Forecast to 2025 - Eâ\200¦ https://t.co/N5Hw7dYtrT
(5.78,6.34]	Agricultural Robots Market 2020-2028 Covid-19 Updates With Key Players - Stock Market Vista https://t.co/OERXVcAs9eâ\200 ¦ https://t.co/24NG99j3GS
(6.34,6.9]	Service Robot Market Trend Shows A Rapid Growth By 2026 | Industry Growth Insights - Aerospace Journalâ\200¦ https://t.co/H4oZycjF31

(6.9,7.47]	Smart Farming Solutions Market Share Analysis, Application, Strategies of Key Players & Forecast to 2026 - PRnews Lâ\200¦ https://t.co/zwIpPA8hVv
(7.47,8.03]	Agricultural Robot Market Global Growth, Opportunities, Industry Analysis & Forecast To 2027 - PRnews Leaderâ\200¦ https://t.co/5o1qa9lsrE
(8.03,8.59]	Global Artificial Intelligence Market Insight Growth Analysis on Volume, Revenue and Forecast to 2019-2025 - Technoâ\200¦ https://t.co/m5xrXWqJXm
(8.59,9.17]	Agricultural Robots and Mechatronics Market 2020 Analysis by Industry Trends, Size, Share, Company Overvie ... - Adâ\200¦ https://t.co/8qwtsjIIUF

The third important component of the research is the use of publicly accessible author information on Twitter to predict the behavior of netizens who post comments. The weighted words in PC3 predict a user's commenting behavior and the predictors are: (a) numstatuses – “the number of tweets by a user,” (b) followers—"the number of followers of a user,” (c) friends—"the number of following a user has,” (d) favorites—"the number of topics or subjects a user is following,” (e) verifiedTRUE—"Twitter has verified or not verified the user profile," (f) numlists—“number of lists (groups) subscribed to by a user,” (g) Twitter years – "the age of a user’s account,” (h) numTopicTweets—"the number of trends in a topic that a user is following," and (i) positivity—"the score assigned to the tweet based on the frequency of positive and negative words contained in the tweet." A generalized Shapiro–Wilk test for multivariate normality was conducted using the R package mvShapiroTest, and the results showed that the data was not normal (Gonzalez-Estrada & Villasenor- Alva, 2015). A Generalized Linear Model was used to find a link between commenting behavior and publicly available author information (Turner, 2008). Table 3 presents the required statistics.

Table 3. Generalized Linear Model Output

Call: glm (formula = PC3~ numstatuses + followers+ friends + favorites + verifiedTRUE + numlists + twitter_years + numTopicTweets + positivity, family = "gaussian", data = agritech, subset = trainset)				
Deviance Residuals:				
	Min	1Q	Median	3Q / Max
	-1.6886	-0.2895	-0.0922	0.1659 / 6.0260
Coefficients:				
	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-0.4297	0.05378	-7.99	6.74e-15 ***
numstatuses	2.782E-07	4.929E-07	0.56	0.57
followers	5.771e -08	6.353E-08	0.91	0.364
friends	-3.002E-07	0.000004572	-0.07	0.948
favorites	-0.000002344	-0.000001532	-1.53	0.126
verifiedTRUE	-0.07041	0.1303	-0.54	0.589
numlists	-0.00001385	0.00003127	-0.44	0.658
twitter_years	0.005759	0.007286	0.79	0.430
numTopicTweets	1.073e -02	0.003583	2.99	0.00286 **
positivity	0.06751	3.107e -02	2.17	0.03018 *
(Dispersion parameter for gaussian family taken to be 0.4714778)				
Null deviance: 296.06 on 619 degrees of freedom				
Residual deviance: 287.60 on 610 degrees of freedom				
Akaike information criterion (AIC): 1305.2				
Number of Fisher Scoring iterations: 2				

The model's median residual deviation is very close to zero, demonstrating objectivity and a lack of bias in the results. Using a nine-degree loss of freedom training model with a low Akaike information criterion

(AIC) value shows that the training model is suitable since residual deviation is decreased in comparison to null deviance. Regression tree, random forest, and glmnet were used to cross-validate the prediction model's results. The prediction models' performance was compared to mean absolute error (MAE) values, as shown in Table 4.

Table 4. Model Comparison

Model	MAE
Regression Tree	0.47
Generalized LM	0.48
Random Forest	0.48
GLMNET	0.47

When it came to comparing models, mean absolute error (MAE) values were used as a better measure than root mean square error (RMSE) (Willmott & Matsuura, 2005). We may say that the models performed well in predicting outcomes since their MAE values were comparable (Chai & Draxler, 2014). However, the MAE values for all four models are *very* comparable. The regression tree and GLMNET models have the lowest MAE value and therefore are the best predictor of this study.

5 Discussion

Despite the fact that social media provides a platform for open discussion in the agriculture sector, Chowdhury and Odame (2013) note that there is a dearth of research that provides sufficient evidence of their role in fostering dialogue, taking action, and innovating in the context of agriculture and rural development. The present research contributed to the existing literature on technology adoption by examining the emotional and psychological influence of social media communications on technology adoption in the agricultural industry. This was particularly interesting because, unlike other studies that have examined technology adoption by mining data from multiple sources and limiting their analysis to descriptive and sentiment analytics (Chowdhury & Odame, 2013; Ofori & El-Gayar, 2021), this study allowed us to investigate the agriculturists' inherent semantic inclination toward new technology adoption and how social media communications can contribute to the re-alignment of pre-existing attitudes. By employing initial sentiment analysis of the unique tweets, our study found that there is a positive attitude toward technology adoption in agriculture.

Though agricultural technologies propose lucrative solutions to existing farm-related problems, a lack of a proper channel of information dissemination is evident. Younger generations of agriculturists are moving away from agriculture as they are unable to yield profits from traditional means. Agriculturists often tend to refrain from being the early adopters of technology, as also found in the results in Table 3. The major reasons for this attitude can be a lack of technical information, trust in the technology, and the costs involved in technology adoption (Barham et al., 2014; Feder, 1980). This study suggests that this attitude of the agriculturists can be changed through the proper flow of information i.e., agriculturists using social media (Twitter in this case) who follow multiple accounts relating to agritech and as the number of topics being followed increases so does the awareness level and hence the translation of a technology aversive attitude to more technology responsiveness. The study also finds that the attitude of the agriculturists using social media is affected by the number of positive words used in the information being posted on the platform. Thus, the more the use of positive words in posting information, the more positive will be the attitude of the users.

5.1 Theoretical Implications

Recently, there are numerous studies that have researched various aspects of the agriculture ecosystem (Adams, 2021; Heredia-R et al., 2020; Mangla et al., 2018). In contrast to previous studies, only a limited number of researchers (Chowdhury et al., 2011; Modirwa, 2019; Nyareza & Dick, 2012) have explored the probable use of social media as an agriculture information dissemination platform, but their research approach was limited to the use of traditional research methodologies (such as surveys, conceptual writing, and case study research). The use of social media analytics to capture customer emotions differs from traditional research approaches in that it may provide a more precise result because of the unusual commitment to passing time and a thirst for self-disclosure by users (Nabity-Grover et al., 2022).

The study's findings enhance the knowledge of agri-based communications through the employment of social media. This exerts several theoretical contributions. First, agricultural information systems researchers have overlooked social media integration in marketing and information dissemination initiatives. Since social media is a widely-used open-source platform for information sharing, it is vital to evaluate its role in agricultural information systems and attitude development within digital communities of agriculturists, technology enthusiasts, and organisational entities. Second, no prior research in agriculture has used textual analysis to show a link between social media attributes and posting behavior. These findings show Twitter's importance as a tool for agricultural stakeholders, especially small and medium-sized farmers. The results of this research give the first complete description of the characteristics and empirical evidence of the creation of attitudes in the agriculture sector via digital social platforms. Academics may analyse Twitter behavior trends using new technology breakthroughs in online communities. Future researchers may duplicate the study on other social media platforms, discussion forums, and academic disciplines to identify attitude-forming factors.

5.2 Practical Implications

By providing a better understanding of how emotions are developed through the diversified communications of technology adoption over social media, our findings support businesses that must deal with the challenges of emerging technology adoption and help users to better understand the technology by providing in-depth information from authentic sources. The findings of the research have a variety of practical consequences for agricultural organizations, governments, and policymakers interested in using digital social communication platforms to spread agricultural technology information to a global audience. It will enable the agriculture technology managers to capture the sentiments of the consumers (members of the online community) regarding the acceptance of new technological advancements prior to the full launch of the production process. The textual evaluation of the online postings may be helpful in identifying agriculturists and in providing suggestions for upgrading existing technologies.

The adoption of social media analytics for agriculture managers will protect them from the costs involved in physical market research and will enable them to produce a product that has a high acceptance rate by price-sensitive agriculturists. Managers, using social media, can engage in cost-effective information dissemination and relationship management campaigns and conduct online bilateral discussions with agriculturists and other stakeholders. Based on the findings of this research, managers can engage in attitude modification practices through the appointment of influencers already existing in the social media communities. Influencers can be young agriculturists who timely share their experience of the new schemes and technologies launched by governments and businesses. Using well-known users as a bridge between the company and its customers could help businesses build strong relationships with their customers and a positive brand image among social media users.

5.3 Limitations and Future Research Directions

Though the study produces insightful results, it suffers from a few limitations. One of the limitations lies in the selection of the social media platform. The study uses a social media platform that has a relatively lower penetration rate as compared to other social media platforms. Hence, future researchers can replicate this study on other social media platforms and compare the results. Another major limitation lies in the sample size. After determining the data needs of our research, the next step was to determine how we would go about collecting the necessary information. This requirement may be satisfied by the 1% random sample of public Tweets that is supplied by the sampled stream endpoint. This sample gives a tiny subset of data in comparison to the entire quantity of Tweets that are public, therefore it is suitable for gathering the data that is required for this study. In addition, the data was sent to us in real time as it was happening, which ensures that the data would fulfill the condition of being up-to-date while being restricted to a limited dataset. Furthermore, the current research is confined to textual content in netizens' social media postings; nevertheless, additional posted content, such as associated images and emoticons/emotions, might show a diverse collection of emotions and their influence on attitude formation. Future studies should be undertaken to investigate user social media behaviour by taking into account all aspects of posts.

Future researchers may also develop a mechanism for collecting textual data from multiple digital social platforms and replicate the study in several sectors of management science in order to analyze the user's commenting behavior on social media in relation to the adoption of technology. Research might also look at how Twitter features like messages, mentions, media links, and discussions affect digital social interactions.

6 Conclusions

The study uses social media analytics to show that the way people post on social media is inherently negative. However, the number of topics a user follows on Twitter and the number of positive words in the posts of other users have a big effect on a user's posting behavior. This study encourages researchers to enhance their contribution to agriculture information systems and the adoption of social media as a relationship-building platform. The study also suggests managers adopt social media in their information dissemination and relationship-building campaigns and encourage agriculturists to engage in social media-based discussions. In addition to textual analysis, future scholars may use methods such as bigrams, n-grams, and social network analysis to examine the patterns in the postings and the associations between words. As a result of these insights, businesses will be able to craft more effective campaigns to promote new technologies on social media platforms.

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