The Role of Agri-Food 4.0 in Climate-Smart Farming for Controlling Climate Change-related Risks: A Business Perspective Analysis

Abstract

The impact of climate change, including fires, droughts, and storms, on natural resources and agricultural output is increasing. In addition to these problems, resource depletion and greenhouse gas emissions, agriculture also contributes to global warming. To reduce the dangers of climate change, farmers are using sustainable practices. This article aims to link agri-food 4.0 technology with climate-smart agriculture (CSA) to lessen the two-way interaction (both affecting and impacted) between the agricultural sector and global warming, as well as dangers related to the agri-food business. In light of this information, the research methodology of the paper is twofold. Initially, related risks towards climate change and the CSA and agri-food 4.0 technologies to overcome these risks were determined through a literature review. Then, risks and technologies are evaluated by adopting the TODIM (an acronym in Portuguese for Interactive and Multicriteria Decision Making), which is used for evaluating the criteria set with the related technologies to overcome climate change-related risks and provide a guiding map for academics and practitioners to eliminate risks associated with these climate change-related factors. According to the study's findings, the highest-priority concerns in the agri-food industries that are connected to climate change include energy consumption, food safety, and GHG emissions. IoT, bio-innovation, and artificial intelligence are thought to be the most promising technological solutions to address these problems.

Keywords: Agri-food 4.0; Climate-smart agriculture; Climate change; Smart and sustainable agriculture; Environmental sustainability.

1. Introduction

Climate change has a major impact on people's livelihoods, which rely largely on natural resources in terms of crop output, livestock feed, and seafood (Azadi et al. 2021). It boosts the severity and the degree of environmental issues such as drought, high rains, floods, and extreme heat, and these events are anticipated to accelerate in many regions and cause nonproductiveness of agricultural outputs. Therefore, flood and drought risk, as well as altered fire regimes, all represent further hazards to agricultural productivity (Falloon & Betts, 2010). In addition, climate regime uncertainty may also have an impact on how farmers decide things or even whether they spend on critical land inputs and assets (Sherr et al., 2012). For that reason, current worldwide issues about global warming (IPCC, 2011), natural resource exhaustion (Blasi et al., 2016), greenhouse gas (GHG) emissions (Pryor et al., 2017), and increasing social desire to engage in sustainability (Liu et al., 2017) have increased the emphasis on promoting sustainable agriculture (Mazhar et al., 2021).

The agricultural sector is considered a major factor in global warming. Considering that agriculture is the leading industry in the majority of low-income emerging nations, the adaptability of farming methods to global warming is critical (Azadi et al. 2021). One of the important agri-food sector activities for sustainability can be classified as minimizing excess production and waste of food, providing fair access to safe drinking water and nutrition for all humans, supporting sustainable consumption and financial growth, minimizing contaminant emissions that affect the environment, waterways, and soil, and managing natural assets sustainably (Karwacka et al., 2020). To achieve these basic purposes of the farming sector, farmers worldwide need to advance in technologies that will allow them to generate sufficient food to sustain themselves as well as the world's expanding population (Neate, 2013) by considering environmental constraints. Numerous ideas and strategies, including climate-smart agriculture (CSA), crop diversification, better water management, adaptive plant breeding, and conservation agriculture, have been developed and are currently being put into practice to mitigate the negative effects of dealing with these top concerns for agriculture.

CSA is a concept that combines environmental concerns with technology to address challenges in the agricultural sector. It uses modern agri-food innovations such as chemical fertilizers, herbicides, food, feed additives, high-yielding cultivars, agroforestry, and drainage techniques to produce high-yielding systems (Mwongera et al., 2017). CSA has surfaced as a guideline to obtain the notion that farms can be designed and built to concurrently enhance food security and livelihood opportunities and assist mitigation and adaptation (Sherr et al., 2012). CSA aims to boost agricultural production, build adaptive capability for food and nutrition security, advance and reduce GHG emissions and increase carbon sequestration (Campbell et al., 2014). It includes inventory control systems, water stress surveillance, fertilizer optimization, farm animal action meters, sensor data, weather prediction management, soil detectors, soil quality tracking systems, and innovative ware surveillance systems. It also includes drone use and robotized pest control (Biró et al., 2021).

Therefore, the agri-food sector needs to focus on the mechanization of manufacturing operations using environmentally friendly technologies such as greenhouses, robots, drones, sensor-based systems, and enclosed activities. Digital transformation capabilities are crucial for agricultural data management and utilization (Lezoche et al., 2020). In this context, smart agriculture, a contemporary concept, aims to improve the industry's effectiveness and quality by collecting and transmitting data such as rain levels, heat, leaf moisture, soil characteristics, and growing stages (Qureshi et al., 2021). This technology utilizes emerging farming technologies to minimize challenges and improve the overall agri-food sector.

Agri-food 4.0 is based on Industry 4.0 technologies that are altering production and allowing the establishment of a future smart factory (Latino et al., 2021). Agri-food 4.0 aims to deliver producers technological advancements to tackle agri-food production difficulties, resulting in lower open market pricing and lower farmer costs (Lezoche et al., 2020). Because conventional computing models are incapable of handling the massive amounts of data derived by sensors and other Internet of Things (IoT) devices (Perera et al., 2013), cloud computing enables on-demand access to data center processing resources for storing and processing massive amounts of information (Qureshi et al., 2021). Agri-food 4.0 makes use of many technologies, allowing the system to work better and more efficiently and preparing an environment for farmers.

There is a lack of evidence in the current literature regarding the use of both agri-food 4.0 and CSA for achieving both smart and sustainable agri-food sectors in response to the risks arising from climate change. With this motivation, the main goal of this research is to integrate agri-food 4.0 technologies with CSA for mitigating climate-change risks in agri-food. The reason why I4.0 technologies and CSA were chosen is that these technologies address the agri-food sector's climate change resilience problem in a technological, technical, and sustainable manner. For that reason, this research is twofold. First, a study of the literature has been used to identify the risks that the agricultural industry faces in relation to climate change. Additionally, by fusing CSA and agri-food 4.0 technologies, it aims to provide both technological and climate wise answers to these threats. These risks and corresponding technologies have been evaluated by adopting the TODIM (an acronym in Portuguese for Interactive and Multicriteria Decision Making) method to provide a guide map for academics, practitioners, and policymakers. Under this motivation and objective of this paper, the research questions (RQs) of the paper are as follows:

RQ1: What are the climate change-related risks to ensure sustainability in the agri-food sector?

RQ2: How can these risks be mitigated by adopting both smart and sustainable approaches or technologies?

The rest of this paper is structured as follows: a literature review is presented in section two. In the third section, the methodology of the paper, the TODIM method, is explained further for the implementation of the study. In the fourth section, the implementation stages of the paper and the results of the methodology are explained. In the fifth section, the results are discussed, and implications are given. Finally, the paper concludes with a summary of the paper, limitations, further research ideas, etc.

2. Literature review

The agri-food supply chain is engaged with farming commodities from the point of production to the point of consumption (Saetta & Caldarelli, 2020). In this section, of the paper, the risks of climate change and technology integration (agri-food 4.0 & CSA) are explained further.

2.1. Agri-food 4.0 and CSA integration for sustainability

Digitalization has the potential to improve all three elements of sustainability: it has the potential to (1) boost producers' revenue, (2) minimize production hazards and ecological constraints, and (3) alleviate key agricultural labor shortages (Biró et al., 2021). Therefore, the food sector is being seriously challenged by the rising number of capabilities unleashed by technology that facilitate interaction among equipment, services, and people (Carmela Annosi et al., 2020). Producers have begun to implement their action plan for I4.0 advancements, putting them ahead of their opponents, and they can join the next production and distribution age with flexible, effective automation that is maximized by data-driven information, providing them with total control over supply and material flow. (Javaid et al., 2022). Hence, the combination of I4.0 with agriculture allows for the transformation of industrial agriculture into the next generation, termed agri-food 4.0 (Liu et al., 2020).

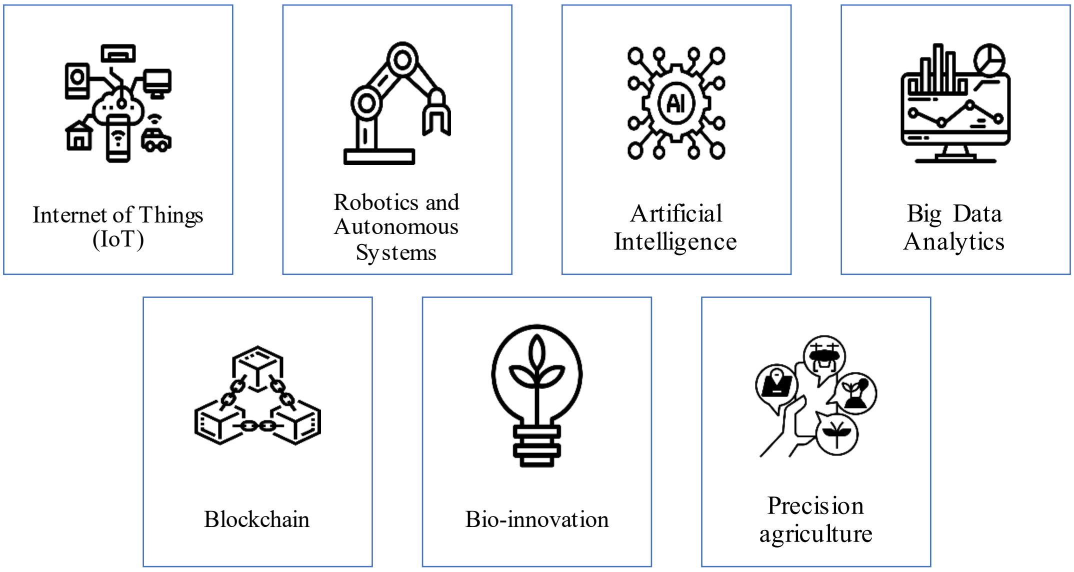

Fig. 1: Adopted agri-food 4.0 and CSA technologies used throughout this study to deal with the risks

In this section, of the study, IoT, robots and self-driving vehicles, artificial intelligence, big data, blockchain, bio-innovation, and precision agriculture concepts are enlightened for proposing both technological and environmentally friendly agendas for achieving sustainability purposes caused by the risks associated with climate change in the agri-food industry. Initially, the term "precision agriculture" defined a farming management philosophy focused on detecting, analysing, and responding to crop variability, which can contain numerous components that can be difficult to quantify, but technology has progressed to compensate for these challenges. Furthermore, AI technologies can be beneficial for the agri-food sector from various angles. For instance, AI can predict the appropriateness of a novel seed type for growing in diverse microclimates, reducing the time to market. It can accomplish this by assessing previous seed performance metrics, meteorological conditions, soil data, and projected climate data to identify new places where the seeds will perform best (Forbes, 2021). Therefore, we can claim that the integration of artificial intelligence (AI) and/or predictive analytics tools assists in employing existing data to advise farmers on crop rotation, ideal planting and harvesting periods, and soil management (Bahn et al., 2021).

The use of IoT systems in agriculture also adds new information sources defining agricultural aspects (Lezoche et al., 2020). The IoT enables real-time information gathering and sharing, improved communication, collaboration, and coordination among supply chain components (Saetta & Caldarelli, 2020). In this context, these IoT systems receive help from cloud and fog computing, which are services that give nearly infinite computing, storage, and communication resources as commodities, including on-demand and pay-per-use (Latino et al., 2021). Another important technology is blockchain technologies, which supply chain benefits such as knowledge continuity, traceability, and a link between information and material flow (Saetta & Caldarelli, 2020). Furthermore, the incorporation of big data technologies in agri-food projects is critical for expanding farmer data to generate new knowledge, developing IT service providers and software developers to provide novel services and procedures, and extending and adapting ICT and future factory (FoF) agriculture-related big data models and patterns (Lezoche et al., 2020).

2.2. Risks towards climate change in the agri-food supply chain

Agriculture's historical and current contributions to climate change, as well as the mechanisms within which agricultural systems may adjust to changing conditions, are being increasingly recognized, as is agriculture's ability to ameliorate our climate effect (Neate, 2013). Statistics show that agriculture accounts for approximately 14% of total GHG emissions and contributes substantially to emission levels generated by shifts in land usage, particularly the destruction of forestry, which accounts for 17% of global GHG emissions (Seebauer, 2014). Carbon dioxide (CO2), methane (CH4), and nitrous oxide (N2O), which are frequently produced in large quantities by farming systems, are the principal greenhouse gas emissions that cause global climate change (Garnett, 2011). Similarly, considerable amounts of energy are demanded during many phases of crop production, covering previous on-time and post-farm operations, all of which generate GHG emissions. In addition, depending on recent projections, global food production must increase by over 70% by 2050 to fulfil the expected 9 billion global population food requirement (Pye-Smith, 2011). The unprecedented increase in the world's population created a treble burden for satisfying people's nutrition, fresh water, and power sources, putting additional strain upon this ecosystem and exacerbating drastic global warming. (FAO, 2017).

Hence, the agriculture sector is considered a major factor in global warming. Considering that farming is the leading industry in the majority of low-income emerging nations, the adaptability of farming methods to global warming is critical (Azadi et al., 2021). One of the important agri-food sector activities for sustainability can be classified as minimizing excess production and waste of food, providing fair access to safe drinking water and nutrition for all humans, supporting sustainable consumption and financial growth, minimizing contaminant emissions that affect the environment, waterways, and soil, and managing natural assets sustainably (Karwacka et al., 2020). To achieve these basic purposes of the farming sector, farmers worldwide need to advance in technologies that will allow them to generate sufficient food to sustain themselves as well as the world's expanding population (Neate, 2013) by considering environmental constraints.

Worldwide population and economic growth on the demand side and climate change circumstances on the supply side will intensify competition for limited resources in future years (Lotze-Campen et al., 2010). Therefore, resource constraints will soon become a great threat to agriculture. Soil, freshwater, power, and other supplies for agricultural production are becoming increasingly scarce (Campbell et al., 2014), and agriculture is widely acknowledged as the main reason for contamination of water resources (Dabrowski et al., 2009). Specifically, agricultural food production accounted for 90% of world freshwater usage on average throughout the previous century (Scanlon et al., 2007). Hence, water shortages are a serious problem since 1.1 billion people out of the world's 6 billion do not have access to safe drinking water (WHO, 2003). Water resource management of agricultural output is an essential component in resolving some of the most challenging trade-offs among increasing agricultural output, which can contribute significantly to food security and economic growth on the one hand, and handling the loss of vital environmental advantages, which also create sustainable well-being and livelihoods on the other (Gordon et al., 2010).

Another important risk that threatens sustainability in agriculture is soil degradation. Soil degradation, which is regarded as one of the primary drivers of slowing productivity development, refers to the processes, mostly human-induced, through which soil quality deteriorates and becomes less suitable for a given use, such as crop production (Bindraban et al., 2012). It indicates a long-term loss in soil production and its ability to moderate the environment (Lal, 2001). In particular, cultivating a particular crop across the same acreage year after year deteriorates soil quality and nutrients, which cannot be supplied by the surrounding environment because monoculture agriculture lacks biological variety (Liu et al., 2020). Soil degradation continues to be a severe concern for future food security issues (Bindraban et al., 2012) and is also considered another substantial risk throughout this paper.

Food loss is also a critical concern that is neglected by authorities. While food loss is a waste of money that can diminish farmer revenue and raise consumer prices economically, it also has several environmental consequences, including unneeded GHG emissions and wasteful water and land usage, which can result in reduced natural ecosystems. In this context, economically preventable food wastage and losses are critical in the fight against hunger and enhance safe food in both developing and developed countries. (Beretta et al., 2013). Thus, it poses a high risk for the agriculture sector. In addition, deforestation is another risk that leads to climate change, biodiversity loss, decreased timber supply, floods, siltation, and soil degradation, all of which have an impact on economic activity and people's livelihoods.

Because of the increased need for food worldwide, the misuse of synthetic pesticides and fertilizers in traditional agriculture has become critical, but it has also generated threats to the environment in recent years (Durán-Lara et al., 2020). In China, for example, synthetic fertilizers have been overused, which leads to environmental degradation. As a result, the Chinese central government announced the 'Action Plan for Zero Increase in Fertilizer Use' (APZIFU) in 2015 to reduce the misuse of synthetic pesticides and fertilizers by 2020 (Durán-Lara et al., 2020). Therefore, agriculture and food systems have a vital role in determining nutrition; by extension, however, understanding of the links among farming, food systems, nutrition, and public health, as well as the accompanying policy mechanisms, is still in its early stages. (Kanter et al., 2015). Agriculture is essential for good health since it produces the majority of the world's nutrition, fibre, and building supplies as well as therapeutic plants; it is also a major source of income for many impoverished people in developing nations (Hawkes & Ruel, 2006). Therefore, examining health in an agricultural environment is crucial since agriculture provides both opportunities for enhancing health and dangers to health.

In addition, the importance of GHG emissions (methane, nitrous oxide, etc.) in global warming cannot be overstated (Okorie & Lin, 2022). The agriculture sector is also predicted to contribute significantly to the fraction of GHG emissions caused by global warming (Israel et al., 2020). According to Czyżewski & Kryszak (2018), agricultural activities generate approximately 25-30% of GHG emissions. On the other hand, OECD (2015) claims that agricultural practices account for approximately 17% of GHG emissions and 7-14% of land use change. Because of the utilization of fossil fuels, chemicals, overapplications of fertilizer, pesticides, and contemporary agro-based technology, the amount of energy used in agricultural production has grown significantly (Koondhar et al., 2021). Numerous of the same measures that minimize GHG emissions can also enhance resource efficiency and work in tandem with rural development and food security goals (Ogle et al., 2014).

More energy consumption increases carbon footprints, global warming, and human health consequences; consequently, it is critical to use a sustainable amount and energy quality to produce enough food to fulfil demand while conserving existing natural resources (Koondhar et al., 2021). The agri-food industry has been significantly affected by resource shortages, food waste and loss, and waste creation along the entire supply chain (Agnusdei et al. 2022). Last, labor exploitation or displacement is another risk that threatens social sustainability in the agricultural sector and requires immediate attention. The criteria listed in Table 1 below were chosen after a thorough literature analysis of the agri-food industry. First, a list of criteria was determined via the literature, and then, a group of experts discussed these criteria set depending on their importance. After the discussions, the most prevalent criteria in the literature were narrowed down by considering the comments of the experts composed of academicians to eleven criteria, which were then enumerated and presented with references from the literature. The latest version of the narrowed criteria set is shown below.

Table 1: Climate change-related risks and descriptions

Criteria	A brief description	Support references
Deforestation & Biodiversity loss (C1)	Deforestation is the process of removing a forest or tree clump from the ground and converting it to a different use. The biodiversity and deforestation are two connected topics that lead to another. For instance, the irreversible extinction of certain tree species, their failure to migrate and thereby extinction, etc.). Additionally, by decreasing the amount of food, shelter, and breeding areas that are accessible to animals, the removal of trees and other plant types can directly result in the loss of wildlife habitat.	Cuadros-Casanova et al., (2023); Levy et al., (2023); van der Ven, & Barmes, (2023); Silvestri et al., (2022); Bastos Lima, (2021); Masi et al., (2021).
Energy consumption	The quantity of energy used for routine agricultural tasks is referred to as usage. Agriculture immediately consumes energy using equipment (such as trucks for cultivating areas) and through the heating of greenhouses and animal stables. Energy is indirectly used in agriculture in the creation of field equipment, structures, and livestock.	Abbate et al., (2023); Derakhti et al., (2023); Silvestri et al., (2022); Masi et al., (2021); Belaud et al., (2019); Miranda et al., (2019); Zhu & Pan, (2010).
Food loss	The sustainability of our food systems is weakened by food loss and waste, which also results in the waste of all the resources used to create these foods, including water, land, energy, labor, and money. It has negative impacts on the ecosystem, such as food production, which increases greenhouse gas pollution and poses a danger to our world.	Abbate et al., (2023); Trevisan & Formentini, (2023); Silvestri et al., (2022); Bahn et al., (2021); Masi et al., (2021).

Food safety	Food security, nutrition, and health are intertwined because unsafe foods lead to a vicious circle of sickness and malnutrition that disproportionately affects infants, young children, the aged, and patients. The key to preserving life and encouraging health is having access to secure and nourishing food. Dangerous bacteria, viruses, parasites, or chemicals ingested from contaminated food cause diarrhoea, which is a serious health concern.	Derakhti et al., (2023); Silvestri et al., (2022); Bahn et al., (2021); Oruma et al., (2021); Masi et al., (2021).
GHG emission	Warming of the earth is caused by GHG, which absorbs heat. One-fourth of all world GHG emissions come from changes in farmland and land use. Agriculture as an industry generates non-CO2 emissions from products and animal operations at the agricultural gate as well as CO2 emissions from natural habitats, primarily woodland, and natural peat, when they are converted to agricultural land use.	Abbate et al., (2023); Bahn et al., (2021); Masi et al., (2021); Higgins et al., (2015).
Labor exploitation or displacement	Agricultural mechanization's impact on labor jobs and the propensity for labor displacement, as well as farming movement, are both too high. Due to factors like labor fraud, proof of recruitment abuse, exploitative employment, child labor, employee freedom of union, salary and time breaches, dangers to employees' health and safety, etc. has long been a problem in the farming sector, particularly globally.	Saha, (2023); Silvestri et al., (2022); Bahn et al., (2021); Oruma et al., (2021).
Public health	Agriculture and public health are two interrelated problems that must be improved for the good of civilization. This is done to maintain pure air and water supplies, reduce farming practices that are bad for public health, increase natural space, and regulate the use of pesticides and antibiotics that are bad for the public. includes limitations like. Restricting the use of these dangerous chemicals, for instance, addresses uses like supporting manufacturing techniques that have been demonstrated to have little negative impact on public health.	Abbate et al., (2023); Silvestri et al., (2022); Bahn et al., (2021); Oruma et al., (2021); Masi et al., (2021).

Reduction in water quality & quantity	Poor agricultural effluent management is causing severe water quality issues worldwide, which is escalating the water catastrophe. By causing erosion, transporting fertilizers, pesticides, and heavy metals, as well as by lowering the quantity of water that naturally moves through streams and waterways, excessive irrigation can have an adverse effect on water quality. These unintentional farming practices gather and clear both natural and man-made contaminants, ultimately discharging them into regions through lakes, rivers, marshes, coastal waterways, and even our groundwater sources for drinking.	Abbate et al., (2023); Derakhti et al., (2023); Trevisan & Formentini, (2023); Silvestri et al., (2022); Bahn et al., (2021); Bastos Lima, (2021); Masi et al., (2021); Oruma et al., (2021).
Resource constraints	New dangers have emerged because of the susceptibility of farming systems around the world to a growing number of resource limitations (related to soil, water, and energy in general) and global environmental changes.	Gao et al., (2023); Han et al., (2023); Silvestri et al., (2022); Ahumada & Villalobos, 2009.
Soil degradation	It is a severe environmental issue when soil quality declines or worsens due to improper use or administration for farming, industrial, or urban reasons. The quality, amount, and diversity of the goods created are all impacted by changes in soil quality, which is an essential natural resource for agriculture.	Abbate et al., (2023); Silvestri et al., (2022); Bahn et al., (2021); Bastos Lima, (2021); Masi et al., (2021); Oruma et al., (2021).
Synthetic material overuse	Synthetic material overuse such as pesticides bioaccumulate in food chains when they are used carelessly, presenting a serious danger to mammals and other nontarget species (Liu et al., 2016). Additionally, pesticides' direct or indirect effects on creatures other than their intended targets cause an environment to become unbalanced.	Silvestri et al., (2022); Bahn et al., (2021); Masi et al., (2021).

3. Proposed Methodology

The flowchart of the study is presented below in Figure 2.

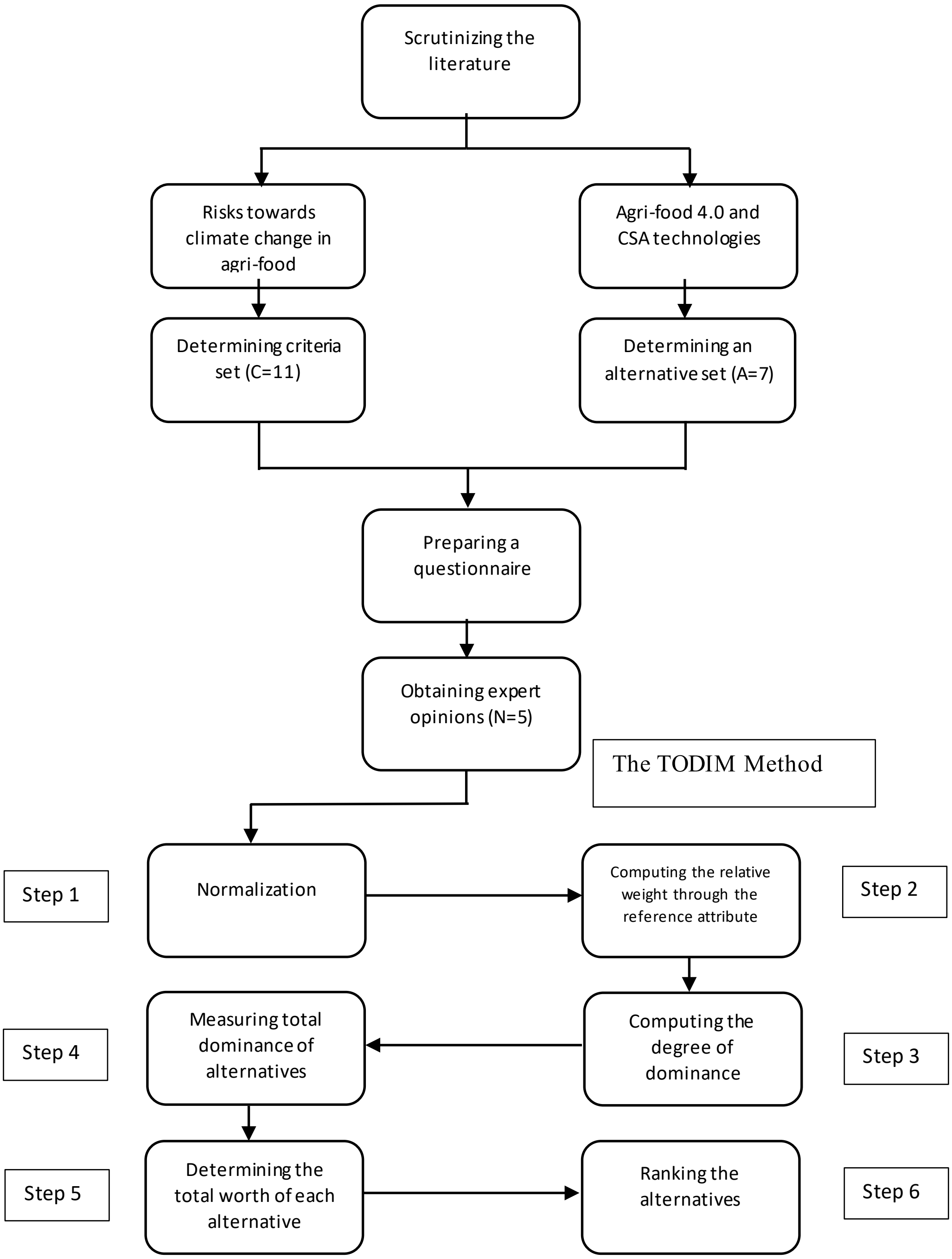

Fig. 2: Flowchart of the study

3.1. The TODIM Method

Gomes and Lima developed the TODIM approach in 1992 (Gomes et al., 2015). The TODIM method is based on the theory of prospect, which describes how people make riskaverse judgments, and the central tenet of the theory is that people react asymmetrically to gains and losses (Alali & Tolga, 2019). The fundamental concept is to use the total value to quantify the degree of dominance of every option for each alternative, and then the alternatives are evaluated and ranked (Alinezhad & Khalili, 2019). The traditional TODIM technique can only be implemented for the multiattribute decision-making (MADM) issue when attribute values are in the form of crisp integers (Fan et al., 2013). The algorithm of the TODIM approach is described here to assist examination and subsequent developments.

The reason why the TODIM method has been adopted for this research is that the TODIM approach is based upon a value function that offers the degree of dominance of one choice over other choices in terms of the many criteria, with the goal of reflecting the DM's attitude of gain and loss upon every criterion. By implementing this method, we can assist stakeholders in selecting the best alternative depending on our variables. In the TODIM method, this value function reflects the decision maker's (DM) behavior in relation to profits and losses (Llamazares, 2018). The gains and losses are then transferred to the prospect function to generate partial dominances, which are then aggregated to make the ultimate dominance (Lourenzutti & Krohling, 2015). Various types of MCDM methods, such as the analytic hierarchy process (AHP), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and Elimination and Choice Translating Reality (ELECTRE), are used in this study. However, while all of these techniques aim to support multicriteria decision-making, they differ in their algorithms and methodologies, making them appropriate for various choice circumstances and preferences. The features of the problem in our study and the decision maker's priorities and preferences influenced the selection of the TODIM approach. With the ability to modify preferences and tolerances, TODIM is an interactive decision-making system that evaluates options based on the decision-maker's risk attitudes and criterion scores.

Considering that there is a group of n alternatives that must be sorted when m quantitative or qualitative criteria are present, one of these criteria serves as the reference criterion. The decision-makers calculate the weight of each criterion based on a numerical scale (1-5 scale) for normalization. The abovementioned steps of the TODIM methods were taken by Fan et al. (2013).

Step 1: Normalize $X = [x_{ij}]_{m\times n}$ (1) into $Y = [y_{ij}]_{m\times n}$ (2) by using the normalization, which x_{ij} referred to as a crisp number,$i \in M, j \in N,$

Step 2: Compute the relative weight w_{jr} of attribute C_j through the reference attribute C_r, i.e.,

$$w_{jr} = w_j/w_r, \quad j,r \in N, \tag{3}$$

where $w_r = max\{w_j \,|j \in N\}$.

Step 3: Compute the degree of dominance of alternative A_i over alternative A_k considering attribute C_j, $i.e.$,

$$\phi_j(A_i, A_k) = \begin{cases} \sqrt{(y_{ij} - y_{kj})w_{jr}/(\sum_{j=1}^{n} w_{jr})} & (y_{ij} - y_{kj}) > 0, \\ 0, & (y_{ij} - y_{kj}) = 0, \\ -\frac{1}{\theta}\sqrt{(y_{kj} - y_{ij})(\sum_{i=1}^{n} w_{jr})/w_{jr}}, & (y_{ij} - y_{kj}) < 0, \end{cases} \tag{4}$$

where θ denotes the loss attenuation factor. $y_{ij} - y_{kj}$ signifies the advantage of alternative A_i over alternative A_k in terms of attribute C_j if $y_{ij} - y_{kj} > 0$ and the loss if $y_{ij} - y_{kj} < 0$.

Step 4: Measure alternative A_i's total dominance over alternative A_k, i.e.,

$$\delta(A_i, A_k) = \sum_{j=1}^{n} \phi(A_i, A_k), \;\; i, k \in M. \tag{5}$$

Step 5: Determine the total worth of each alternative A_i, $i.e.$,

$$\xi(A_i) = \frac{\sum_{k=1}^{m} \delta(A_i, A_k) - \min\limits_{i \in M}\{\sum_{k=1}^{m} \delta(A_i, A_k)\}}{\max\limits_{i \in M}\{\sum_{k=1}^{m} \delta(A_i, A_k)\} - \min\limits_{i \in M}\{\sum_{k=1}^{m} \delta(A_i, A_k)\}}, \quad i \in M. \tag{6}$$

Step 6: Rank every alternative and select the most desired alternative(s) based on their total merits. The larger $\xi(A_i)$ is, the better alternative A_i will be.

Step 7: Conduct a sensitivity analysis by systematically changing the weights given to the criterion. To do this, one or more weights must be changed while the other weights are held constant. Recalculate the outranking and dominance matrices for each weight situation.

4. Application

The main goal of this study is to identify and analyse the risks associated with implementing I4.0 technologies in the agri-food sector with regard to climate change-related environmental risks, as well as to suggest an environmentally friendly and technological road map for the various stakeholders to achieve this goal. Because of the uncertainties inherent in weather, yields, pricing, government regulations, global marketplaces, and other variables that influence farming, the agriculture industry has a large amount of risk (USDA, 2022). The agri-food sector is dramatically affected by environmental changes, and it has a unique position compared to the other sectors. For this purpose, this paper mainly investigates the risks associated with climate change and tries to find a solution to solve these risks by integrating both environmentally friendly and technological approaches to minimize harm to nature. Initially, the climate-change-related agri-food risks and related novel and environmentally friendly digital technologies were scrutinized throughout the literature to evaluate them to observe which of these technologies can be adopted for the purpose of overcoming these predetermined risks through climate change.

To implement this method, a matrix that contains both risks, which are the criteria, and technology options, which are referred to as alternatives, was prepared in a matrix format as a questionnaire in Excel to be asked to experts from the agri-food sector with various tiers, experience, and titles. Prepared questionnaires were sent to the experts (see Table 2) via e-mail, and the experts' evaluations were gathered in Excel format for the calculations. The expert profiles were selected based on various firms, positions, years of experience, responsibilities, and backgrounds to obtain a range of viewpoints on the subject. In addition, these experts were chosen from different firms, regions, job descriptions and backgrounds to address various tiers of agri-food sectors. Most specifically, the experts were from firms in the Aegean region of Turkey. Because of this, there were discrepancies in many of the experts' qualifications. For instance, the specialists' experience ranged from 6 to a maximum of 19 years. The positions held by the experts also varied, including those of production manager, food engineer, sustainability analyst, etc.

Table 2: Expert profiles and experiences

Experts	Position of the Participants	Years of Experience (In Total)	Key Responsibilities
1	Food Engineer	6	Product development; process optimization; quality assurance, food safety; ingredient selection; and equipment design.
2	Sustainability analyst	13	Environmental impact assessment; carbon footprint analysis; energy efficiency; waste management; sustainable development; renewable energy; energy conservation.
3	Agricultural engineer	11	Crop management; precision agriculture; pest and disease management; agricultural automation; harvesting and postharvest technology; sustainable agriculture.
4	Production manager	19	Production planning; resource allocation; manufacturing efficiency; quality control; production scheduling; inventory

5	Agriculture consultant	9	management; cost optimization; process improvement. Farm assessment; crop selection; soil analysis; nutrient management; sustainable farming practices; farming systems optimization; irrigation and water management.

5. Results

After obtaining the evaluations from the experts, the steps of the TODIM method were implemented as suggested in section 3. Depending on these results, the criteria weights were presented as follows (see Table 3). Depending on this table, we can deduce that C2: energy consumption, C4: food safety, and C5: GHG emissions were prioritized by the experts as the high-priority risks in agri-food sectors that are caused by climate-change-related factors.

Table 3: Average values of each criterion

Criterion Number	Criterion Description	Average
C1	Deforestation & Biodiversity loss	0,098
C2	Energy consumption	0,122
C3	Food loss	0,073
C4	Food safety	0,122
C5	GHG emission	0,122
C6	Labor exploitation or displacement	0,024
C7	Public health	0,073
C8	Reduction in water quality & quantity	0,098
C9	Resource constraints	0,073
C10	Soil degradation	0,098
C11	Synthetic material overuse	0,098

Then, the expert evaluations of 5 experts for the criterion over each alternative were normalized and presented in Table 4.

Table 4: Matrix of normalized alternatives over each criterion

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	0,140	0,161	0,165	0,180	0,145	0,171	0,165	0,177	0,168	0,163	0,143
A2	0,088	0,168	0,173	0,156	0,145	0,289	0,147	0,108	0,109	0,093	0,112
A3	0,169	0,153	0,165	0,133	0,159	0,105	0,119	0,131	0,134	0,155	0,153
A4	0,103	0,102	0,144	0,109	0,130	0,184	0,156	0,100	0,101	0,093	0,092
A5	0,184	0,146	0,129	0,141	0,167	0,105	0,128	0,131	0,160	0,140	0,112
A6	0,162	0,139	0,144	0,172	0,167	0,066	0,193	0,169	0,151	0,171	0,194
A7	0,154	0,131	0,079	0,109	0,087	0,079	0,092	0,185	0,176	0,186	0,194

After the normalization of the matrix, the related calculations for alternative selection were performed and are presented in Table 5 below. In this table, the ranking of the alternatives and their gross and normalized values are presented. As you can see, the attenuation factor of losses, also known as teta (ϕ), is determined to be 1, which indicates that the losses shall provide their real value to the global value for the implementation of the study. The calculation of the normalized values is made depending on the gross values. The ranking of the TODIM method shows that

The value with the highest normalized value is the highest in the ranking. Depending on that, the table shows that A1: IoT is the most promising technology alternative, with a value of 1,000 for the criteria set. Then, A6: Bio-Innovation (0,748) and A3: Artificial intelligence (0,599) are the second and third most favorable technologies, respectively. In addition, blockchain ranked in fourth place with a score of 0,516 and has a substantial effect on overcoming the risks determined throughout the study.

Table 5: Ranking alternatives, gross, and normalized values

Ranking	*Teta (ϕ)=1*		
	Performance		
	Descriptions	Gross	Normalized $\xi(A_i)$
1	IoT	-7,975	1,000
5	Robotics and Autonomous Systems	-21,487	0,492
3	Artificial Intelligence	-18,644	0,599
7	Big Data Analytics	-34,567	0,000
4	Blockchain	-20,848	0,516
2	Bio-Innovation	-14,689	0,748
6	Precision Agriculture	-29,249	0,200

5.1. Sensitivity Analysis

This phase examined how a parameter in the suggested framework affects the rankings (Ji et al., 2017). In this sense, the stability of the results should then be evaluated using a sensitivity analysis, which might be done on the criteria weights, the selection of the reference criterion, and performance assessments, among other things (Gomes et al., 2009). Sensitivity analysis is a method used in many disciplines, such as decision-making, engineering, and finance, to determine whether modifications in input variables would affect the output or result of a model or system. It aids in determining how susceptible or responsive a specific model or system is to various circumstances. The robustness of the TODIM is significantly confirmed by sensitivity analysis (Liang et al., 2019).

By methodically changing the input variables throughout a predetermined range, sensitivity analysis aims to assess the degree of uncertainty and unpredictability in a model's output. Sensitivity analysis reveals which data variables have the greatest effect on the outcome as well as how adjustments to those variables influence the outcomes. Understanding whether input variables influence outputs allows decision-makers to discover key variables, evaluate robustness, estimate risks, and make decisions. It aids in determining the most important variables, determining the stability of the model, and assessing potential dangers and uncertainties. Sensitivity analysis also helps in decision-making by showing how changes in input factors affect desired outcomes.

Decision-makers can learn how changes in the weights of the criteria affect the overall ranking of the alternatives by undertaking sensitivity analysis in the TODIM technique. Understanding the decision's resilience and the effect of uncertainty on the decision-making process is aided by this. The TODIM method's sensitivity analysis aids in determining the stability and dependability of the selected alternative under various weight situations. For the implementation of the sensitivity analysis in TODIM, the ranking ordering of alternatives in Table 6 was determined to be constant when the parameter had values between 0.1, 0.3, 0.5, 0.7, 0.9, and 1, which shows that the suggested TODIM approach is valid, effective, and stable when the attenuation parameter is changed. As a result of the sensitivity analysis, the ranking of the alternatives has not changed despite the changing teta values in different simulations.

Table 6: Sensitivity analysis for different teta values

	Teta (ϕ)=0.1			*Teta (ϕ)=0.3*			*Teta (ϕ)=0.5*			*Teta (ϕ)=0.7*			*Teta (ϕ)=0.9*			*Teta (ϕ)==1*		
Alternatives	Gross	$\xi(A_i)$	Rank	Gross	$\xi(A_i)$	Rank	Gross	$\xi(A_i)$	Rank	Gross	$\xi(A_i)$	Rank	Gross	$\xi(A_i)$	Rank	Gross	$\xi(A_i)$	Rank
A1	-102,866	1,000	1	-32,576	1,000	1	-18,518	1,000	1	-12,494	1,000	1	-9,146	1,000	1	-7,975	1,000	1
A2	-229,421	0,490	5	-75,396	0,491	5	-44,591	0,491	5	-31,389	0,491	5	-24,054	0,492	5	-21,487	0,492	5
A3	-202,373	0,599	3	-66,277	0,599	3	-39,058	0,599	3	-27,393	0,599	3	-20,912	0,599	3	-18,644	0,599	3
A4	-351,192	0,000	7	-116,655	0,000	7	-69,748	0,000	7	-49,645	0,000	7	-38,476	0,000	7	-34,567	0,000	7
A5	-223,392	0,515	4	-73,360	0,515	4	-43,353	0,515	4	-30,493	0,516	4	-23,349	0,516	4	-20,848	0,516	4
A6	-170,298	0,728	2	-55,032	0,733	2	-31,979	0,737	2	-22,099	0,741	2	-16,610	0,746	2	-14,689	0,748	2
A7	-308,410	0,172	6	-101,624	0,179	6	-60,266	0,185	6	-42,542	0,191	6	-32,695	0,197	6	-29,249	0,200	6

6. Discussion

Industry 4.0 technologies lay the foundation for technological and social change that will profoundly alter the global landscape (Javaid et al., 2022). Transformation to digitalization is viewed as a crucial revolutionary factor in the agricultural industry, namely, through notions such as digital agriculture and/or agriculture 4.0 (Parra-López et al., 2021). Digitized agriculture has many advantages, as it increases food output while decreasing manual labor (Liu et al., 2020). Sensorization, radar systems, drones, big data analytics, artificial intelligence robotics, IoT, blockchain, and other digital technologies alter the agri-food system's production, marketing, and consumption processes (Parra-López et al., 2021). Hence, with real-time farm management, greater levels of mechanization, and data-driven smart decision-making, the agricultural environment is significantly enhancing efficiency, the agricultural supply chain, food security and safety, and resource usage (Liu et al., 2020). In this context, the incorporation of these I4.0 technologies and additional CSA technologies may be vital for eliminating the risks in the agriculture industry and building sustainability. For that purpose, this research examined which of these integrated technologies can be used for mitigating the risks resulting from climate-change-related issues. The TODIM results revealed IoT as the most promising technological solution for climate-change risks in the agri-food sector, followed by robotics, autonomous robots, and artificial intelligence. Big data analytics significantly mitigate identified hazards in this sector.

For instance, IoT technology assists the agri-food industry practices and CSA by gathering real-time information on variables including humidity, temperature, moisture levels in the soil, and crop health. This information facilitates predictive analytics, machine learning algorithms, and remote monitoring and administration of agricultural activities. It also improves resource management. In the agri-food industry, these technologies increase accuracy, efficiency, and sustainability. By fostering CSA, crop development, carbon capture, waste management, environmentally friendly aquaculture, and data-driven decision-making, concepts such as bioinnovation may have an enormous influence on the agri-food sector. Farmers may maximize resource utilization, lower GHG emissions, and improve soil health by using precision farming methods, biodegradable fertilizers, and biocontrol agents. Agriculture systems, crop cover, and perennial crops that trap more carbon may all be developed with the aid of bioinnovation, which encourages environmentally friendly agricultural practices and climate change mitigation.

In addition, AI helps agriculture by offering crop yield and price forecasts, intelligent spraying, predictive insights (e.g., when to plant seeds for maximum productivity, weather conditions, etc.), agro robots, crop and soil monitoring, disease diagnostics, and so on. With the use of artificial intelligence, helpful insights such as predicting the best time to sow seeds, crop selection, hybrid seed selection, detecting illness in plants, pests, and inadequate farm nutrition, and automating harvesting may be anticipated. When integrated with other technologies, AI can help with the most complicated and ordinary activities by gathering and analysing large amounts of data on a digital platform, determining the best course of action, and even initiating that action. Furthermore, AI can analyse the market by streamlining crop choice and assist farmers in determining which products will be the most profitable, managing risk and reducing errors, analysing the soil and providing precise predictions of missing nutrients, thus predicting diseases, identifying and removing weeds, and recommending effective pest treatment. Through improved traceability, carbon footprint tracking, smart agreements for sustainable practices, effective supply chain management, incentives for sustainable practices, and enabling the sharing of expertise among stakeholders, blockchain technology can increase transparency, traceability, and efficiency in the agri-food sector. Blockchain allows stakeholders to monitor and verify the origin, procedures involved in the production, and distribution of food goods by offering a decentralized ledger that keeps track of all transactions and the transfer of agricultural products. Direct peer-to-peer transactions are made possible by blockchain-based systems, which also cut down on paperwork and intermediaries, thus encouraging climate change prevention and lowering GHG. In addition, robotics and autonomous smart agricultural robots are other substantial technologies that can be beneficial for agriculture. It can be used with a variety of instruments, such as hooks, streamers, or spikes, as well as advanced sensors to eliminate weeds without the need for pesticides for various purposes. Furthermore, by combining autonomous precision seeding and robotics, a map of a field can be generated, comprising data on soil parameters such as density and soil conditions, and automated seeders can seed more accurately than traditional broadcast spreading seeders or drone seeders. Functions such as self-driving, weeding, seeding, spraying, picking, robotics, and autonomous devices are potentially developing a smart and sustainable future for the agri-food sector.

7. Implications and Research Propositions

Depending on the findings of the investigation, associated propositions and implications are developed in this section.

Proposition 1. Environmentally friendly technology must be integrated into agri-food systems to successfully mitigate the dangers associated with climate change.

By monitoring farms and decreasing inputs such as water, fertilizer, and pesticides, smart and environmentally friendly farming technology provides a more productive, safer, environmentally friendly, and profitable agri-food system in line with the Sustainable Development Goals (SDGs) (Musa & Basir, 2021). Assessing the effects on the efficiency of resources, emissions reduction, and adaptive capacity via various environmentally friendly technologies, such as energy from renewable sources, precision agriculture tools, biodegradable inputs, and water conservation techniques, can offer various insights into the advantages and challenges in the agri-food sector.

Proposition 2. To ensure efficient tracking, data-driven decision-making, and adaptive management methods in the face of climate change-related threats, CSA operations must be surrounded by IoT technology.

According to Muangprathub et al. (2019), IoT can be used in agriculture to increase agricultural yields, enhance crop quality, and save expenses. For instance, IoT systems based on wireless sensor networks can irrigate domestic veggies and citrus trees in the best way possible (Akhter & Sofi, 2022). IoT applications aid farmers in monitoring water levels, resource consumption, and seed maturity. Sensors track data such as soil moisture, humidity, light, and temperature for crop production, providing real-time observations. These technologies, linked to the cloud via cellular/satellite networks, enable farmers to access real-time data for insights such as crop health scanning, plant counting, yield prediction, and climate forecasting. IoT-based smart agriculture also offers environmental benefits such as more efficient water consumption and treatment optimization. This technology also offers time savings, simplified usage, and increased agricultural yields. These integrated measures would boost the capacity of agricultural output and natural systems for adaptation by tracking not only carbon storage but also water quantity and quality, biodiversity, and other ecosystem services that are essential to a climate-smart landscape (Scherr et al., 2012).

Proposition 3. The agri-food industry's sustainability, resilience, and climate change mitigation efforts may be greatly aided by incorporating bio-innovation into CSA practices.

The effects of bio-innovation include raising crop output, lowering GHG emissions, and improving soil health. Precision agriculture, a rapidly expanding bio-innovation industry in Colombia, offers examples of the targeted, focused use of microorganisms (fungi and bacteria) that promote higher yields by either serving as biofertilizers or shielding plants from ailments or high humidity levels (Hodson de Jaramillo et al., 2017). Biobased solutions can offer invaluable insights into the advantages and difficulties of adopting bio-innovation in CSA for a more resilient and sustainable agri-food sector by examining their potential in promoting sustainable agriculture and mitigating climate-related risks.

Proposition 4. Using AI-based technologies to customize the workplace can lead to more effectiveness, productivity, and assistance with agricultural tasks.

To give farmers real-time insights and recommendations, AI models and algorithms can assess data from numerous sources, such as sensors, drones, and satellite photography. In addition, AI-based technologies can enhance crop management techniques, reduce resource waste, and lessen hazards associated with climate change. By assisting in the improvement of predictive skills, process optimization, and overall efficiency, AI-based solutions might strengthen the robustness of agricultural production systems (Usigbe et al., 2023). As suggested in Abbasi and Choukolaei (2023), integrating suitable climate-smart (CSA) agricultural technologies into agricultural production systems and supply chains could result in a significant reduction in carbon emissions and present sustainable methods for enhancing climate resilience in agricultural systems (Raihan, 2023; Mikhaylov et al., 2020; Qi et al., 2016; Lipper et al., 2014).

Proposition 5. By implementing blockchain technology, climate change-related challenges in the agri-food business may be efficiently handled.

The agri-food business may be able to communicate data with various parties in an easy and frictionless manner thanks to the upcoming blockchain technology (Reeves, 2020). Transparency, traceability, security, accountability, and accuracy are just a few of the qualities and capabilities of blockchain technology that may assist the circular economy idea in a variety of ways, including trash tracking for resource recycling and real-time CO2 emissions monitoring (Yildizbasi, 2021; França et al., 2020; Khaqqi et al., 2018; Risius & Spohrer, 2017). In addition, blockchain-based technologies can help the agri-food industry encourage sustainable practices and reduce climate risks by enabling traceability, transparent supply chains, and decentralized governance structures. Implementing blockchain-based technologies can improve supply chain resilience, reduce GHG emissions, and increase trust and accountability in the agri-food industry. This includes smart contract agreements for carbon offsets, decentralized certification processes for organic farming, and transparent traceability platforms for verifying sustainable sourcing.

Proposition 6. By maximizing resource utilization, lowering labor requirements, and mitigating climate-related risks, broad human-machine interactive techniques, such as robotics and autonomous smart agricultural robots, will ensure enhanced productivity, sustainability, and CSA practices.

Drones and other autonomous mobile robots with varying technical characteristics are made for a variety of agricultural tasks (Kiani et al., 2022). For instance, by increasing production and yields while using fewer pesticides, fertilizers, and water, robots might assist farmers in overcoming these difficulties (Ghobadpour et al., 2022). Agricultural field robots may also assist in boosting yields, enhancing soil health, and promoting operational safety (Duckett et al., 2018). These autonomous systems may make decisions based on data in real-time by accessing data on the health of crops, soil health, and weather patterns, resulting in enhanced resource management, less environmental impact, and greater output. These technologies can help to create CSA techniques and pave the path for a more resilient and environmentally friendly agri-food system by grasping the possibilities of human-machine collaboration in the agri-food industry.

8. Conclusions

Agricultural production is impacted by climate change, which also adds to global warming. The increasing demands of the population for freshwater, energy, and nutrition cause further environmental stress. Farmers must employ cutting-edge techniques, technology, and sustainable practices in this situation to address threats, including resource depletion and GHG emissions. To overcome these obstacles and increase food supply while reducing environmental impact, effective agricultural methods, geographically based techniques, and inventive thinking are needed.

Due to resource shortages, overoutput, and food waste, the agri-food industry confronts environmental issues. The sector has to advance technology and implement agri-food 4.0 and CSA technologies for sustainable consumption to address these problems. The TODIM approach, the MCDM tool, is used in this study to examine hazards associated with climate change and to determine the best options. The report presents recommendations for the agri-food industry to use these technologies for sustainable consumption and explores the key findings.

According to the analysis, IoT is the most effective technological solution for addressing climate change in the agri-food industry, followed by robotics, autonomous robots, artificial intelligence, and big data analytics, which are essential for reducing risks in this field. For further research ideas, the technology alternatives can be elaborated and can be ranked with other methods. Additionally, the set of risks can be extended not only to climate-change-related risks. It can also be extended into social, sociocultural, and economic risks as well.

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Appendix 1. Abbreviation list

ABBREVIATIONS	MEANING
CSA	Climate-smart agriculture
I4.0	Industry 4.0 (Fourth industrial revolution)
AI	Artificial intelligence
IOT	Internet of Things
ICT	Information & communication technologies
FOF	Future factories
GHG	Greenhouse gases
CO2	Carbon dioxide
CH4	Methane
N20	Nitrous oxide
RQS	Research Questions
DM	Decision maker
WHO	World health organization
IPCC	Intergovernmental Panel on Climate Change
OECD	Organization for Economic Co-Operation and Development
FAO	Food and Agriculture Organization
APZIFU	Action Plan for Zero Increase in Fertilizer Use
USDA	U.S. Department of Agriculture
SDGS	Sustainable Development Goals
MADM	Multiattribute decision-making
MCDM	Multicriteria decision-making
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
ELECTRE	Elimination and Choice Translating Reality
AHP	Analytic Hierarchy process
VIKOR	An acronym in in Serbian that means multicriterion optimization and compromise solution
PROMETHEE	Preference ranking organization method for enrichment evaluation
TODIM	An acronym in Portuguese for Interactive and Multicriteria Decision Making