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New trends in the global digital transformation process of the agri-food sector: An exploratory study based on Twitter

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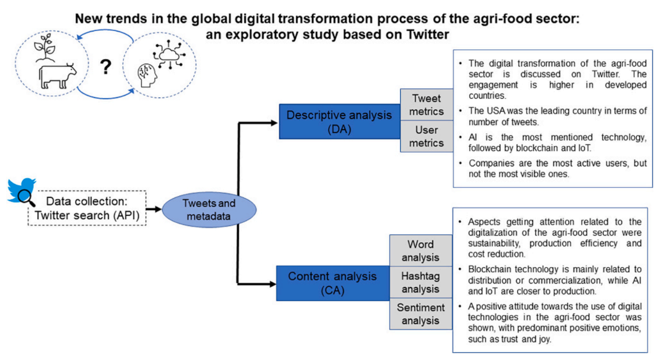
HIGHLIGHTS

- The adoption of new digital technologies in the agri-food value chain has been influenced by the COVID-19 pandemic crisis.
- Data mining of Twitter content is useful to analyse the perceptions towards new digital technologies in the agri-food sector.
- About 80% of the tweets regarding digital transformation of the agri-food sector showed a connection to positive emotions.
- Understanding of the new digital technologies within the sector is related to sustainability and climate change concerns.
- USA, India, UK, and Nigeria show higher number of tweets that relate new digital technologies to the agri-food sector.

GRAPHICAL ABSTRACT



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ABSTRACT

CONTEXT: The agri-food system is undergoing pervasive changes in business models, facilitated by the use of digital technologies. Although today it is almost inevitable for any business to adopt some level of digital transformation to strengthen their competitiveness, this transition in the agri-food sector could be more complex, given its characteristics.
OBJECTIVE: The aim of the study is to analyse worldwide the perceptions of new digital technologies in the agri-food sector expressed within social media platforms, identifying the differences that may exist between them regarding its objectives and social acceptance.
METHODS: This paper examines the information regarding digital transformation process in the agri-food sector disseminated worldwide on Twitter. For that purpose, Twitter API is used to gather tweets and descriptive and content analyses, including a sentiment analysis, are performed using R and MAXQDA software.
RESULTS AND CONCLUSIONS: We found that the digitalization of the agri-food sector is broadly discussed within Twitter. Different actors participate in these information flows, being companies and digital solution

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providers the most active users and academics and governmental institutions the most visible. Artificial Intelligence was the most mentioned technology, that together with the Internet of Things, Big Data, Machine Learning, and Cloud Computing, was related to improving production efficiencies, crop yield, or cost reduction. In the case of Blockchain Technology, it was closer to food supply chain actors, such as distribution companies and marketers. However, all these technologies are connected to the concept of sustainability. The sentiment analysis showed a generally positive tone, indicating social acceptance regarding the starting phase of the adoption of these technologies. The study also identified differences among countries, pointing to a stronger level of engagement with these technologies in developed regions. Moreover, the COVID-19 pandemic was seen as a chance to boost the digital transformation in the sector all over the world.

SIGNIFICANCE: Our results demonstrate that data harvested from Twitter provide useful insight into perceptions of digital transformation and different digital technologies in the agri-food value chain across different countries. Information that could be useful for researchers, but also for agricultural firms and policymakers.

1. Introduction

The process of innovation development and adoption is perceived as complex, dynamic and uncertain (Silvestre and Ţîrcă, 2019). However, it is considered essential to enhance firms' sustainable performance, to achieve the Sustainable Development Goals (Sachs et al., 2019). In this regard, sustainable innovation adopted by firms and the entire supply chain must include the adoption of new digital technologies aimed at improving the health of the planet and people, as well as efficiency and firm performance (Mondejar et al., 2021). Additionally, innovation in the agri-food sector has also been described as imperative to respond to new challenges related to sustainability, changing demand, and increased competition. The COVID-19 pandemic has also brought to light a need to build resilient food systems, motivating innovative collective actions along the entire agri-food chain (Bakalis et al., 2020).

The use of new digital technologies, such as the Internet of Things (IoT), Big Data, Artificial Intelligence (AI), and Blockchain Technologies, provides new opportunities to face these threats. Today, it is almost inevitable for any company to adopt some level of digital transformation to strengthen its competitiveness (Lu, 2017; Verhoef et al., 2021). Digital transformation is changing the way companies conduct business because it affects operational routines and creates new ways to network with customers, suppliers, and stakeholders (Cheng and Wang, 2021). It is evident that the development of this new business model requires the strengthening and redefining of firms' capabilities (Matarazzo et al., 2021; Tortora et al., 2021). However, the transition towards digitalization could be complex in the agri-food sector, characterised by small and medium-sized enterprises (SMEs), and problems of generational renewal (Żmija et al., 2020), as well as a supposedly low level of Information and Communication Technology (ICT) skills and engagement (Marshall et al., 2020).

Some authors have addressed the broad topic of digital transformation in agriculture, but most of them are focused on technical aspects of specific productions, such as improving productivity or logistic processes (Hunt and Daughtry, 2018; Rutten et al., 2013; Wathes et al., 2008; Wolfert et al., 2017). The social science field has recently started investigating various aspects of digital agriculture in relation to farm production systems, value chains, and food systems as a whole, regarding technology adoption and adaptation, farmers' skills and attitudes, or policy processes (Klerkx et al., 2019). Although there is data available regarding the innovation management of companies, there are few studies regarding digital transformation processes in this sector, and most of them are focused on the adoption of particular technologies by farmers (Haberli et al., 2019; Yoon et al., 2020; Zeng et al., 2021). Furthermore, the recent COVID-19 pandemic has forced companies, including the rural actors, to look into digital solutions to continue functioning, but our knowledge about its effect on the sector is still limited (Galanakis et al., 2021).

Hence, a wider perspective including the overall societal acceptance of the digital transformation process of the agri-food sector is required to understand the adoption level, the importance and dynamics of different technologies, as well as the role played by different agents involved in the diffusion and adoption of this digital transformation, which will serve to define policy interventions promoting it (Parra-López et al., 2021; Rijswijk et al., 2021). To fill this gap, the present study aims to explore worldwide the public perceptions towards different new digital technologies in the agri-food sector and identify the putative differences regarding its social acceptance. We address this objective using the content published on this topic within a popular social media platform.

In this regard, social media has become a usual tool to express opinions and sentiments or just share relevant information, changing the way in which people communicate (Li and Kent, 2021). This phenomenon presents opportunities and challenges for companies that are increasingly adopting social media as a communication channel, changing the ways they operate and relate to stakeholders (Paniagua et al., 2017). For these reasons, social media data has become a popular information source for academic research and other actors. Although it has been mainly focused on the analysis of food consumer behaviour (Mishra and Singh, 2018; Mostafa, 2013; Pindado and Barrena, 2020), Twitter has been also used as an entry point for understanding perceptions of specific digital innovations in the agri-food sector by the "*industry, farmers, and the broader public*" (Duncan et al., 2021, p. 1185).

Among different social media platforms, Twitter was selected to conduct this study because it is not only one of the most popular social platforms, but it is also easy to find topics, trends, attitudes, and sentiments on it (Chamlertwat et al., 2012). Through Twitter data analysis, the main objective of this research is to assess the digital technology development stage in the agri-food sector, identifying differences between different technologies regarding its social acceptance across different countries. We analyse and compare the level of engagement towards different types of digital technologies, given their different technological intelligence functions and their disruptive character (Yang et al., 2021a). The research technique starts with Twitter data collection performed through the Twitter API (Academic Research access level). Keywords such as "digital transformation", "artificial intelligence" or "agri-food" were used in the search query. The analysis of Twitter data to extract intelligence combined descriptive and content analysis, considering frequencies and the study of sentiments and emotions. The findings of this study will help us to acquire insights into the current and future digitalization trends in the agri-food sector and calibrate the influence of social networks' impacts. In this regard, it will be possible to extract suggestions in order to improve the communication strategy regarding innovation adoption by different actors of the agricultural sector.

The paper is organised as follows. Section 2 presents a literature review of research work done in the use of social media data in the agri-food sector and offers an overview of the digital transition of the sector. Section 3 shows the research procedure and methodology, and Section 4 presents the results. Section 5 presents the discussion and conclusions, including managerial and research implications and future research perspectives.

2. Background

2.1. Digital transformation of the agri-food sector

Innovation in our society is considered necessary to solve the current global challenges. In that regard, it has been argued that innovation systems need to be mission-oriented, trying to focus research and investments on solving critical problems, providing a solution or a concrete approach (Mazzucato et al., 2020). This view has also reached agricultural innovation systems, enabling a food system transformation (Klerkx and Begemann, 2020; Klerkx and Rose, 2020). Among other concepts, digital technology implementation and development (i.e., digital transformation) is one of the main pillars supporting the achievement of these challenges in the agri-food system (Shepherd et al., 2020). This kind of technology can be also considered as part of the Key Enabling Technologies (European Commission, 2009), which are seen as drivers for innovation applicable in multiple industries.

The digital transformation process is a complex phenomenon discussed by experts, researchers, policymakers, and entrepreneurs, and it is considered to be a radical change in economy and production on a global scale (Kaplan and Haenlein, 2019; Verhoef et al., 2021). In the recent academic literature it is possible to identify three phases in the digital transformation process: digitization, digitalization, and digital transformation (Brenner and Hartl, 2021; Verhoef et al., 2021). The concept of digitization refers to the conversion of information into digital formats by computers, in a bid to enhance efficiency (Loebbecke and Picot, 2015). Digitalization entails a deeper transformation that changes value creation activities or existing business processes, such as enhancing customer experiences, communication and distribution (Leviäkangas, 2016; Ramaswamy and Ozcan, 2016). Finally, digital transformation is the most pervasive phase, that involves the emergence of entirely new business models considered new to the focal firm or industry (Brenner and Hartl, 2021; Verhoef et al., 2021). It can be also argued that the digital transformation process could be different depending on the size and sector of the companies concerned because it is determined by some important characteristics, such as knowledge, R&D intensity, and technological assets (Aboelmaged, 2014; Chatterjee et al., 2021). In relation to these assets, (Garzoni et al., 2020) introduced a four-level approach to SMEs' engagement in the adoption of digital technologies: digital awareness, enquirement, collaboration, and transformation. This outlook could be even more complicated when the diversity and complexity of the new digital technologies are taken into account (Ciarli et al., 2021). These can be categorised into four groups regarding their main application: efficiency technologies (e.g., Cloud Computing), connectivity technologies (e.g., IoT), trust disintermediation technologies (e.g., Blockchain), and automation technologies (e.g., AI and Big Data) (Brenner and Hartl, 2021; Lanzolla et al., 2020).

The implementation of these technologies in the agri-food sector has been happening for decades, however, it was mainly considered behind the concepts of precision agriculture, smart farming, digital agriculture, agriculture 4.0 or farm management decision systems (Klerkx et al., 2019). All of these terms could be part of the digital transformation because implies that management tasks in any part of the food system are based on data obtained from the use of different technologies (Duncan et al., 2021; Eastwood et al., 2019). However, Wolfert et al., (2017) discern between precision agriculture and smart farming, considering that the former is only focused on in-field variability but does not takes into account data. This idea could be refutable, given that precision agriculture involves a range of technologies that generate data to help in decision making (Bronson and Knezevic, 2016; Duncan et al., 2021). Nowadays, it seems that these enabling technologies have reached the whole food supply chain as part of the so-called Industry 4.0 (Lezoche et al., 2020; Trivelli et al., 2019).

On the one hand, although positive effects of this revolution in the agri-food system in terms of the increased efficiency, productivity, and sustainability could be expected, there is a discussion about its socio-ethical implications (Eastwood et al., 2019) and the possible disagreement with agroecological approaches to reach a responsible innovation in the sector (Rotz et al., 2019). Moreover, there is a concern about the inequity in the design of digital farming innovations (Bronson, 2019) and the unequal relationships of power that the digital revolution could promote between players in the food system (Bronson and Knezevic, 2016), or even its potential to directly include and exclude these players from the generated benefits (Klerkx and Rose, 2020). On the other hand, it has been reported that digital technologies could accelerate post-COVID-19 recovery (Rowan and Galanakis, 2020). In fact, the last report from the (World Bank, 2021) outlines how digital technologies based on data are springing up in transforming sectors, among which we can find agriculture.

However, evolving from digitization to digital transformation appears to be challenging in the sector. Some reviews have identified the most common barriers to the adoption of digital technologies in the agri-food sector (Annosi et al., 2020; Giua et al., 2020; Jespersen et al., 2013). Some of them are related to firms' internal resources, such as farm business characteristics, size, infrastructure, and financial availability (Bronson, 2019; Lawson et al., 2011). Other challenges are related to external resources, data complexity, transfer, and privacy, internet connectivity, the lack of appropriate incentives, and a suitable adequate legislative operating environment (Kernecker et al., 2020; Pivoto et al., 2019). Regarding firm factors, the development of specific competencies, named dynamic capabilities, is also considered essential to achieve the digital transformation of businesses (Matarazzo et al., 2021; Warner and Wäger, 2019). Finally, factors related to farmers' personal characteristics, such as age, education, skills and knowledge of using ICT, perceived profitability, environmental-related behaviours, availability of time, or simply the willingness to implement new technologies, could be decisive to make possible the adoption of new digital technologies in the farming and food sectors, allowing its digital transformation (Alvarez and Nuthall, 2006; Bowen and Morris, 2019; Fountas et al., 2015; Tey and Brindal, 2012).

All of these emergent digital technologies have been considered as part of the game-changing innovations that will transform food production (Klerkx and Rose, 2020). However, given the aforementioned barriers to technology adoption, it is reasonable to assume that Agriculture 4.0 is still limited to a few innovative firms (Zambon et al., 2019), indicating that the sector could still be in a starting phase inside the digital transformation process. Currently, there is a lack of awareness about which are the most frequently adopted technologies, their limitations, and the conception of the agents involved, as well as those of society, all of which could strongly influence this process. More investigations are needed to explore if the theory around new digital technologies has been put into practice.

2.2. Agri-food sector and social media data

Nowadays, social media applications, such as Facebook, LinkedIn, Twitter and YouTube, among others, are widely used in diverse settings and with different purposes. As an increasing number of users are moving towards social media platforms, companies find it imperative to use social media for brand building in order to create opportunities for customer engagement (Schaefers et al., 2021; Shawky et al., 2020). Over the past decade, social media has been recognized as a key strategic element of companies' competitiveness (Braojos et al., 2019). For agri-food firms, the usage of social media has grown very fast. Indeed, the food industry is at the forefront of innovation in interactive marketing (Caiazza and Bigliardi, 2020). As an example, some of the major brands, such as Dr. Pepper, Kellogg's and CocaCola, have experienced increased attention from digital marketing within these platforms (Montgomery et al., 2011). However, other studies indicate that agri-food SMEs and cooperatives are still on the way to achieving effective communication and interaction with their target public in the digital environment (Cristobal-Fransi et al., 2020).

Leaving commercial purposes aside, many issues related to the agri-food sector are likely to be present in social media (Stevens et al., 2016). Discussion and interaction of people regarding topics such as animal welfare, GMO and food safety are very frequent (Price, 2021). This generates an opportunity for different actors in the agri-food system. For instance, social media applications are used for learning and collaboration among experts, entrepreneurs, farmers (Chowdhury and Odame, 2013; Mills et al., 2019; Phillips et al., 2018), and even the education community (Aguilar-Gallegos et al., 2021). It provides the opportunity to overcome the physical distance between actors and create networks directed to supporting agricultural innovation (Fielke et al., 2020).

Hence, the analysis of social media data allows for studying real events, social interactions, network analysis and user behaviour. In this regard, Twitter can be considered one of the most popular micro-blogging platforms with 199 million monetizable daily active users and 500 million messages tweeted every day (Aslam, 2022), providing the opportunity to interact with the audience without restriction and disseminate information rapidly (Moe and Schweidel, 2017). Moreover, Twitter data is considered to be "open data" because it allows businesses, practitioners or researchers to collect and analyse tweets through its API. Consequently, it has been already used for academic research in many fields (Karami et al., 2020) in order to analyse the current scenario but also to forecast upcoming trends related to any phenomenon in different locations. However, the study of Twitter to analyse the digital transformation process in general, and especially in the agri-food sector, is at a very early stage. Only a few authors have used social media data to analyse attitudes towards new digital technologies without considering the agri-food sector, such as public perception of the IoT (Bian et al., 2016) or Blockchain Technology (Mnif et al., 2021), the intention to accept robotics in the workplace (Sinha et al., 2020) and AI utilisation (Grover et al., 2020), in some cases combined with other methodologies. For that reason, our study tries to specifically analyse the perception of these technologies in the sector. Another important aspect is the possibility to analyse sentiments to gain an understanding of the opinions from which the engagement could be addressed (Caetano et al., 2018; Veltri and Atanasova, 2015). The emotional component of tweets has been used to understand social perception towards a specific phenomenon also in the agri-food sector, such as precision agriculture (Ofori and El-Gayar, 2021), consumer opinions towards food attributes (Borrero and Zabalo, 2021; Samoggia et al., 2020) and new food trends (Pindado and Barrena, 2020). However, these studies do not go in depth in the different technologies or the user profile that are key aspects of the current study.

3. Research procedure

3.1. Data collection

In this research, we acquired Twitter data using R software and the Twitter application programming interface (API) through the "academictwitteR" package (Gentry, 2015). Twitter API, through the Academic Research access level, enables access to the full archive of tweets published on Twitter, providing a way to collect tweets and metadata. To get this access several requirements must be complied with, and an application form must be completed and approved[1]. To access the Twitter API the API key, API secret, access token and access token secret are required. These can be obtained from the Twitter Developer Platform. The "academictwitteR" package allows researchers to collect tweets containing specified words or sets of words, but it is possible to specify more complex queries to incorporate into the API call, such as geographic location, URLs and media content (Barrie and Ho, 2021). First, data is stored as separate JSON files (JavaScript Object Notation), but after applying a parsing method the output data can be stored as Comma Separated Values (CSV) or Excel files.

Twitter data gathering can be difficult, considering that about 500 million tweets are generated per day (Karami et al., 2021). That makes 6000 tweets every second, and that makes essential a data sampling process, based on keywords and hashtags, as well as a time period restriction to extract relevant information. In this way, Twitter data related to new digital technologies in the agri-food sector were collected for a period of six months, from October 2020 to March 2021. This period of time, furthermore, was selected as representative of COVID-19 pandemic disruption in the agri-food sector which seems to have boosted the adoption of new digital technologies in the food industry and agriculture (Di Vaio et al., 2020; Rowan and Galanakis, 2020).

The data collection methodology consisted of retrieving tweets containing any of these English words: "*digitalization*", "*digital transformation*", "*big data*", "*blockchain*", "*artificial intelligence*", "*AI*", "*internet of things*", "*IoT*", "*machine learning*", "*smart technologies*", "*cloud computing*", "*smart agriculture*", "*agriculture 4.0*", "*smart farming*", "*digital agriculture*", always accompanied by "*agri-food*", "*agrifood*" or "*agriculture*". The use of these terms as keywords in the search query was based on their popularity and their presence in previous works related to digital transformation trends in the agri-food sector and the adoption of agriculture 4.0 or smart farming (Annosi et al., 2020; Klerkx et al., 2019; Rose and Chilvers, 2018)[2]. In this way, a majority of messages related to the broad topic of digital innovation in the agri-food sector were captured. An initial sample of 27,787 tweets was[1] obtained, but due to the possibility of redundancies, duplicate tweets were removed, leaving 27,500. A filter criterion was applied and only geolocalised tweets were considered, obtaining a final number of 18,001 tweets that composed the working dataset.

Although the above methodology to extract information from Twitter has been extensively used to investigate trends and public opinions regarding specific topics such as the digital transformation of tertiary industries (Sullivan et al., 2021), it is important to point out its potential to properly contextualize this research. Mainly, it cannot be considered that social media users are representative of the general population due to their users tend to be younger and more educated than non-users (Vaccari et al., 2013). Consequently, research using this source of information should be interpreted according to this self-selection (Mellon and Prosser, 2017). Furthermore, there may be other potential biases like the organic nature of the data —instead designed data—, bot intervention, dependence on the quality of the search terms, or the "*the black box of APIs*" (Chen et al., 2022). However, this data is especially useful to study emerging research topics due to the newness of the data, the inherent features of social media discussions (e.g., they are emergent and actual), and the easiness to capture data over large time periods (Chen and Tomblin, 2021; Groves, 2011; Klašnja et al., 2017).

3.2. Analytical framework

We have to consider that the captured data and metadata from Twitter is in the form of unstructured text (informal expressions) but, at the same time, it is enriched (hashtags, followers, users, etc.) compared to traditional data stored in companies' databases. It makes the analysis more challenging, especially without an available methodology, although some analytical frameworks have been proposed (Chae, 2015; Mishra and Singh, 2018). In this way, it turns out to be necessary to apply some research methods to mine intelligence from social media data. The detailed description of the proposed analytical framework that includes such methods is depicted in Fig. 1. It consists of two methodologies: descriptive analysis (DA) and content analysis (CA), the latter

[1] We would like to thank the Twitter developer community for permission to access the Academic Research product track and gather a high number of tweets.

[2] We previously conducted a series of searches on Twitter using MaxQDA Software, that led us to find out which were the most relevant words.

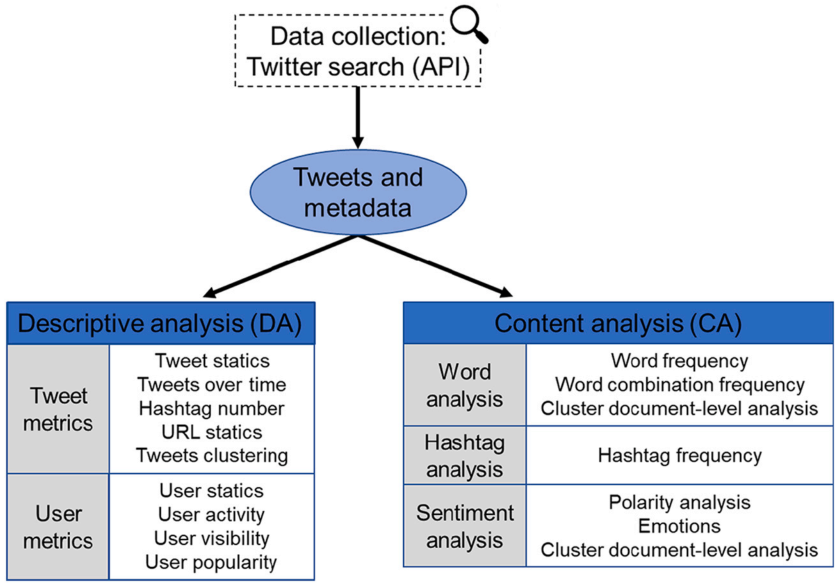

Fig. 1. Proposed Twitter analytics framework.

encompassing a sentiment analysis. Furthermore, the tweets were clustered by country (based on the most active countries in Twitter) or divided into six major digital technologies. Concretely, we use a technology classification that allows to capture the main I4.0 technologies within the agri-food sector discussed by Yadav et al. (2022) namely "Blockchain", "IoT", "Big Data" and "Cloud Computing". Furthermore, we also classify the tweets that address "Machine Learning" technologies due to their relevance to the agricultural sector, as well as "AI" technologies due to this term tend to be used interchangeably with machine learning despite it is a specific approach of "AI" (Storm et al., 2020).

3.2.1. Descriptive analysis (DA)

The main social analytics techniques include a descriptive analysis that allows for establishing the nature of both tweets and users when it is applied to analyse information coming from Twitter (tweets and metadata). It is based on various metrics and statistics, such as the number of tweets, the number of hashtags, unique users, retweets and classification of tweets into different types, among others (Bruns and Stieglitz, 2013). This analysis is especially useful for intelligence extraction in Twitter analyses, given the enormous size and the enriched nature (e.g., users, hashtags, and URLs) of Twitter data. A broad but crucial view of the data could be obtained as prior knowledge on which to base a more detailed analysis. The information regarding the number of tweets per user, replies or retweets of each tweet shows the most active or visible users, groups of users regarding their activities, and other useful user-related information (Joseph et al., 2017). It must be recalled that other metrics could be used to address different problems but they must be appropriately selected for each case of study.

3.2.2. Content analysis (CA)

CA allows for mining intelligence from the captured tweets that are in the form of unstructured texts (Krippendorff, 2004). An important step in text analysis and classification, previous to the CA, is data preprocessing (e.g., cleaning, removing noise), which includes the removal of links, non-Latin characters, numbers and users (Pindado and Barrena, 2020). CA can be performed by automatic text processing methods, based on text capturing and machine learning algorithms. First, text capturing techniques (Weiss et al., 2005) transformed the initial unstructured text into formatted data. Then, the techniques that we used for mining intelligence were word frequency analysis, term association analysis, thematic clustering, hashtag analysis and sentiment analysis (Mishra and Singh, 2018). Word frequency is based on detecting the number of occurrences of a word in a tweet or at the entire dataset level. The hashtag analysis (frequency and association) served as an information source about the fields that were more related to the topic of interest and demonstrated how popular the topics are and how topics are related (Petersen and Gerken, 2021).

Sentiment analysis can be considered to be part of CA, dealing with people's opinions, attitudes, and emotions about any topic expressed in written texts (Liu, 2015). In general, sentiment analysis methods are based on opinion extraction and sentiment classification into positive, negative, or neutral categories. The analysis can be performed on an entire tweet dataset to reveal the overall sentiment, but it can be also applied to clusters or specific sub-groups. One of the most widespread methods is called the dictionary-based method, based on using a pre-existing lexicon with information about which words and sentences are positive and which are negative (Wilson et al., 2009) so that sentiment scores are calculated by pointwise mutual information measures. We followed this method using the Syuzhet dictionary (Jokers, 2017), using the "Sentimentr" package (Rinker, 2017), which takes into account contextual valence shifters of the sentences contained in each tweet. Finally, we conducted an analysis of variance (ANOVA) and Tukey's HSD post hoc test to address significant differences among the average emotion scores of each digital technology.

4. Results

4.1. Descriptive analysis (DA)

Tweet metrics. The collecting method described in the previous section resulted in the identification of 18,001 original tweets involved in the use of digital technologies in the agri-food sector (without considering retweets). This highlights the relevance of Twitter as a way to spread the latest trends about digitalization in the sector. Although the number of tweets could be considered stable over the analysed period, we can see a decrease in the number of those posted during the Christmas season and also a periodic decrease at weekends (Fig. 2). 45% of tweets in this data collection were retweeted by other users and close to 14% of them were replied to. Additionally, 38% of tweets refer to other users and address messages to them. We found tweets coming from a total of 142 countries. However, there were important differences among them regarding the number of posted tweets due to the use of English words in the search query language. The USA was the leading country in terms of the number of tweets with 28.6% of the total dataset.

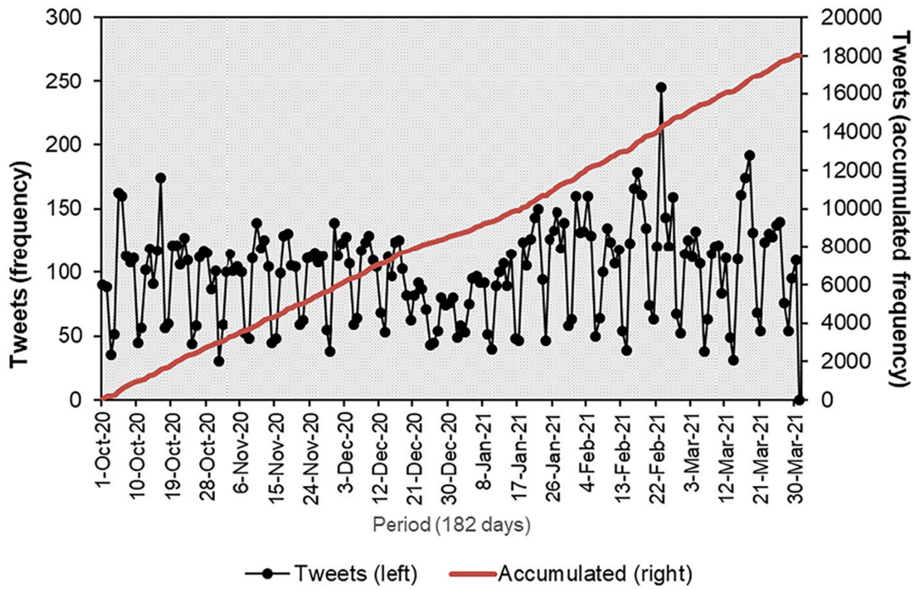

Fig. 2. Tweets posted during the analysed period.

It was followed by India, the UK and Nigeria, with means of 14.3%, 10.9%, and 5.6%, respectively. The 25 most active countries represent >90% of tweets in the dataset (Supplementary Table 1).

Regarding hashtags (i.e., words or phrases prefixed by #) that highlight certain topics, we found 7970 different hashtags in the tweets with 65% of them (11,649 tweets) containing one or more hashtags. Additionally, nearly 90% (16,102) of the total tweets contained one or more URLs. The most popular URLs were companies' websites and articles about initiatives or examples that described how to implement the new digital technologies in agriculture. We also clustered the tweets in terms of six popular digital technologies found in the dataset. From 18,001 tweets, 4125 specifically mention AI technology (23% of tweets). It was followed by blockchain and IoT with 7.3% and 6.7%, respectively. Machine Learning and Big Data are less frequently mentioned and are present in 4.5% and 3.6% of the tweets, respectively. Cloud computing is noticeably the least popular technology (0.3%). It is worth mentioning that half of the tweets did not contain a specific mention of any of these technologies, they were related to more general concepts such as digitalization or smart farming.

User metrics. We found 9004 unique users in the dataset. It means that each user posted two tweets on average. However, this does not reflect reality, because we found important differences regarding the activity of users. Indeed, we found that 10% of users accounted for 47% of tweets. The most active users were calculated based on the number of posted tweets (Table 1). At the same time, we have the most visible users, defined by a higher number of received retweets and replies (Table 2). Comparing both kinds of users, we found that they were not the same; the users with more tweets were not necessarily the most visible ones. The company FarmWise was one of the most active accounts and it was also in a good position regarding its visibility (20th position). The most active users tend to be companies, mainly from North America, India, or Europe (Table 1). In the case of the most visible users, they are mainly individual accounts, some of them belonging to governmental institutions, predominantly from Asia and Africa (Table 2). Moreover, we found users with different profiles, such as consultants, media, or foundations/groups, pointing to different technology adoption phases depending on these more dynamic agents. We observed that 7% of unique users identified were verified accounts, which are "*accounts of public interest*", corresponding to significant entities such as academic institutions, governments, politicians, news organizations, journalists, companies, activists, as well as other influential individuals[3].

Regarding the number of followers —the most basic popularity measure of Twitter users—, we found that >70% of the users had between 100 and 10,000 followers (Fig. 3), indicating that the majority of users interested in the digital transformation of the agri-food sector cannot be considered to be opinion leaders. However, we found 12 users with >5 million followers (Fig. 3), mainly accounts of media firms or news agencies. It is worth mentioning that the account of the United Nations is involved in this topic, as also is Microsoft.

Table 1
Most active users (top 10 users by number of tweets).

User name	N° tweets	%	Location	Profile
Future of Ag	759	4.22	USA	Individual
Amolexis Ltd	214	1.19	UK	Company
ukiot.store	153	0.85	UK	Company
Suriya Subramanian	146	0.81	UK	Consultant
FarmWise	137	0.76	USA	Company
agriculturerobots	113	0.63	Germany	Individual
Valuer News	95	0.53	Denmark	Company
akin alabi®	93	0.52	Nigeria	Individual
UrbanVN	80	0.44	Canada	Company
FOUNDERS CUBE	75	0.42	India	Company

Table 2
Most visible users (top 10 users by number of retweets and replies).

User name	N° retweets + replies	Location	Profile
STPI	3988	India	Government
Dr.Omkar Rai	2411	India	Individual
Iain Brown, PhD	1680	UK	Individual
World Economic Forum	1522	Switzerland	Group
NITDA Nigeria	754	Nigeria	Government
nelson chamisa	719	Zimbabwe	Government
akin alabi®	619	Nigeria	Individual
蔡英文 Tsai Ing-wen	578	Taiwan	Government
Thabi Leoka	557	South Africa	Individual
yadu yadav	553	India	Individual

[3] See https://help.twitter.com/en/managing-your-account/about-twitter-verified-accounts

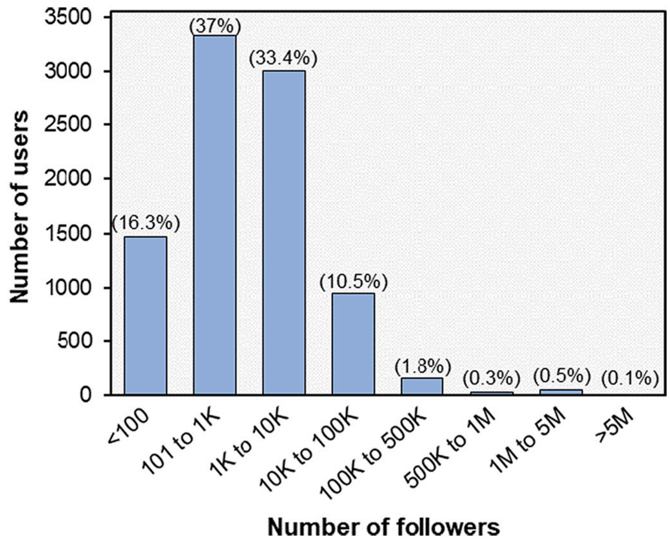

Fig. 3. Frequencies of users involved according to the number of followers.

4.2. Content analysis (CA)

We performed an in-depth analysis tackling tweets' content through a word, hashtag, and sentiment analysis. Word analysis involved word frequency and word combination frequency at the dataset and clustered document levels according to tweet location (countries) or six top technologies (AI, Big Data, IoT, Blockchain, Machine Learning and Cloud Computing). Hashtag analyses included hashtag frequency analysis. Sentiment analysis, including polarity and emotion analysis, was conducted of the entire number of tweets and clustered documents (by country or technology).

Word analysis. The most popular words in tweets (once we remove those that were used as keywords in the search query) were food (found in 1740 tweets), climate (1606), farmers (1526) and technology (1319), among others (Table 3A). We then analysed how many times a particular sequence of two words appears in the dataset (Table 3B). This provides information regarding those aspects which were getting attention on Twitter related to the digitalization of the agri-food sector. It is worth mentioning that words related to the COVID-19 pandemic were present in the data set, such as “covid”, “pandemic”, “vaccine”, “coronavirus” and “lockdown”. In general, 2.5% of tweets contained a reference related to the COVID-19 pandemic, showing a link with the use of digital technologies in the agri-food sector. Some of the most frequent word combinations were: “impact of covid”, “agriculture market covid” or “producers overcome covid”.

Table 3
Word analysis. A) Word frequency; B) Two-word combination frequency.

A)	Word	Freq	%	B)	2-word combination	Freq	%
	food	1740	9.67		climate smart	1250	6.94
	climate	1606	8.92		agriculture market	596	3.31
	farmers	1526	8.48		precision agriculture	340	1.89
	technology	1319	7.33		supply chain	265	1.47
	new	1295	7.19		food security	256	1.42
	market	1166	6.48		climate change	220	1.22
	industry	1036	5.76		agriculture sector	225	1.25
	help	942	5.23		agriculture industry	223	1.24
	future	874	4.86		sustainable agriculture	175	0.97
	agricultural	778	4.32		smart cities	156	0.87
	global	765	4.25		food supply	153	0.85
	sector	706	3.92		agriculture platform	153	0.85
	solutions	706	3.92		food production	140	0.78
	farm	688	3.82		digital technology	127	0.71
	world	640	3.56		food systems	123	0.68

We further performed word analysis in the four most active countries: USA, India, UK, and Nigeria. In this case, we kept the words that are part of the search query in order to analyse the differences regarding the technologies among countries. We showed that AI was the most often mentioned technology in these four countries (Supplementary Table 2 and 3). The least common technology was the same in all countries; Cloud Computing. However, we found differences regarding the popularity of the remaining technologies among countries. IoT and Blockchain are the second and third most popular technologies in all of them except for Nigeria, where Big Data is more frequent than these two technologies. Regarding COVID-19, we found that around 3.2% of tweets in both the USA and UK were associated with this pandemic. By contrast, India and Nigeria only showed 1.8 and 1.3% of tweets directly related to COVID-19. We further clustered the tweets in terms of six popular digital technologies (Blockchain, IoT, Big Data, Cloud Computing, AI and Machine Learning) and then conducted word analysis (Table 4). When we analysed the association of each technology with COVID-19, we found that Big Data, Blockchain and AI seems to be more related to the pandemic (close to 3% of tweets) compared with the remaining technologies (lower than 1% of tweets). In the case of Cloud Computing, we could not find any reference to the COVID-19 pandemic.

Hashtag analysis. In our dataset 7971 hashtags were found and they appeared 53,766 times. Moreover, 65% (11,649) of these tweets contained one or more hashtags. The most popular hashtags, without considering the digital technologies, were: #agriculture, #technology, #farming, #smart, #agtech, #agitech, #futureofag, #digital, #innovation, #sustainability, #robotics, #digitaltransformation, #farmers, #datascience, #agribusiness, #automation, #food, #startup and #climatechange, among others. It has not escaped our notice that hashtags related to the COVID-19 pandemic were also present, but to a lesser extent (e.g., #covid19, #covid, #coronavirus, #pandemic).

Sentiment analysis. Fig. 4 shows the sentiments at the entire dataset level. The most important idea was that >80% of tweets (14,691) tended to be slightly positive with a score from 0 to 1. Close to 10% were considered neutral (score = 0) and only 8% of tweets were slightly negative with a score from 0 to −1. Very few tweets showed a relatively strong positive or negative sentiment.

Table 5 shows some exemplar tweets with a relatively positive, neutral or negative sentiment. When we performed this analysis in the clustered documents by countries or digital technologies, we found a similar pattern to that of the entire dataset, but we could not find significant differences among the countries or technologies for each category of sentiments.

In order to go into detail about sentiment analysis, we performed an analysis of emotions, mining different kinds of sentiments from the tweets. In Fig. 5, we can see the most frequent emotions in the entire dataset. The emotions considered to be positive were predominant, especially trust and joy. When we analysed the emotions in the clustered documents by technology, we found that they were quite similar to those observed for the entire dataset (Fig. 5). However, among technologies, it can be highlighted that there was a significantly higher sentiment of trust in tweets associated with machine learning compared with the other technologies. Another positive emotion, as is joy, was more associated with machine learning and AI, followed by blockchain. However, it can be seen that AI is also more significantly related to fear, which is a negative emotion, compared with other technologies.

5. Discussion and conclusions

The broad topic of digital transformation in the agri-food sector is addressed on Twitter because it was possible to identify >18,000 geolocalised related tweets in a period of 6 months. However, compared to the 500 million tweets that are sent per day (Karami et al., 2021), this is a very small proportion. We found that the USA was the main country involved in this topic, as well as the leading country in terms of the number of Twitter users worldwide (Statista, 2021). However, we

Table 4
Detailed word analysis (2-word combination frequency) in clustered documents by technology.

Blockchain			*IoT*			*Big data*		
2-word comb.	Freq	%	2-word comb.	Freq	%	2-word comb.	Freq	%
supply chain	182	13.8	smart agriculture	88	7.3	agriculture market	40	6.2
food supply	119	9.0	precision agriculture	88	7.3	artificial intelligence	40	6.2
global food	77	5.8	smart farming	61	5.1	the future	33	5.1
chain market	74	5.6	agriculture industry	50	4.2	future of	24	3.7
food security	73	5.5	real time	49	4.1	precision agriculture	23	3.6
digital agriculture	73	5.5	in 2021	45	3.8	agriculture industry	20	3.1
to track	68	5.1	to improve	45	3.8	platform for	20	3.1
agriculture giants	62	4.7	agriculture market	44	3.7	smart farming	18	2.8
track grains	62	4.7	crop yields	43	3.6	agriculture needs	16	2.5
ai strawberries	61	4.6	iot sensors	43	3.6	smart agriculture	15	2.3
agri food	50	3.8	potential to	42	3.5	can help	15	2.3
agriculture market	39	3.0	food production	41	3.4	cgiar platform	15	2.3
blue nova	39	3.0	machine learning	40	3.3	cruises over	15	2.3
supply chains	35	2.6	production costs	36	3.0	robotic buggy	15	2.3
covid 19	26	2.0	agricultural efficiencies	35	2.9	over crops	14	2.2
Cloud computing			*AI*			*Machine learning*		
2-word comb.	Freq	%	2-word comb.	Freq	%	2-word comb.	Freq	%
grand farm	7	11.5	agriculture market	324	7.9	artificial intelligence	129	16.1
trilogy networks	7	11.5	can help	137	3.3	help to	55	6.8
precision agriculture	4	6.6	to improve	127	3.1	agriculture stimulates	53	6.6
rural cloud	4	6.6	the future	123	3.0	fresh produce	53	6.6
smart farming	4	6.6	machine learning	123	3.0	growth infrastructure	53	6.6
artificial intelligence	3	4.9	agriculture daily	116	2.8	need help	53	6.6
cloud based	3	4.9	future of	109	2.6	stimulates growth	53	6.6
farm launch	3	4.9	the potential	106	2.6	to improve	52	6.5
future of	3	4.9	potential to	103	2.5	end hunger	51	6.4
launch rural	3	4.9	in 2021	101	2.4	the potential	42	5.2
networks joins	3	4.9	precision agriculture	97	2.4	food production	41	5.1
provide cloud	3	4.9	improve agriculture	77	1.9	crop yields	40	5.0
retrieve from	3	4.9	smart agriculture	65	1.6	improve crop	40	5.0
send to	3	4.9	the world	64	1.6	in 2021	40	5.0
store in	3	4.9	agriculture industry	62	1.5	potential to	40	5.0

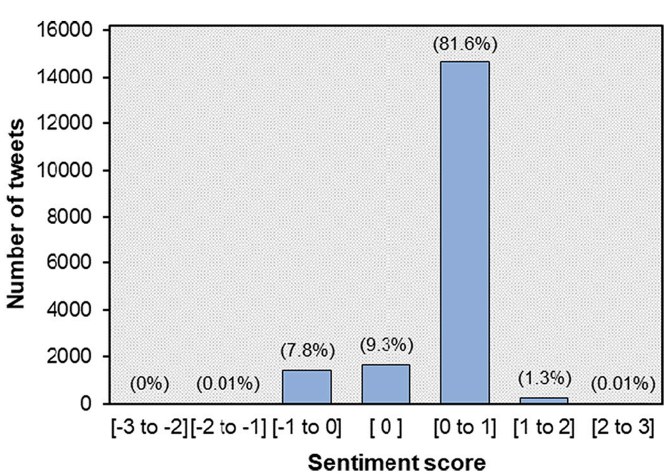

Fig. 4. Sentiment analysis at the entire dataset level. Polarity of tweets (−3 more negative to +3 more positive).

showed that the countries where Twitter is particularly popular (Statista, 2021) are not necessarily the countries that were tweeting more about digital technologies in the agri-food sector. In general, our data indicate that there were few countries with a relatively important activity in this regard: USA, India, and UK. The analysis also revealed information about the characteristics of the users. We found that some of the most active users (higher number of tweets in the analysed period) were shown to be companies advertising digital solutions. However, these companies did not have a high level of visibility (in terms of replies and retweets), indicating that the aim of their social media strategy is more related to promotional and advertising activities, rather than to engaging with business partners or clients (Juntunen et al., 2020).

The most visible users were individual users, some of them related to academia, but also governmental institutions and politicians. It means that the information tweeted by this kind of user was more widespread than those posted by companies. In fact, it is said that a user retweets when he has trust in the author (Firdaus et al., 2018), so it seems that official or institutional Twitter accounts are more reliable in the view of other Twitter users. Indeed, we found that percentage of verified

Table 5
Exemplar tweets with relative positive (score > 0), neutral (score = 0) or negative (score < 0) sentiment.

Exemplar tweets	Score
Advanced farming solutions to improve productivity, efficiency and sustainability using deep learning https://t.co/jq4OQ7kI9T #agtech #Augmenta #agriculture #automation #IoT #cloud #ArtificialIntelligence #DeepLearning https://t.co/ROebs0c8wW	2.03
Digital farming is providing farmers new ways to provide more food with more precise information. Learn how technology is changing farming for the better: https://t.co/6ASBMZh0pY	1.80
Technology is of extreme importance in agriculture and #Plant_Scope helps farmers find more efficient ways to protect their crops from diseases by leveraging computer vision, Machine learning and Deep Learning to monitor and precisely detect plant diseases. https://t.co/B2XlMbLoWT	1.68
Agricultural sensors for monitoring soil water and climate https://t.co/lU8V8N6SEC	0
Viewpoint article from myself and @d_christianrose in @GeneticLiteracy: Genetics and AI have launched an agricultural revolution but 'blind techno-optimism' could have harmful consequences. #Agriculture https://t.co/fRT5Vm5ygc	−0.86
Obstacles to big data in agriculture: data error, inaccessible or unusable data, incompatible systems, inconvenience, unclear ROU and unclear ownership #bigagdata https://t.co/DFunhpgnlJ	−1.02

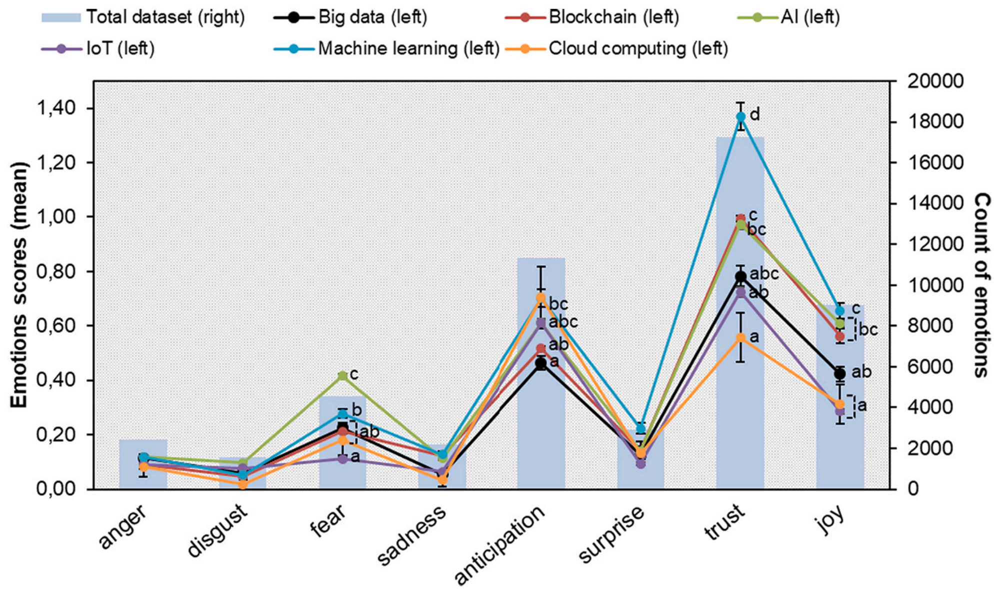

Fig. 5. Emotion analysis. Count of emotions indicates the strength of emotion present in the dataset (sum of each tweet). Emotions scores represent the average value for each cluster of tweets by technology (mean ± SE). Different letters indicate significant differences ($p < 0.05$, ANOVA).

accounts (7%) in the dataset is higher than the average of Twitter 2%, which reveals that verified accounts with supposed high-credibility play an important role in the dissemination of the information regarding the digital transformation of the agri-food sector compared to other public discussions (Yang et al., 2021b). However, despite the growing interest in digital agriculture within policy circles (Klerkx et al., 2019), governmental accounts do not seem to participate actively in the discussion of this process within the social media platforms. This is in line with the fact that agricultural extension services traditionally have used farmer field days and workshops, as well as face-to-face programs, to diffuse agricultural innovations (Norton and Alwang, 2020). The use of social media like Twitter has started to gain increasing relevance as a diffusion mechanism for governments and agricultural extension services but they use these platforms to disseminate information in a top-down approach with lower levels of engagement (Phillips et al., 2021). Consequently, we found that despite the higher levels of these accounts in terms of their visibility they do not fully exploit Twitter as a platform of knowledge exchange for the digital transformation of the sector (Klerkx, 2021).

The analysis also showed that users involved in the digital transformation process of the agri-food sector could be less active compared to those interested in other topics in terms of the average number of original tweets per user (Chae, 2015). Furthermore, the mentions of this topic on Twitter are not concentrated in a few users (Chae, 2015). These results, linked to the different profiles of these users (e.g., individual users, companies, institutions, media), indicate that a broad range of users were generating content on Twitter without clear leadership. This could suggest that different actors in the agri-food sector are involved in the process of digital transformation, from farmers, producers, through to the food industry, the supply chain and finishing in the market. This evidence is supported in the literature, where it can be seen that all agri-food related stakeholders are making efforts to apply these technologies that play a key role in their operations and decision-making (Lezoche et al., 2020).

Additionally, it must be considered that Twitter supports a variety of communicative practices, and tweets are disseminated to converse with individuals, groups and the general public. We found that the number of direct conversations regarding digital transformation in the agri-food sector is higher than other studies addressing other topics within the sector, such as supply chains (Chae, 2015). Moreover, the proportion of tweets that were retweeted is high compared to other studies (Boyd et al., 2010; Chae, 2015), indicating that the content regarding digital transformation process in the agri-food sector is more widespread. Likewise, we found that the percentage of tweets that contained, at least, one hashtag is higher than other studies analysing new technologies in other sectors (Bougie et al., 2011). All these aspects indicate that tweets related to the digital transformation of the agri-food sector seem to be more conversational and engaging than random tweet samples or tweets related to other topics. This finding reveals how Twitter may serve as a useful platform for collective and individual learning regarding the digitalization of this sector (Klerkx, 2021; Phillips et al., 2021).

Regarding the content, we found that more than half of tweets dealt with general aspects of the digital transformation process in the sector, such as smart farming or precision agriculture, rather than mention the use of specific digital technologies. However, it is interesting to specify that a quarter of the tweets were related to AI, which seems to be the most popular technology by far. This popularity could come from the conception of AI as an umbrella term that encompasses, in many cases, IoT (sensors that collect huge amounts of data), Big Data and Machine Learning (algorithms to analyse the data). Despite that, our results indicated increasing attention on the potential of AI in the agri-food sector. A recent study suggested a more active adoption of AI in North America and Europe, although Asia and Africa were also making smaller but increasing efforts (Lakshmi and Corbett, 2020), that are in accordance with our results. It is also remarkable that Big Data technology, which is considered to be at an early stage but with high potential in agriculture (Moysiadis et al., 2021), is one of the least mentioned digital technologies, together with Cloud Computing. These results contrast with the Future of Jobs Survey conducted by the (World Economic Forum, 2020), where business leaders identify the most popular technologies that are likely to be adopted by companies in the agriculture, food and beverages sector in 2025: IoT and Big Data, followed by Cloud Computing and AI. It seems that AI catches more of the attention of the general public compared with that of entrepreneurs in the sector and the reason could be that AI for the extended agri-food supply chain is only beginning to emerge (Monteiro and Barata, 2021).

The word combination analysis of clustered documents by technologies allowed us to differentiate the activities of the agri-food sector that were prone to adopt each digital technology. All of them, except for Blockchain, were related to the digitalization of the agricultural production and highlighted the smart farming or precision agriculture concepts within this digitalization process. This idea is in accordance with a growing body of literature that recognizes the essential role of digital emerging technologies in precision agriculture (Charania and Li, 2020) that allow for the developing of Decision Support Systems based on data analysis and data mining. This links with the recurrent idea found in these tweets about the potential of these technologies to improve efficiencies, crop yields and reduce production costs, especially in the case of AI and IoT. However, it seems that Blockchain technology is mainly applied to distribution or commercialization because those tweets are more related to the supply chain, traceability, and food safety. This evidence is supported in the literature, where it is possible to identify Blockchain applicability to improve food quality, safety standards and supply chain monitoring and tracking, especially when it is integrated with IoT technology (Dey and Shekhawat, 2021; Kamilaris et al., 2019; Torky and Hassanein, 2020). When the word combination frequencies were analysed in the most active countries, what was said in USA, India and UK could be quite similar, focused on the use of these technologies mainly in agriculture. Although comparing India with USA and UK could be noteworthy because this country is predominantly engaged in smallholder agriculture, India can be considered as an emerging economy focused on technology development and the view on how to manage the digital transformation in the sector could be closer to those of developed countries (Mondal and Basu, 2009). However, the speech in Nigeria was different, because most of the tweets were focused on a specific initiative to promote climate smart agriculture in the country. Those differences can be considered understandable, taking into account that the challenges facing the agri-food sector depend on the economic status and development level of each country (Anastasiadis et al., 2018). As an example, AI technology seems to be unevenly distributed between developed and developing economies (Vinuesa et al., 2020). In general, it could be possible to understand that they are in different phases of the digitalisation process, although the phenomenon of digital transformation goes beyond the binary of developed and developing countries (Freidberg, 2017), with an agricultural sector habitually working in a global competitiveness context with a major sustainability supply chain requirements.

The topics linked to the digital transformation process in the agri-food sector in Twitter were very diverse, evidenced by the high number of hashtags in the data. Some of the most frequent words and hashtags in the dataset were related to concern about the environment, such as “climate change” or “sustainable agriculture”. This is not surprising, as it has been globally proclaimed that digitalisation is of critical importance to environmental sustainability (Wyckoff and Pilat, 2017). This is in line with the growing expectations about the potential environmental benefits of digital transformation in agriculture noted by the literature addressing both concepts (Del Río Castro et al., 2021; Isensee et al., 2020). This view is close to the concept of S^3enterprise that can define Agriculture 4.0: “sensing” (detect events, acquire data and measure changes that occur in a physical environment), “smart” (analyse situations and make decisions based on the available data in a predictive or adaptive manner) and “sustainability” (optimise performance considering social, economic and environmental balance) (Miranda et al., 2019). However, the empirical evidence that demonstrates the environmental gains as a result of the adoption of digital technologies in the agri-food sector is still scarce (Clapp and Ruder, 2020; Klerkx and Rose, 2020).

Moreover, it was possible to extract an idea about the connection between COVID-19 and digital transformation in the sector because we found some tweets that regarded the COVID-19 pandemic as a digital push (Amankwah-Amoah et al., 2021). It is true that the impacts of the COVID-19 pandemic and the response mechanisms have been different for large companies, SMEs and small scale farming systems (Lopez-Ridaura et al., 2021). In this regard, we found that in the USA and UK this idea is more broadly supported in social media than in other kinds of countries where the agriculture sector is in a different phase of development. However, many tweets coming from Europe and the USA refer to the potential of implementing digital technologies in the agri-food sector of developing countries to overcome the consequences of the pandemic.

Finally, trying to analyse the perception of new digital technologies in the agri-food sector, we showed that the dataset contained a relatively low sentiment level. This finding is not surprising given the content of tweets is mostly focused on events, news or advertising, that differs from the kind of tweets that usually have stronger sentiments, such as complaints or discussions related to consumer behaviour (Pindado and Barrena, 2020). Although we found a weak level of sentiment, we did find a trend towards positivity, which is interesting considering the disruptive character of these technologies. In fact, the public may perceive digital technologies as a threat in the context of improving agricultural efficiencies (Driessen and Heutinck, 2015). However, our results are in line with a study performed in Germany, where people showed a predominantly positive attitude towards the use of digital farming technologies (Pfeiffer et al., 2021). The analysis of specific emotions supports the idea of the positive tone in the data because trust and joy showed higher scores compared to anger, fear, disgust, or sadness. Most interestingly, it was possible to associate some of these emotions with specific digital technologies. We showed that AI-related tweets were significantly closer to the emotion of fear, which seems negative a priori. However, we realised that the emotion of fear was related to the concern about global issues, such as agriculture, food demand or climate change, and AI was shown as a way to solve them. The significantly higher sentiment of trust in tweets related to Machine Learning, but also to Blockchain and AI compared with the remaining technologies was also notable. The general trend in Twitter was to express confidence towards the potential use of these new digital technologies that could be indicative of a generalised acceptance by society, taking into account the early phase of adoption of these technologies in the sector.

5.1. Implications

Derived from our findings and the proposed approach it is possible to draw some implications for government, rural actors, or researchers. First of all, we have to realise that the use of social media by the government has evolved from the distribution of propaganda to transparent communication and engagement with the general public (Bonsón et al., 2019; Mergel and Bretschneider, 2013). Taking advantage of that new way of interaction, the methodology proposed here could be useful to identify attitudes towards governmental opinions, regulations, or subsidies regarding the digital transformation process in the agri-food sector. Likewise, considering the findings reported in this study, public institutions should improve their interaction with agricultural producers and consumers within the social media platforms to improve the knowledge exchange and learning mechanisms that may boost agricultural digitalization (Klerkx, 2021). In the case of agricultural companies and farmers social media may be used to increase brand loyalty and reputation (Swani et al., 2014). In that case, the descriptive analysis could indicate their popularity and reputation. Sentiment analysis of the tweets mentioning them can enable the measurement of how the content of their tweets is perceived by professionals or clients. Additionally, this approach allows them to identify what kind of users are reacting to their posts, and analyse if they are reaching the target audience or if they need to expand their brand community on social media sites (Zaglia, 2013). Additionally, the research design shows the possibility of using Twitter data for research regarding the digital transformation process in the agri-food sector. Through the Twitter API, researchers have the opportunity to access Twitter data, which is interesting in terms of size, speed, and variety. The analysis of social media data has been recently researched (Ghani et al., 2019), showing its potential as a new data source, which could complement the existing ones in the context of Social Representation Theory (Bäckström et al., 2003; Gaspar et al., 2014; Ribeiro et al., 2016).

5.2. Limitations and future research

Despite the contributions made, this research presents some limitations. Starting from the data source, the use of Twitter data may not be strongly demographically representative of the general population as users tend to be younger, more educated and live in urban areas (Bian et al., 2016; Vidal et al., 2015). However, social media data could be useful for researchers as long as their limitations are recognized (Chae, 2015; Pindado and Barrena, 2020). Related to the data collection, the selected period, keywords, and language, despite being selected to address the specific objective of this study, could be considered to be limitations. In this regard, future research using Twitter data should use extended periods to corroborate the findings revealed here. Moreover, the keywords that we used in the search query were carefully selected but could have been different or included a wider range of concepts that could be contemplated in future studies. Linked to this aspect, we only considered tweets posted in English because it is the predominant language on Twitter but retrieving tweets in different languages could contribute to the understanding of differences among countries and regions. Likewise, the detailed analysis of the geolocation of the tweets could provide relevant insights into how the social representations of digital transformation are determined.

With this overview, we consider that future research related to the transition towards digitalization in the agri-food sector should be focused on the factors that have an influence on its feasible implementation, such as knowledge or awareness of the technologies, their usefulness and perceived adoption costs, given that the disruptive digital technologies are in an emergent phase (Klerkx and Rose, 2020). Finally, we consider that the study of digital technology adoption from a social perspective is urgently needed. The progressive adoption of digital technologies by firms implies the development of new skills and capabilities that will leverage each technology to the fullest to drive innovation and optimise processes. In that regard, companies, including the rural alternatives, have to be aware of this phenomenon regarding digital transformation that accelerates the shift in workforce skills and thus, the analysis of the whole range of factors that could act as drivers and barriers to digital transformation would be required.

CRediT authorship contribution statement

María Ancín: Methodology, Software, Validation, Investigation, Data curation, Writing – original draft, Writing – review & editing. **Emilio Pindado:** Methodology, Data curation, Software, Supervision, Writing – review & editing. **Mercedes Sánchez:** Conceptualization, Supervision, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare that they have no competing interests (financial or personal relationships) that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2022.103520.

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