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The role of generative artificial intelligence in digital agri-food

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ABSTRACT

The agriculture and food (agri-food) sector faces rising global concerns about its sustainability and resilience to climate events. Thus, new solutions are needed to ensure environmental and food security. Artificial Intelligence (AI) offers inventive solutions to improve agricultural and food production practices. Generative AI methods, such as generative adversarial networks (GANs), variational autoencoders, and large language models (LLMs), add to the transformative process initiated by AI and expert systems in agricultural and food-related practices to enhance productivity, sustainability, and resilience. This study categorizes generative AI approaches and their capabilities in agri-food systems and provides a comprehensive review of the current landscape of generative AI applications in the sector. It discusses the impact of these technologies on enhancing agricultural productivity, food quality, and safety, as well as sustainability, presenting potential use cases like combatting climate change and foodborne disease modeling that highlight the practical applications and benefits of generative AI in agri-food. Furthermore, it addresses the ethical implications of deploying generative AI, including privacy, security, reliability, and unbiased decision-making.

1. Introduction

Generative Artificial Intelligence (AI) comprises complex algorithms and models designed to create new content, insights, and solutions by learning from existing data. Generative AI, using techniques like generative adversarial networks (GANs) and large language models (LLMs), can synthesize images, text, and predictive models that can mimic and enhance real-world processes. As global concerns about sustainability, climate change, and food security escalate, the agri-food sector requires innovative solutions like generative AI to ensure environmental resilience, enhance agricultural productivity, and secure a reliable food supply. The Intergovernmental Panel on Climate Change (IPCC) reports that about 21%–37 % of global greenhouse gas emissions are attributable to the food system, contributing significantly to pollution and biodiversity loss [1]. Based on data from 2007 to 2016, this estimate also encompasses emissions from food loss and waste, with notable contributions from crop and livestock activities, deforestation, and peatland degradation. Further, the current food system, which feeds most of the global population and supports over 1 billion livelihoods, is under pressure from climate and non-climate stressors. There is a growing need to produce more quality food while maintaining environmental sustainability and ensuring food accessibility, quality, and safety [2]. AI is already transforming the agri-food sector in numerous ways. For instance, AI is enhancing livestock management through health monitoring systems that predict diseases, improving crop production by optimizing planting schedules and irrigation systems, streamlining food processing and distribution with automated quality control monitoring, and changing food retail through personalized shopping experiences and demand forecasting [3–6]. In this paper, we focus on reviewing the applications and potential of generative AI in the agri-food sector.

Unlike traditional AI, which mainly centers on recognizing patterns and making decisions based on historical data, generative AI creates new data and solutions [7]. It uses complex networks that learn from large datasets to produce outputs such as text, images, and simulations. For example, traditional AI systems like decision trees can predict irrigation needs like water table depth based on historical weather patterns [8], while generative AI can simulate new climate scenarios (e.g., prolonged droughts) to prescribe adaptive irrigation strategies [7,9]. Similarly, the food industry is increasingly adopting maintenance chatbots. Traditional NLP-based systems provide rule-based responses to common issues like troubleshooting equipment, whereas generative AI like LLMs

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can synthesize context-aware solutions [10]. Thus, generative AI has the potential to revolutionize agricultural and food production practices by enhancing the capabilities introduced by traditional AI.

The significance of integrating generative AI into the digital agri-food sector arises from the growing demands of global food security and the need to adapt to extreme and changing climate events. As the world wrestles with the challenges of feeding a rapidly growing population, ensuring the nutritional quality, safety, and sustainability of food sources becomes necessary [11]. In this context, generative AI offers promising solutions to these challenges by creating predictive models needing minimal training data, such as simulating drought-resistant crop rotations or forecasting pest outbreaks under erratic rainfall patterns [12]. Generative AI systems also provide prescriptive solutions, such as dynamically adjusting irrigation schedules during heatwaves or designing nutrient-rich food formulations that withstand supply chain disruptions caused by storms [13,14]. With its capability of using vast datasets ranging from satellite imagery to soil microbiota, generative AI can help the agri-food industry to optimize crop yields, enhance food quality and safety, and develop resilient strategies against the rising threats of climate change.

Despite the progress of AI in the agri-food sector, there remains a gap in the literature regarding the potential applications, impacts, and future directions of generative AI in this sector. Existing reviews, such as those by Javaid et al. [3] and Taneja et al. [4], primarily focus on the broader applications of AI in agriculture. However, there is a need to explore in more depth how generative AI can advance the whole industry. Although Ray [15] discusses the impact of generative AI on the sugarcane industry, its scope is limited to this specific sector. This highlights the need for a more comprehensive review in the broader agri-food field. This paper aims to review and analyze the application of generative AI within the digital agri-food sector. This work targets researchers, policymakers, and agri-food professionals by combining necessary technical background with practical insights on how generative AI can address industry challenges. We want to ensure that AgriFood experts can familiarize themselves with these emerging technologies without requiring extensive prior knowledge of AI systems. Our contributions include a comprehensive examination of how generative AI technologies are being implemented to address the unique challenges faced by the agri-food industry. Specifically, this review will.

- Summarize the current landscape of generative AI applications in agri-food, categorizing them according to their functionalities.
- Discuss the impact of these technologies on enhancing agricultural productivity, food quality, safety, and sustainability.
- Present potential use cases that highlight the practical application and benefits of generative AI in agri-food.
- Discuss the ethical implications of deploying generative AI, including considerations of privacy, security, and ethical AI.

The rest of the paper is organized as follows: Section 2 explores the various approaches that constitute generative AI and elaborates on specific generative AI capabilities that can benefit the agri-food sector. Section 3 presents the literature review, while Section 4 highlights potential use cases. In Section 5, we address the ethical and societal considerations of implementing generative AI in the agri-food sector. Finally, Section 6 provides final remarks and recommendations.

2. Generative AI approaches

AI systems fall into two categories: discriminative AI and generative AI [16]. Discriminative AI focuses on descriptive and predictive analytics of data; it handles tasks such as classification, association, clustering, regression analysis, and prediction [17]. In addition to descriptive and predictive analytics, generative models can offer prescriptive analytics [9]. Generative AI systems can process a wide range of inputs such as text, graphics, videos, art, musical notes, or other data types, including multi-attribute signals like spectral data, which are currently one of the main data sources in food production applications. These systems use several deep learning algorithms to generate new but statistically similar content. Trained on vast data, generative AI models can produce articles, source codes, problem solutions, and more [18]. This section describes the different approaches used in building generative AI systems. As depicted in Fig. 1, a few prominent approaches are transformer models, large language models, and generative adversarial networks. In addition, we have considered approaches like adversarial learning and digital twins that complement generative AI. The following subsections provide an overview of these approaches.

2.1. Transformers

Transformers represent a cutting-edge architecture in machine learning known for their ability to process and learn from vast datasets [19]. These models are distinguished by their capacity to learn without needing normalized or explicitly labeled data. In various contexts, transformers generate diverse types of information. Transformers use input data like images and process them to produce valuable outputs [20,21]. The core feature of transformers is their attention mechanism, which allows the model to focus on different parts of the input data, understanding the context and relationships between words in a sentence or elements in an image [22]. For instance, in natural language processing (NLP), a transformer can process a large document (input) and produce a concise summary (output). Transformers have also shown proficiency in interpreting complex data types, including source code, DNA sequences, and chemical and protein structures [23]. Combined with deep learning models, transformers can also perform real-time food recognition, making them valuable for nutritional analysis [24]. One of the primary advantages of transformers is their ability to handle long-range dependencies in data, making them suitable for tasks that require understanding context over extended sequences [25]. They also excel in parallel processing, which speeds up training times compared to traditional models. However, transformers are computationally expensive and require significant memory resources, a notable limitation for some applications.

2.2. Large language models

Large Language Models (LLMs) represent a significant advancement in generative AI, characterized by their ability to process and learn from data encompassing billions to trillions of features [26]. This extensive data assimilation capacity allows LLMs to attain exceptional proficiency within their training domains. Consequently, these models do more than just store information; they act as creative engines that can generate new content in different forms, including text, images, and sound. Creating new content through LLMs features the progress in Multimodal AI [27]. These models are designed to generate content across various forms of media, such as text, graphics, animations, and videos. Multimodal AI models process different inputs like text descriptions or images and generate corresponding outputs. Given a prompt, ChatGPT can generate text, create pictures, or even converse with users. In agri-food systems, LLMs can provide agricultural advice to farmers by analyzing weather, soil, and crop data [10]. A notable benefit of LLMs is their ability to produce creative and diverse outputs from minimal input; this makes them invaluable for applications ranging from automated content creation to interactive virtual assistants. However, developing and deploying LLMs is accompanied by computational costs and requires extensive data for successful training [28]. Additionally, ensuring the ethical use of these models, particularly in terms of bias and misinformation, remains a challenge.

2.3. Generative adversarial networks

Generative Adversarial Networks (GANs), introduced by Ian

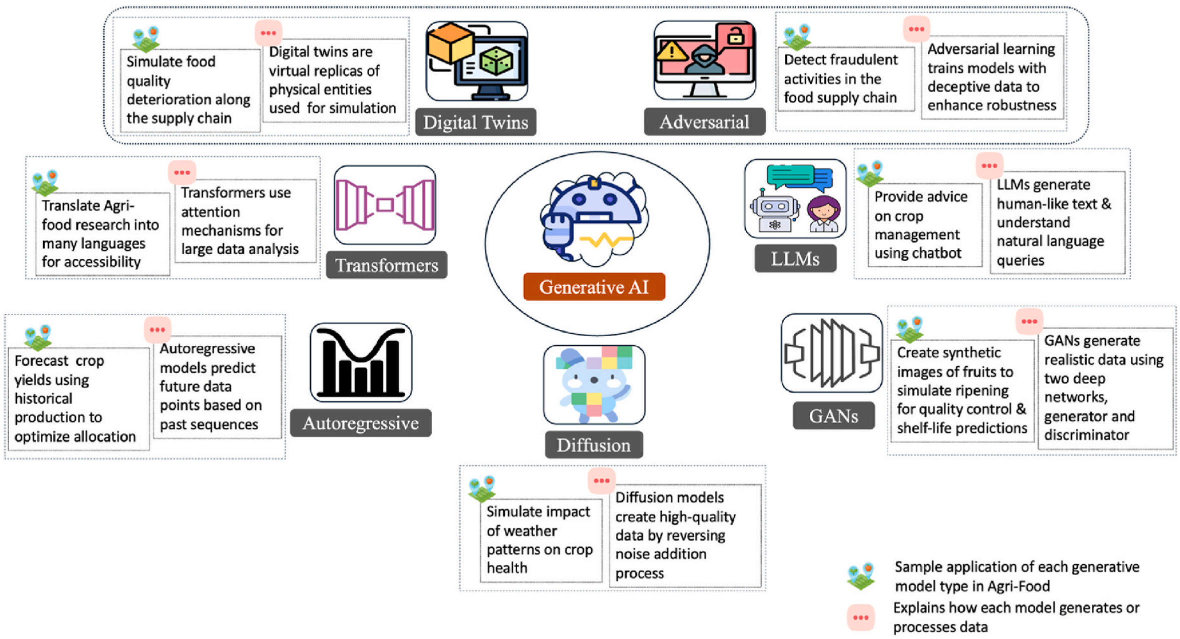

Fig. 1. Generative AI Approaches. The figure highlights various approaches used in generative AI, including transformers, GANs, and diffusion models alongside complementary techniques like adversarial learning and digital twins, which enable secure and context-aware deployment of generative solutions.

Goodfellow in 2014, have revolutionized generative AI by offering a unique framework for producing new data instances that closely resemble authentic datasets [29]. The architecture of GANs includes two primary components: the generator and the discriminator. The generator creates data starting from random noise, aiming to produce outputs that mimic real-world data. In contrast, the discriminator evaluates this generated data, distinguishing between fake and genuine instances. This adversarial process drives both components to continuously improve, resulting in the generation of increasingly realistic outputs. GANs exhibit remarkable versatility across a wide range of applications; they are capable of creating high-quality, realistic images, videos, and music [30]. For example, in the agri-food sector, GANs have been used to generate synthetic images of crop diseases for early detection and intervention in cases where real-world data is difficult to obtain [31]. A primary advantage of GANs is their ability to produce high-fidelity and diverse outputs, which can be particularly useful in creative industries and scientific research. However, training GANs is computationally intensive and potentially unstable, requiring careful tuning of hyperparameters and substantial computational resources [32]. Additionally, the outputs of GANs can sometimes suffer from issues like mode collapse, where the generator produces a limited data variation.

2.4. Diffusion models

Diffusion models have emerged as an advanced generative AI technique, enhancing the generation of realistic and consistent content, particularly images and videos [33]. The diffusion process manipulates the pixels of an image or frames of a video to produce content that closely resembles real-life visuals. These models operate by gradually introducing noise into an image and then learning to reverse this process, effectively modeling the probability distribution of the original image's pixels through mathematical and statistical methods [34]. These models enable the design of pictures and videos with specific tones, textures, or themes with realism and detail. Furthermore, they are instrumental in advancing research where high-quality synthetic visual content can aid analysis and decision-making [35]. For example, diffusion models in agriculture can generate high-resolution synthetic satellite images to simulate different climate and soil conditions. The benefits of diffusion models include their ability to generate highly realistic and diverse outputs, which can significantly enhance visual content creation and research methodologies. However, they require substantial computational resources and expert tuning to achieve optimal performance.

2.5. Autoregressive models

Autoregressive models are known for their predictive capabilities of sequential data. These models excel in forecasting the next element in a sequence by analyzing the attributes of preceding elements, making them suitable for handling time-series data or any data that unfolds over sequential intervals [36]. The fundamental principle of autoregressive models is that past observations provide insights into future occurrences, which enables the generation of new, previously unknown components within a data sequence. The generative potential of autoregressive models extends to various applications, from predicting stock market trends and weather patterns to generating coherent text or music [37]. In the context of generative AI, autoregressive models play a crucial role in creating new information that adheres to the underlying patterns and structures of the training data. This ability to maintain continuity and accurate sequential prediction makes them valuable in numerous scenarios where preserving the logical flow of generated content is essential. For example, autoregressive models can predict food spoilage timelines by analyzing historical temperature, humidity, and storage conditions to optimize supply chain logistics. A notable limitation of autoregressive models is that they are only effective for probability distributions where prefix probabilities are easily computable [38]. While this makes training efficient, without allowing for increased runtime or larger parameter sizes, these models are less expressive than those that can marginalize suffixes or latent variables.

2.6. Adversarial machine learning

Adversarial machine learning is a specialized area within machine learning focused on creating robust models by training them with intentionally deceptive or adversarial data [39]. This approach aims to enhance the model's ability to distinguish between genuine and manipulated data inputs. While GANs employ adversarial training, adversarial ML itself is not inherently generative but enhances generative systems by ensuring reliability in dynamic environments. For example, in cybersecurity, adversarial learning helps develop systems that can detect and neutralize sophisticated phishing attempts or malware that traditional detection methods might miss [40]. The mechanism of adversarial machine learning involves feeding models with both authentic and intentionally altered data during the training phase. This includes generating adversarial examples by slightly modifying input data to create deceptive patterns that the model must learn to identify. The input data could range from text and images to transactional records and network traffic. The model processes this data through iterative training, adjusting its parameters to minimize errors in distinguishing between real and adversarial examples. Due to their training on various manipulated data, these models are better equipped to handle unexpected or malicious inputs. This training makes them particularly valuable in high-stakes fields such as cybersecurity, supply chain, and food authenticity and safety, where the cost of fraudulent activities can be significant. However, a drawback of adversarial training is the computational resources it demands; each iteration of stochastic gradient descent requires the standard gradient computation for updating network parameters and necessitates multiple gradient calculations to generate adversarial examples [41].

2.7. Simulation and digital twins

Simulation and digital twins combine real-world operational dynamics with virtual modeling. A digital twin is a virtual replica of a physical entity or system, continuously updated with data from its physical counterpart to simulate, analyze, and predict its behavior in the digital realm [42]. This dual-world approach enables detailed analysis, optimization, and innovation by exploring "what-if" scenarios without the constraints of real-world experimentation. Creating digital twins begins with data collection, capturing the physical and chemical properties of food products, including microbiota [43]. Real-time sensors facilitate continuous data exchange between the physical entity and its digital counterpart, enabling accurate modeling and monitoring. While not exclusively generative, they often incorporate synthetic data from GANs or scenario modeling via transformers to simulate rare events [13, 42]. Generative AI enhances digital twins by simulating numerous scenarios that may not be directly observable in real life or historical data [13]. This includes generating synthetic data for rare events, such as food supply disruptions caused by environmental disasters. The main advantage of digital twins is the ability to test and optimize strategies in a risk-free virtual environment. However, challenges include the need for high-quality, real-time data and the complexity of creating accurate models [44]. Additionally, the integration of generative AI can add to the computational requirements, making it essential to balance detail and performance.

2.8. Generative AI capabilities in the context of agri-food

Generative AI offers many avenues to solve various problems in the agri-food sector. The key features and characteristics of generative AI relevant to agri-food are discussed in the following subsections.

2.8.1. Synthetic data generation

One of the key features of generative AI models is the generation of synthetic data using deep learning models [45]. In the agri-food sector, synthetic data refers to machine-generated information that models real-world agricultural or food manufacturing and distribution scenarios. This is particularly useful in agriculture and food production, where data collection can be challenging due to various factors such as remote locations, the complexity of biological systems, privacy and confidentiality, and the variability of environmental conditions [46]. GANs and diffusion models are pivotal in creating high-quality synthetic data in agri-food [31,47]. GANs, with their adversarial structure, generate realistic data by training the generator and discriminator in tandem. In contrast, diffusion models use a noise-adding and denoising process to learn the data distribution, allowing them to produce complex and realistic data and scenarios. In agriculture, synthetic data can simulate crop growth under various conditions, model the spread of plant diseases, or predict livestock health trends. In livestock management, synthetic data can model the spread of diseases like avian flu by forecasting different scenarios and helping farmers prepare proactive measures to prevent outbreaks [48,49]. In food product and packaging development, processing, and distribution, generative AI can create data to optimize formulations, packaging designs, processing workflows, and logistics [50]. For food safety, quality, authenticity, and sustainability, synthetic data can help develop models to predict chemical or biological contamination, microbial growth, or inactivation, improve quality control, assess sustainability, and curtail fraud [51].

2.8.2. Content-focused generation

Generative AI can synthesize content specific to a topic or theme. Such systems are trained in a way that they can produce new content on a particular niche [52]. In the agri-food sector, Generative AI's ability to create content offers significant potential, especially for producing specialized agricultural information, precision farming strategies, and customized nutritional plans for livestock. For example, generative AI can produce images of pests that are hard to identify, helping with early intervention [53]. In food production, generative models can develop food formulations and processes that meet specific dietary requirements, optimize nutritional content and safety, or even generate new food product concepts [14]. Further, generative AI can contribute to educational materials, producing text and visuals for training modules for farmers and food producers on sustainable practices, new technologies, or market trends. The content-focused generation can extend to marketing within the agri-food sector, where AI-generated content can tailor advertising materials to specific audiences [54], create realistic product images before production, or even predict consumer trends and generate content that aligns with future market demands.

2.8.3. Evaluation and judgement

In the agri-food sector, generative AI systems' ability to evaluate and refine the content they generate is valuable [55]. This self-evaluation ensures that AI-generated recommendations, reports, and analyses meet coherence, accuracy, and relevance before being used in agricultural and food production decision-making processes. For example, an AI system might generate a report on optimal planting strategies for a specific crop or food processing conditions [3], including the ability to evaluate its output to ensure that the advice is grammatically correct, coherent, contextually appropriate, and technically sound [56]. Furthermore, generative AI's ability to assess generated content quality can enhance educational resources and training materials for the agri-food sector [57]. These models can help transfer knowledge more effectively to farmers, agricultural students, and food professionals. When creating product descriptions, marketing copy, or consumer information, generative models can ensure the content is engaging, persuasive, accurate, and informative.

2.8.4. Predictive analytics

Generative models can forecast future agri-food outcomes using vast amounts of data, ranging from satellite imagery and sensor data to genetic information and market trends. For crops, predictive analytics can forecast yield sizes, assess crop health, and predict the optimal times for planting and harvesting by analyzing weather patterns, soil conditions, and historical yield data [58]. In food manufacturing, storage, and distribution, predictive analytics can help optimize orders for raw materials, adjust processing requirements, estimate actual remaining shelf-life, assess food safety risks, and even assist in programming training [59]. Although regular AI and machine learning offer notable predictive capabilities, generative AI adds the ability to perform few-shot learning and handle out-of-domain data [60]. Consequently, generative models can make accurate predictions with limited examples and extend their applications to various scenarios. In food retail, generative models can predict the demand for different products, which helps retailers manage inventory better; by analyzing consumer purchase data, generative models can predict which products will be in more demand during certain times, like holidays or sales events. In livestock management, generative models help predict health issues, growth rates, and breeding outcomes [61].

2.8.5. Monitoring and control systems

Integrating generative AI into automated monitoring and control systems [62] can enhance the ability to manage and optimize crop cultivation and livestock rearing. In crop management, generative AI systems utilize a constellation of sensors, drones, and satellite imagery to continuously monitor field conditions, including soil moisture, nutrient levels, and plant health [63]. Despite traditional AI playing an important role in monitoring and control systems, generative AI can create synthetic data to simulate and predict various scenarios and conditions [64]. In livestock management, generative models like variational autoencoders can enhance animal behavior monitoring by generating augmented time-series data from wearable inertial sensors attached to livestock [65,66]. This approach can improve the accuracy of behavior classification and health status detection, even in cases where data is limited [66]. Generative AI also plays a role in other sectors, such as food processing, storage, and distribution, where it can optimize workflows and enhance safety protocols and quality assurance. For example, automated systems can monitor the production line in a food processing plant, identifying any deviations from standard quality parameters and making real-time adjustments [67]. Automated monitoring and control systems using generative AI can lead to agri-food operations and management in a highly scalable manner [68]. These systems can manage vast agricultural and food manufacturing operations across multiple locations, adjusting to the specific requirements of different crops, livestock breeds, or products and responding dynamically to changing environmental conditions.

3. Existing research in transforming agri-food using generative AI

The globe is seeking out intelligent and smart solutions to achieve the ambition of food security. Countries around the world are investing their capital to become self-guarantors in food so that they may provide sufficient, high quality and safe food to their masses but also export extra food to earn a valuable trade surplus. Following this vision, in 2023, a declaration led by the United Nations (UN) climate change conference was signed by 159 countries [69]. This declaration aimed to focus on ensuring food security, sustainable farming, better climate control, and sustainable food systems. At this conference, the joint coalition announced to address climate change issues for better agriculture innovations by investing over $85.1 billion.[1]

Advancements in generative models like large language models have improved the analysis of agronomic data from farm-lands [70]. These technologies can effectively analyze diverse datasets without extensive training, including weather data, soil nutrition data, and water quality data to aid agricultural decision-making. The digital agri-food sector is the future of modern farming and food production. Generative AI can provide farmers with advanced insights on crop yield, quality, and optimal planting times, leveraging synthetic data and predictive models based on seed selection and seasonal variations. The following subsections explore the promising role of generative AI in agri-food.

This thematic review considered state-of-the-art research, focusing on articles published within the last two years. Specifically, 94.3 % of the works reviewed were from within the past year (between 2023 and 2024), which ensured the inclusion of the most recent advancements. The literature is categorized based on the models and algorithms used, such as language models, metaverse, digital twins, and computer vision. We conducted a literature review to explore the application of generative AI in the agri-food sector. Following the PRISMA extension for scoping reviews [71], we ensured transparency and consistency in our methodology. The review process included structured search strategies, data extraction, and reporting guidelines. To identify relevant literature, we used ScienceDirect, Google Scholar, and IEEE Xplore, using specific search terms related to generative AI and the agri-food sector. Key search terms included: "generative AI in agriculture," "GANs in food and agriculture data," "digital twins in agriculture," "transformers in agri-food," and "AI applications in food production." Boolean operators were utilized to refine searches, such as "(generative AI OR GANs) AND food safety."

Our search and inclusion criteria were as follows.

- Publication Type: We included peer-reviewed conference papers, journal articles, and reputable preprints that focused on generative AI applications in agriculture and food-related sectors.
- Year Range: 2022–2024. This range allowed us to capture the most recent advancements in generative AI applications within agri-food.
- Language: Only papers published in English were reviewed.
- Database Scope: We accessed IEEE, Elsevier, and other recognized scientific databases through platforms like ScienceDirect and Google Scholar.

Exclusion criteria were defined as follows.

- Non-English publications and materials not directly related to the generative AI applications in the agri-food industry were excluded.
- Non-peer-reviewed works unrelated to agri-food or lacking substantial discussion on generative AI's application in this context were also excluded, though some reputable preprints were reviewed.

3.1. Large language models

The application of Large Language Models (LLMs) in the agri-food sector shows promise in various areas of food design, production, and agricultural advisory services, particularly in improving information accessibility and decision-making processes. In this context, Razzaq et al. [72] introduced the EvoRecipes framework, which combines LLMs with evolutionary algorithms to address the limitations of LLMs in understanding complex recipe semantics. This framework illustrates the potential of LLMs to generate novel, customized culinary creations that align with consumer preferences and needs [73]. Additionally, the use of LLMs to improve food recognition processes is demonstrated by Ref. [74], who developed a method for fine-grained food recognition using LLMs. This method uses multi-modality embeddings to enhance classification across diverse food categories, showing how LLMs can be integrated into existing classification systems to improve food categorization.

A cluster of studies examines the use of LLMs in question-answering and chatbot systems within agricultural contexts. Ibrahim et al. [10] assessed the effectiveness of LLMs by implementing an AI chatbot to provide agricultural advice to farmers. Their study provides empirical evidence that LLM-based systems outperform traditional extension agents in delivering high-quality, relevant advice, despite challenges in accurately addressing complex agronomic practices. Although evaluators preferred chatbot responses in 78 % of cases, the chatbot had difficulties with specific agronomic practices such as planting time, seed rate, and fertilizer application. Yang et al. [75] provided a comprehensive review of advancements in agricultural question-answering systems by emphasizing the integration of LLMs with corpora and knowledge graphs to improve the efficiency of information retrieval in agriculture.

[1] https://www.cop28.com/en/.

They highlight the role of LLMs in transforming access to agricultural knowledge, aiding informed decision-making, and addressing sustainability challenges.

In the broader scope of agricultural services, Tzachor et al. [70] and Kuska et al. [76] examine the potential of LLMs to democratize access to scientific knowledge and improve agricultural extension services. The capability of LLMs to provide data-driven, personalized, and location-specific recommendations to farmers is significant. However, there are challenges and risks associated with deploying these technologies, particularly in regions like the Global South where digital divides are prominent [70]. LLMs still present substantial opportunities for consulting, documentation, and educational efforts, though they require high-quality, context-specific data to be effective [76]. These studies highlight the benefits and risks of using LLMs in agricultural settings and emphasize the need for high-quality data.

In the context of integrating LLMs into agricultural advisories, Stoyanov et al. [77] developed an advisory service within the ZEMELA platform to support Bulgarian farmers. This service uses LLMs to evaluate risks and ensure compliance with local agricultural laws and requirements. The authors provide a comprehensive model for technology deployment tailored to regional needs. This indicates that LLMs can be crucial in assessing complex regulatory and environmental factors affecting agriculture. Finally, De Clercq et al. [78] analyzed the adoption of LLMs in agriculture, weighing potential benefits against risks such as misinformation and job displacement. Their study highlights how LLMs can improve agricultural efficiency by simulating the roles of an expert to provide on-demand agronomic advice and answer context-specific farming queries via chatbots. Additionally, these models can simulate farmer behavior and market reactions, helping policymakers test the potential outcomes of agricultural policies before implementation. Table 1 summarizes the recent advances of LLM use in agri-food.

Table 1
Summary of large language models (LLMs) applications in agri-food.

Reference	Year	Application	Model/ Framework	Results
[10]	2024	Agricultural chatbots	ChatGPT	Outperforms traditional extension agents (78 % preference); struggles with agronomic specifics
[70]	2023	Democratizing agricultural knowledge	GPT for extension services	Provides personalized, location-specific advice; challenges in Global South adoption
[72]	2023	Customized culinary creations	Genetic algorithm combined with GPT	Generates novel recipes aligned with consumer preferences and addresses complex semantics
[74]	2023	Fine-grained food recognition	LLM (Falcon-7B) and lexical encoders	Improves food classification accuracy across diverse categories
[75]	2024	Question-answering systems	LLMs and knowledge graphs	Improves information retrieval efficiency and aids decision-making
[76]	2024	Educational and consulting	LLMs for documentation	Enhances knowledge sharing; requires high-quality, context-specific data
[77]	2023	Regulatory compliance advisory	LLM-based advisory service (ZEMELA platform)	Evaluates risks and ensures compliance with local agricultural laws
[78]	2024	Policy simulation	LLMs for policy testing	Simulates market reactions and tests policy outcomes pre-implementation

3.2. Analysis, simulation, and modeling

The analysis of generative AI applications in agri-food highlights various approaches to enhancing agriculture and food production through advanced modeling, simulation, and analysis. These studies focus on optimizing resource utilization, reducing environmental impacts, and improving productivity. Maraveas et al. [79] discussed the challenges of greenhouse gas emissions in agriculture and highlight the need for advanced resource management technologies to reduce CO_2 emissions. Their review covers energy-saving techniques such as fuzzy logic and neural networks that are necessary for achieving sustainable agriculture with minimal environmental impact. In a closely related study, Ajagekar et al. [80] proposed a deep reinforcement learning-based control framework that significantly improves energy efficiency in greenhouse climate regulation. The proposed framework adapts to changing conditions and demonstrates substantial reductions (57 %) in energy consumption while maintaining optimal growth conditions (26.8 % improvement) for crops like tomatoes.

Expanding on the theme of climate control in agriculture, Hosseini Monjezi et al. [81] and Morales-García et al. [12] investigated precise temperature management in greenhouses, which is essential in regions with extreme climatic conditions. Hosseini Monjezi et al. [81] used radial basis function and Gaussian process regression to achieve high accuracy in temperature forecasting (RMSE of 0.82 °C). Conversely, Morales-García et al. [12] used GANs to generate synthetic temperature data, enhancing the predictive accuracy for climate control in greenhouses. This method addresses the challenges of scarce and unreliable data commonly encountered in precision agriculture.

Exploring the role of synthetic agricultural data, Akkem et al. [51] studied the generation of synthetic data using variational autoencoders and GANs. Their research aims to create high-quality data for crop recommendation systems and explores how synthetic data can increase the datasets available for training generative models in agriculture to improve decision-making and crop management strategies. Similarly, Morales-García et al. [12] used GANs to generate synthetic temperature data to improve the predictive accuracy of generative models for greenhouse climate control. The authors address the issue of scarce and unreliable data often found in precision agriculture.

In the broader context of generative AI use in agri-food, Bose et al. [82] reviewed the integration of deep generative models in advanced crop improvement techniques. These technologies can analyze large-scale phenotypic datasets, helping in selecting superior genotypes and improving the efficiency, specificity, and safety of crop breeding practices. This approach is less resource-intensive than traditional methods and enhances prediction model accuracy by leveraging extensive genomic data. Lastly, the study "From Plate to Production" [83] explores how generative models like LLM and adversarial networks transform consumer-driven food systems by incorporating digitalization and big data analytics. This shift from traditional farm-to-fork models to a consumer-centric approach aims to achieve sustainable and nutritious diets through food synthetic biology. Table 2 summarizes the existing works using Generative AI for analysis, simulation, and modeling in agri-food.

3.3. Metaverse and augmented reality

Researchers have examined the role of the metaverse in improving operational efficiency, advancing crop management, and enhancing sustainability practices. The Agricultural Metaverse (AgriVerse) represents a significant shift toward integrating virtual and real-world agricultural activities [84]. In this system, generative AI plays a crucial role

Table 2
Summary of generative AI applications in analysis, simulation, and modeling.

Reference	Year	Application	Model/ Framework	Results
[12]	2023	Greenhouse climate control	GANs	Generates synthetic temperature data to improve predictive accuracy in greenhouses
[79]	2023	CO2 emission reduction	Fuzzy logic and neural networks	Reviews energy-saving techniques for sustainable agriculture with minimal environmental impact
[80]	2023	Energy-efficient greenhouses	Deep reinforcement learning	Reduces energy consumption by 57 % while improving crop growth conditions by 26.8 %
[81]	2023	Precision temperature forecasting	Radial basis function, gaussian process regression	Achieves high accuracy in temperature prediction (RMSE = 0.82 °C)
[51]	2024	Synthetic crop data generation	Variational autoencoders, GANs	Enhances crop recommendation systems by augmenting datasets for improved decision-making
[82]	2024	Crop breeding optimization	Deep generative models	Improves genotype selection efficiency and safety in crop breeding practices
[83]	2023	Consumer-driven food systems	LLMs, adversarial networks	Transforms food systems via digitalization and synthetic biology for sustainable diets

by creating highly realistic virtual environments that support training, scenario planning, and decision-making for farmers and agronomists. For instance, generative AI can simulate different farming conditions, allowing users to test various crop management strategies in a risk-free digital space. Additionally, synthetic data generated within these environments can be used to model and predict outcomes such as plant growth patterns or disease spread. Notable elements of AgriVerse include the agricultural foundation model, which integrates sensor data and predictive models for decision support, decentralized agricultural organizations (DAO), and decentralized science (DeSci), which democratize knowledge sharing and collaboration in plant modeling and agricultural research [84].

Augmented reality (AR) applications are also being explored for their potential to revolutionize training and operational procedures in agriculture [85]. AR and mixed reality technologies contribute to food science areas such as dietary assessment, traceability, and food safety [86]. Generative AI enhances these technologies by providing realistic simulations and predictive models that can improve training effectiveness and operational efficiency.

In the context of enhancing food traceability, Ellahi et al. [87] discussed integrating metaverse computing with the secure record-keeping potential of blockchains. Büyükakin & Soylu's study looks at the evolution of agricultural technologies from Agriculture 1.0 to Agriculture 4.0 and future advancements [88]. The authors assess how virtual and augmented reality technologies can transform interactions between consumers and producers, improve food safety, and enhance the sustainability of agricultural and food processing practices. Generative AI can further create immersive virtual environments to simulate different agricultural practices and generate data to support sustainability efforts. A summary of metaverse and AR applications in agri-food is presented in Table 3.

Table 3
Summary of metaverse and augmented reality applications in agri-food.

Reference	Year	Application	Model/ Framework	Results
[84]	2023	Agricultural metaverse (AgriVerse)	Generative AI, simulation models	Simulates farming conditions for risk-free strategy testing; predicts plant growth/disease spread
[85]	2024	Operational training and food science applications	AR, mixed reality	Enhances training and operational procedures in agriculture through immersive simulations
[86]	2022	Food science applications	AR, generative AI	Improves dietary assessment, traceability, and food safety via predictive models
[87]	2023	Traceability	Metaverse, blockchain	Secures food traceability records; enables transparent supply chain tracking
[88]	2023	Consumer-producer interaction	AR/VR Technologies	Transforms interactions for improved food safety and sustainability; simulates agricultural practices

3.4. Robotics

Robotic technologies have significantly advanced agriculture, with applications ranging from basic field operations to complex autonomous decision-making systems. Early research focused on mechanical tasks like planting and harvesting but has expanded to include sophisticated AI-driven systems that integrate sensing, decision-making, and actuation technologies [89,90]. Generative AI enhances these robotic systems by providing advanced algorithms that can simulate various scenarios, optimize robotic operations, and generate synthetic data to train robotic systems [91]. This integration shows a trend toward fully autonomous robotic solutions that enhance productivity and precision in crop management. For instance, Wakchaure et al. [92] and Mallinger and Baeza-Yates [93] discuss integrating expert systems and sensor technologies in agricultural robots. These systems use various approaches, including fuzzy logic, neural networks, and genetic algorithms, to provide comprehensive solutions for all phases of agriculture, from cultivation to harvesting. This shift reflects a move from labor-intensive practices to technology-driven solutions that promise increased efficiency and reduced reliance on human labor. Balaska et al. [94] explored the concept of Agriculture 5.0, where digital technologies like generative AI and robotics combine to create smarter, more sustainable farming practices.

Chang et al. [95] and Nasir et al. [96] highlight the application of robotics in field navigation and plant management, using deep learning and other generative methods to improve precision in tasks such as spraying and plant identification. These technologies enhance operational efficiency and contribute to environmental sustainability by reducing pesticide use and optimizing resource allocation. The design and testing of mobile platforms equipped with Cartesian serial manipulators [97] further demonstrate the capabilities of robotics in handling complex tasks like picking heavy fruits and navigating challenging terrains. These innovations are essential for ensuring the adaptability and effectiveness of robotic solutions in various agricultural settings. In the food industry, robotics automate processes like packaging, cutting, and sorting as robots handle repetitive and physically demanding tasks while maintaining precision, hygiene, and safety standards. Several challenges exist in robotics for food preparation, such as the complexity of replicating human sensory interactions (vision, tactile, sound) during tasks like cutting, trimming, and mixing without damaging fragile food materials. Generative AI can help bridge this gap by simulating human-like interactions, generating data for machine learning models, and optimizing robotic movements and performance in real time through learning from multiple operational scenarios [98,99]. Table 4 summarizes recent robotics applications in Agri-Food.

3.5. Digital twin

This section looks at how digital twin and generative AI are transforming traditional agricultural practices into efficient, data-driven operations. Ubina et al. [100] proposed using digital twin infrastructure in intelligent fish farming, describing an agile Artificial Intelligence Internet of Things (AIoT) system for aquaculture. This system uses smart devices, like sensors and actuators, embedded in fish farming machinery to collect and transmit data for real-time and remote monitoring. The study highlighted four main digital twin services: automated fish feeding, metric estimation, environmental monitoring, and health assessment. Each service is enhanced by AI models to support optimization, prediction, and analysis and can lead to better decision-making, increased profitability, and improved production efficiency in aquaculture. Generative AI enhances digital twin technology by simulating a wide range of scenarios, creating synthetic data for training, and providing predictive analytics that can optimize operations.

Liu et al. [101] explored how integrating digital twin and generative AI technologies can improve efficiency and sustainability in agriculture. Digital twins involve continuous interaction and data flow between the physical and digital units. In the context of food systems, this entails collecting detailed data on the physical, chemical, and microbial properties of food products, as well as real-time sensing to facilitate data exchange [102]. When combined with predictive and generative models like transformers and diffusion models, digital twins can simulate physical entities and optimize operations such as precision farming, resource management, and equipment monitoring. The bidirectional data exchange enables enhanced decision-making by simulating and adjusting real-world processes in response to digital model predictions. Digital twin applications in agri-food are summarized in Table 5.

Table 4
Summary of robotics applications in agri-food.

Reference	Year	Application	Model/ Framework	Results
[89,90]	2023	AI-Driven robotic systems	AI-integrated Robotics; sensing, decision-making, actuation	Advances autonomous crop management; integrates AI for precision tasks (planting, harvesting)
[91]	2023	Generative AI for robotics	Scenario simulation, synthetic data	Enhances robotic training and optimization; improves adaptability to dynamic farm conditions
[92,93]	2023, 2024	Expert systems in robots	Fuzzy logic, neural networks	Provides comprehensive solutions for cultivation to harvesting; reduces labor dependency
[94]	2023	Agriculture 5.0	Generative AI and robotics	Promotes sustainable farming via smart, autonomous systems
[95,96]	2023	Precision field navigation	Deep learning, generative methods	Reduces pesticide use by 30 %; optimizes resource allocation in plant management
[97]	2023	Complex task handling	Mobile platforms and cartesian manipulators	Enables heavy fruit picking and navigation in challenging terrains
[98,99]	2024, 2022	Food industry automation	Generative AI for sensory simulation	Automates packaging, cutting, and sorting with 95 % precision and mimics human tactile interactions

3.6. Computer vision and image generation

The integration of computer vision is increasingly important in transforming the agricultural and food industries. Javaid et al. [3] provided an overview of computer vision in agriculture and highlighted its role in crop health monitoring, pest management, and optimizing farming operations using imaging techniques like hyperspectral imaging and 3D laser scanning. Generative models can precisely analyze soil conditions, recommend necessary nutrients to improve soil quality and determine the best seeding times and methods. Expanding on the use of specific imaging technologies, Subudhi et al. [103] explored hyperspectral imaging, which provides detailed spectral data from the Earth's surface and is integrated with interactive visualization tools. This technology aids in precise crop monitoring and promotes sustainable farming by offering crucial spectral data for environmental and crop health assessments. To improve operational efficiency and address specific agricultural tasks, Debnath et al. [104] introduced a framework using GANs and U-Net, optimized by the Taylor Coot algorithm, for plant region segmentation and biomass estimation. This method demonstrates the potential of generative models in capturing accurate phenotypic data essential for crop breeding and genetic research.

The use of visual data extends beyond crop monitoring to automating farming operations. Pan et al. [61] present a deep-learning sorting mechanism for pig farming that overcomes the limitations of traditional electromechanical systems. By integrating a Kalman filter-based algorithm, the system enhances dynamic sorting precision, recognizes pigs individually based on weight monitoring, and identifies potential illnesses through irregular body appearances. Additionally, the research incorporates Wasserstein GAN for image enhancement, improving the system's ability to recognize and manage livestock under various conditions. Experimental results show significant improvements over traditional methods, with increases in livestock ID recognition (89 %), obscured image recognition (32 %), and categorization accuracy (95 %). This is echoed in the work of Akbar et al. [105], who review the application of deep learning and computer vision in greenhouse environments, focusing on growth monitoring, pest detection, and yield

Table 5
Summary of digital twins applications in agri-food.

Reference	Year	Application	Model/ Framework	Results
[100]	2023	Intelligent fish farming	AIoT system	Automated fish feeding, environmental monitoring, and health assessments improve production efficiency by 25 %
[101]	2023	Sustainable agriculture	Digital twins and generative AI	Optimizes precision farming and resource management; reduces water/fertilizer waste by 15–30 %
[102]	2024	Food traceability	Digital twins and real-time sensing	Enhances food safety by monitoring physical, chemical, and microbial properties in real time

estimation to optimize production in controlled settings. They note challenges such as model adaptability, the scarcity of labeled greenhouse data, computational limitations, and the need for integrating multi-modal sensor inputs. Harvesting operations in agriculture require robust machine vision systems that can accurately detect and localize objects in cluttered environments. Haggag et al. [106] investigated the impact of dataset variations on the generalization ability of Mask-RCNN models for detecting tomatoes and stems in greenhouse conditions. Their results highlight that camera perspective and illumination significantly affect detection performance.

The application of computer vision has been explored in specific areas like horticulture and weed detection. Baniya et al. [107] discuss using visual signals in horticulture, where 2D images, videos, hyperspectral images, and 3D point clouds are increasingly used to enhance plant cultivation. These visual data types are crucial for monitoring plant growth, detecting pests and diseases, estimating quality and yield, and facilitating automated harvesting. However, a significant hurdle is the scarcity of high-quality training and evaluation datasets, which are essential for the efficacy of deep learning models in horticulture. One proposed solution is a deep learning-based super-resolution model to improve the quality of visual signals. Sapkota et al. [108] explored using synthetic images to train convolutional neural networks (CNNs), specifically Mask R-CNN, for weed detection in agriculture. They generated synthetic images from real plant instances clipped from UAV images and used GANs for creating fake plant instances. The study found that synthetic images based on real plant instances achieved near-comparable detection and segmentation performance to real images, with optimal results using 40–50 plant instances per image. Mixed datasets of real and synthetic images showed slight improvements in bounding box detection accuracy, and canopy mask areas from model predictions provided more reliable biomass estimates than bounding box areas. Similarly, Veres et al. [109] proposed a deep learning-based density estimation approach to localize fire blight symptoms in apple and pear orchards. They demonstrate that multi-spectral sensors enhance detection and argue that incorporating temporal models and background removal could further improve accuracy. We summarize recent computer vision applications of agri-food in Table 6.

Table 6
Summary of computer vision applications in agri-food.

Reference	Year	Application	Model/ Framework	Results
[3]	2023	Crop health monitoring	Hyperspectral imaging, 3D laser scanning	Optimizes farming operations, detects pests, and monitors soil quality
[61]	2023	Livestock management	Kalman filter, Wasserstein GAN	Achieves 89 % livestock ID recognition, 32 % obscured image recognition, and 95 % categorization accuracy
[103]	2023	Crop health assessment	Hyperspectral Imaging	Provides detailed spectral data for environmental and crop health assessments
[104]	2023	Plant phenotyping	GANs and U-Net	Accurately segments plant regions and estimates biomass for crop breeding
[105]	2024	Greenhouse automation	Deep learning, computer vision	Monitors growth, detects pests, and estimates yield; challenges include data scarcity
[106]	2024	Greenhouse automation	Deep learning, computer vision	Generalization varies based on dataset size, camera angle, and illumination; perpendicular views perform better for stem detection
[107]	2023	Horticulture automation	2D/3D Imaging, super-resolution models	Enhances plant cultivation; addresses dataset scarcity via improved visual signal quality
[108]	2022	Weed detection	Mask R-CNN and GANs	Synthetic images achieve near-real performance (40–50 instances per image optimal)
[109]	2024	Fire blight detection	Deep learning	NIR channels improve accuracy; model benefits from symptom density estimation

4. Potential use cases of generative AI in the agri-food sector

The previous sections highlighted various domains of the agri-food sector where generative AI is making significant contributions. In this section, we will explore additional areas where generative AI can play a role in enhancing agri-food processes.

4.1. Food product and process design

The use of generative AI in food design is quickly advancing, offering significant changes to food production systems. Al-Sarayreh et al. [110] highlight how deep generative networks are being used in food science and engineering to handle the growing complexity of food systems and meet consumer demands. They discussed inverse design, which uses resources like recipes or formulations, databases, and ontologies to create new food products. Moreover, Bedoya et al. [111] reviewed new technological trends in the food industry, focusing on 3D food printing (3D-FP). They explored new protein sources from plants, insects, fungi, algae, and microbial proteins, due to their high protein content and functional properties. The authors also discussed additive manufacturing for creating personalized nutrition solutions, using new ingredients, and enhancing sensory experiences.

In the future, generative AI could significantly transform food design, using advanced technologies to create more personalized, sustainable, and innovative food solutions. For example, LLMs could analyze and synthesize large amounts of dietary data to create highly tailored nutrition plans that match individual health profiles and dietary preferences [112]. This personalization could extend to dietary plans based on medical needs, lifestyle choices, or specific flavor preferences. Also, deep generative networks [113] could design recipes or develop food products that mimic the taste and texture of traditional foods using sustainable, plant-based, or lab-grown ingredients.

Furthermore, multimodal models [114] could optimize flavor and texture by combining data from various sources (such as sensory analysis, consumer feedback, and market trends) to predict and create successful new food products. This would enable food manufacturers to respond quickly to changing consumer preferences and emerging market trends. For added personalization, diffusion models can also simulate the gradual transformation of ingredients in recipes to enable fine-tuning of sensory properties like flavor intensity and texture. AI agents [115] could also play a key role in reducing food waste by optimizing food production and supply chain processes. These agents can predict the shelf life of products and adjust production schedules dynamically, aligning food production more closely with real-time consumer demand to minimize surplus and waste. Finally, generative AI could enhance sustainability analyses by evaluating the environmental impacts of various production options. Using generative deep learning simulation models [116] producers can analyze data on carbon footprints, water usage, and overall ecological impacts to make informed decisions about the most sustainable practices.

4.2. Animal welfare

Advances in precision and digital livestock farming are significantly improving animal welfare in the agri-food sector. Neethirajan [117] argues that while digital transformation can enhance animal health and welfare, it also introduces ethical challenges. One issue is the digital divide, where unequal access to technology among farmers could lead to varying standards of animal care. Additionally, the extensive use of AI and other digital tools might reduce natural interactions between farmers and livestock, potentially treating animals more like data points. Building on this, Zhang et al. [118] examined the use of AI to improve animal welfare in areas like behavior analysis and living conditions. Their review shows how AI models can provide deeper insights into animal behaviors, including using environmental management systems and automated cleaning and disinfection processes to ensure animals live in safe and healthy habitats.

The potential applications of generative AI to enhance animal welfare in the agri-food sector are promising and varied. Future efforts could focus on using advanced multimodal models [114] to create predictive health monitoring systems. These systems would anticipate health issues before they become evident by integrating various data types (audio, visual, and physiological signals) to ensure comprehensive and proactive care. Additionally, the development of emotion recognition systems could greatly benefit from these multimodal models [119]. These systems could provide more accurate assessments of animal stress levels using visual cues, vocal patterns, and behavioral data. Another potential application is the development of automated behavioral modification technologies that use reinforcement learning and deep generative models to simulate and adapt animal behaviors based on real-time data [120]. This constitutes developing a "world model" that simulates animal behavior, identifying patterns that indicate illness or stress to offer proactive interventions in animal care. Finally, autoregressive models can predict health events based on historical patterns in animal behavior to allow early interventions [121].

4.3. Combatting climate change

Agricultural production is increasingly threatened by climate change worldwide. Climate-smart agriculture (CSA) aims to transform agri-food systems into more sustainable and climate-resilient practices.[2] Zhao et al. [122] reviewed the progress, future directions, and challenges of CSA in both developed and developing countries. They suggest ways to improve CSA, such as enhancing cropping patterns, integrating internet and weather services, and expanding agricultural insurance to respond to weather conditions. Malik et al. [123] examined how climate change affects agriculture, which is vital for food security, livelihoods, and economies. They proposed a framework to assess exposure, adaptation, and sensitivity to climate change, focusing on wind variability and agricultural performance. This framework uses an index-based approach to determine the vulnerability of sub-regions, highlighting challenges to agricultural development.

To effectively combat climate change, generative AI can play a transformative role in advancing CSA practices. For example, advanced predictive analytics using multiple experts (AI agents) [115] can improve forecasting of climate variables and agricultural outputs, leading to better preparation and response strategies for farmers and policymakers. Additionally, deep generative models [116] can simulate various climate scenarios and their potential impacts on agriculture. This helps develop resilient agricultural practices that can withstand erratic weather patterns and changing climate conditions. Generative AI can also support the expansion of internet-based technologies in agriculture, enabling real-time data collection and analysis to inform climate-adaptive practices. Moreover, integrating blockchain technology with generative AI [124] can enhance transparency and traceability in CSA initiatives. Blockchain can provide a secure and immutable record of data regarding climate conditions, crop health, and resource usage to provide more accountable and efficient environmental management practices [125]. Digital twins can simulate scenarios to support climate adaptation by modeling the effects of climate conditions on factors like crop yield, water needs, and resource availability.

4.4. Food sustainability

Holzinger et al. [126] examined how AI intersects with biotechnology and its significant impact on the agri-food sector. The authors call for integrating biotechnology to create a more sustainable and efficient agricultural system by offering solutions for optimizing food production. Partha Pratim Ray [15] explored how generative AI can improve crop health, yield, and early disease detection. The optimization of resource usage and harvest processes is also discussed, highlighting generative AI's potential to enhance agricultural sustainability. However, Ray points out several challenges, such as the high capital investment required, the need for infrastructure development, data privacy concerns, and the necessity for workforce training to effectively operate these advanced technologies.

Looking ahead, the application of generative AI in food sustainability could expand in several promising directions. First, advanced predictive analytics using multiple AI agents could be used more extensively to anticipate crop failures, pest outbreaks, and nutrient deficiencies, enabling timely and precise interventions. Automated robotic systems powered by generative AI [127] could implement these interventions, reducing waste and increasing efficiency. Additionally, generative design [128] could be employed to develop new plant varieties that are more resilient to environmental stresses such as drought, heat, and salinity. Finally, AI-driven simulation models [116] could be used to assess the long-term sustainability of agricultural and food production practices [129]. These models could predict the environmental and economic impacts of different farming techniques to help policymakers and farmers make informed decisions. In food safety, generative models can predict contamination risks and identify potential hazards in real-time to ensure that food products meet safety standards before reaching consumers. For example, GANs can analyze patterns in historical data to forecast possible contamination events and suggest preventive measures.

4.5. Disease modeling and prediction

Pillai et al. [130] conducted a comprehensive literature review to assess the role of AI in studying zoonotic diseases, which are diseases transmitted between animals and humans and represent a significant portion of new infectious diseases. The authors examined how AI is used to predict the occurrence and spread of foodborne and zoonotic pathogens and identify the associated risk factors. The authors highlight that predictive models can improve our understanding of the dynamics and transmission patterns of these diseases. Yousefinaghani et al. [131] presented a decision support framework for avian influenza, using AI-driven tools to predict disease events at various geographical scales, which helps healthcare authorities respond promptly by increasing situational awareness and enabling early control of outbreaks.

The application of generative AI in disease modeling and prediction can be expanded to include more advanced techniques that improve prediction accuracy and could be used to better understand the surveillance and prevention of foodborne diseases. For instance, GANs could generate synthetic data for rare or emerging zoonotic diseases where historical data is lacking to allow for better model training and improved prediction capabilities. Deep reinforcement learning [132] could simulate different intervention strategies for controlling or

[2] https://www.fao.org/climate-smart-agriculture/en/.

preventing the spread of zoonotic diseases and provide insights into the potential outcomes of various public health responses. Additionally, transfer learning [133] could leverage data from similar diseases to quickly improve models when new zoonotic diseases emerge, speeding up response times and potentially saving lives. To support faster detection, transformers can be used to synthesize genomic and epidemiological data. Integrating multimodal AI systems that combine text, image, and sequential data could offer a more comprehensive view of disease dynamics. For example, combining genomic data with clinical and environmental data could reveal more complex interactions and risk factors associated with disease spread. Finally, AI-driven simulation models [116] could forecast the long-term impacts of zoonotic diseases under various climate scenarios and human interaction patterns, which would be crucial for planning and resource allocation in anticipation of future outbreaks.

4.6. Supply chain optimization and traceability

In supply chain optimization, generative algorithms analyze large datasets, including production rates, weather forecasts, market demands, and logistics to predict disruptions before they occur [134]. By identifying potential bottlenecks or shortages in advance, these systems help stakeholders make adjustments ahead of time. For example, generative AI can optimize harvest schedules and transportation routes using real-time data, which reduces the time it takes for produce to reach the market. Generative AI also enhances traceability by tracing, tracking and recording every step of the food production and distribution process. Integrating generative models with technologies like blockchain and IoT devices [135] allows each product to be traced back to its source, including the specific farm, batch, and growing conditions. Adversarial machine learning can also identify vulnerabilities in agri-food data systems and ensure robust, safe AI applications.

The application of generative AI in agri-food supply chain optimization and traceability can be further improved with advanced AI technologies to boost efficiency and reliability. Firstly, creating digital twins of the supply chain allows businesses to simulate and optimize processes in a virtual environment [136]. This approach helps manage resources better, reduce costs, and minimize environmental impact by identifying potential issues and testing solutions before implementing them in the real world. Further, integrating data from various sources, such as IoT devices, RFID tags, and online market data can provide a comprehensive view of the supply chain. This integration enhances traceability systems built with multimodal AI [119], which enables more accurate tracking of products from farm to table and ensures compliance with safety and quality standards. Finally, generative models can be useful for simulating various supply chain scenarios to test responses to hypothetical situations like sudden demand spikes or supply shortfalls.

4.7. Emerging technologies

Artificial general intelligence (AGI) represents a type of AI that can understand, learn, and apply intelligence across a wide range of tasks, similar to human cognitive abilities [137]. Lu et al. [138] explored AGI and its potential applications in agriculture, including food, fiber, and fuel production. Their study highlighted agricultural challenges, such as climate change, soil degradation, and water scarcity, and suggests AGI as a solution to these problems. By analyzing large datasets that include phenomic and genomic data, environmental factors, and real-time farm data, AGI could revolutionize farm management. AGI could significantly improve decision-making by analyzing vast amounts of agricultural (weather, soil data, crop health indicators, market trends, etc.) and food production (equipment conditions, processing parameters, storage temperature, food safety training) data to make predictions and decisions on a larger scale comparable to or better than human experts. Moreover, as depicted in Fig. 2, AGI could oversee and manage the entire lifecycle of food products in terms of food safety and quality, ensuring compliance with safety standards and regulations from farm to table.

Quantum computing represents a shift in computing power, capable of processing complex calculations at unprecedented speeds, which can significantly enhance the application of generative AI [90]. Using quantum computing, generative AI models can handle more extensive datasets and offer improved precision and efficiency in various agricultural processes [139]. For instance, quantum-enhanced generative AI can optimize crop planting schedules by simultaneously simulating

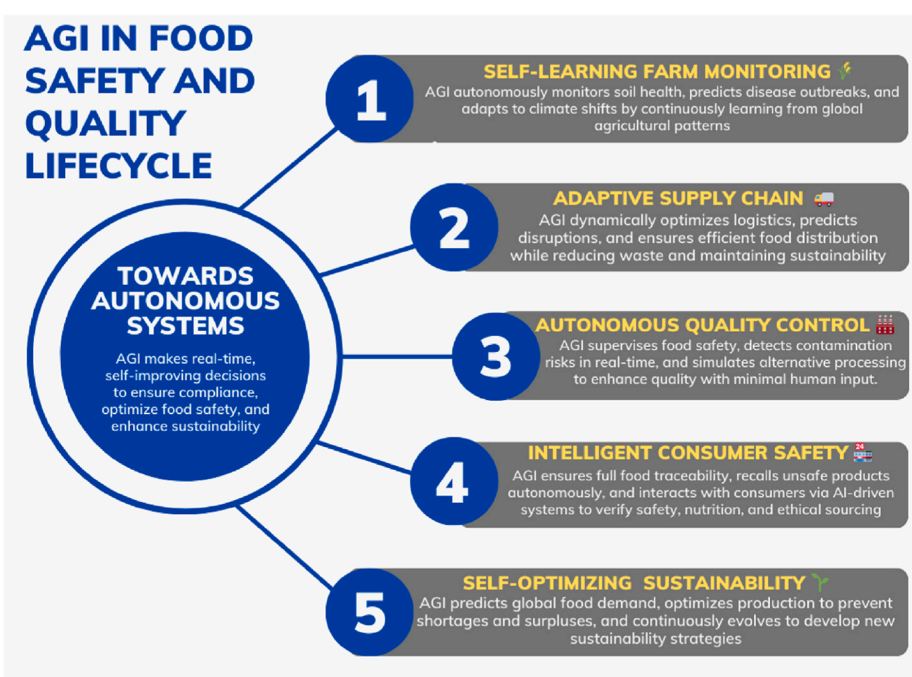

Fig. 2. Conceptualizing AGI in food safety and quality lifecycle.

numerous environmental conditions and inputs for better yield predictions and resource management. Quantum-enhanced generative models can simulate the effects of different packaging materials on food shelf life and enable manufacturers to select the most sustainable options. Integrating quantum computing and generative AI also offers promise for enhancing sustainability [140]. These advanced technologies can draft strategies that minimize carbon footprints and optimize water and nutrient usage, including simulating various climate scenarios to predict their effects on crop and livestock production.

5. Discussion and considerations for generative AI in agri-food

This section discusses the multifaceted considerations of generative AI deployment in Agri-Food, from ethical applications and unbiased decision-making to the imperatives of transparency, privacy, and security.

5.1. Case studies and real-world implementations of generative AI in agri-food

Generative AI has seen practical implementation across various domains in agriculture, from synthetic data generation to decision support systems and digital twins. One notable application is the use of GANs to generate synthetic crop disease images for enhancing pest detection. For instance, Karam et al. [141] demonstrated how GANs improved pest detection by generating synthetic whitefly images, which improved dataset diversity. While traditional data augmentation alone significantly boosted recall, incorporating GAN-generated pest masks led to an additional 1.4 % recall increase. Industry-driven solutions like Microsoft's FarmBeats leverage forecasting models to predict micro-climate using sensor data, reducing soil moisture forecasting error [142]. LLMs have also proven effective in agricultural advisory services. The ZEMELA platform integrated LLMs to provide regulatory compliance advice to Bulgarian farmers [77]. Comparative studies further validate the effectiveness of LLM-based advisory systems. Ibrahim et al. [10] found that LLM-driven chatbots were preferred by farmers in 78 % of cases over traditional extension agents, though iterative human feedback was necessary to refine agronomic recommendations. Similarly, Calone et al. [143] explored the potential of LLMs in supporting plant disease risk forecasting by translating model-based predictions into advisory messages. Their study found that GPT-4 generated more context-aware, strategic messages, while GPT-3.5 produced concise, routine-friendly advice. Sentiment analysis revealed GPT-4's adaptability in shifting tones based on risk levels, whereas GPT-3.5 remained neutral. Although expert reviews highlighted their potential in drafting technical bulletins, both models required domain-specific training to improve precision.

5.2. Evaluation challenges of generative AI

Evaluating generative AI systems in the agri-food sector presents unique challenges to traditional predictive machine learning models. While conventional models are assessed using well-established metrics like accuracy, generative AI requires multi-dimensional evaluation frameworks to account for creativity, fidelity, and utility. The lack of objectivity in determining the output quality of generative models remains a notable challenge. Generative models (e.g., GANs, LLMs) produce outputs such as synthetic images, text, and simulations that lack ground-truth comparisons. Traditional metrics like the Structural Similarity Index or Peak Signal-to-Noise Ratio for images fail to capture agricultural relevance (e.g., whether synthetic soil moisture data aligns with real-world agronomic conditions) [144]. Moreover, agri-food systems operate in highly variable conditions (e.g., fluctuating weather, soil heterogeneity). A generative model trained on data from one region may fail in another due to unseen environmental factors, complicating cross-regional validation. Table 7 presents a comparison of traditional AI evaluation and generative AI evaluation.

Table 7
Comparison of traditional and generative AI evaluation.

	Traditional AI	Generative AI
Primary Focus	Prediction accuracy, generalizability	Creativity, fidelity, safety, and real-world utility
Validation Data	Labeled datasets with ground truth	Expert judgment, hybrid metrics (quantitative + qualitative)
Key Metrics	Accuracy, AUC-ROC, RMSE	Fréchet Inception Distance, human evaluation
Considerations	Overfitting, bias	Ethical misuse, ecological impact, hallucination

We recommend several strategies for robust evaluation of generative AI in agri-food. First, hybrid approaches combining quantitative measures (e.g., FID for image quality) with qualitative expert reviews (e.g., agronomists rating synthetic crop disease images) would represent a more comprehensive evaluation. Second, human-in-the-loop validation involving farmers, food scientists, and policymakers in iterative testing would increase the reliability of AI-based agri-food systems. Finally, we encourage the creation of benchmarks for domain-specific (e.g., crop health, livestock management, food quality) and task-specific (e.g., synthetic data generation, real-time anomaly detection) applications.

5.3. Integration challenges and barriers of generative AI

The integration of generative AI in the agri-food sector presents several technical, economic, and social challenges that must be addressed for widespread adoption. Technical barriers include the high computational costs of training and deploying generative AI models [145], particularly for synthetic data generation, climate simulations, and digital twins. These models require substantial processing power, cloud infrastructure, and real-time data pipelines, which can be inaccessible for small agricultural enterprises. Additionally, the lack of high-quality, diverse, and labeled datasets for training AI models in agriculture poses a notable limitation, as many farms operate in unique environmental conditions that are not well-represented in existing datasets [146]. Economic considerations further complicate the adoption of generative AI, as high upfront investment costs for hardware, software, and AI expertise can be prohibitive [147]. Many farmers in developing regions may lack the financial resources to integrate AI-driven solutions into their operations [148]. Furthermore, the return on investment for AI implementation in agriculture is often uncertain, especially in small-scale farming where operational margins are already thin. While AI has the potential to increase yields, optimize resource allocation, and reduce waste, the long-term economic benefits are yet to be determined.

From a social perspective, the successful deployment of generative AI depends on farmer adoption, trust, and technical literacy [149]. Many agricultural workers and decision-makers may be unfamiliar with AI technologies or lack the necessary skills to integrate AI into existing workflows. Without proper training programs and user-friendly AI interfaces, the digital divide between technologically advanced farms and smaller resource-limited operations may widen, leading to further disparities in agricultural productivity. Additionally, concerns over the environmental impact of generative AI may hinder adoption as their high computational need may contribute further to the climate crisis [150]. To overcome these challenges, policymakers, researchers, and technology providers should collaborate to develop cost-effective, scalable AI solutions tailored to the agricultural sector. Investments in edge computing [151], decentralized AI models, and energy-efficient hardware can reduce computational costs [152]. Moreover, training programs and AI-assisted decision-support systems should be designed with usability and accessibility.

5.4. Limitations of generative AI

The earlier subsections highlighted the existing role that generative AI plays in the Agri-food sector. However, several challenges need to be addressed when implementing generative AI in agriculture and food production.

- High-Quality Data and Training: The accuracy of generative AI predictions depends heavily on the quality of the data and the effectiveness of model training. Poor-quality data can lead to unreliable results, undermining the benefits of AI models [153]. For example, noisy data, such as sensor errors in soil moisture readings, can lead to inaccurate predictions, potentially causing over or under-fertilization.
- Managing Risks: Generative AI systems can be prone to various risks and vulnerabilities, such as bias in data, adversarial attacks, and unintended consequences. These risks need to be carefully managed to ensure the reliability and safety of AI in farming and food manufacturing [154]. Adversarial attacks on farm robotics, which use generative models to guide navigation, could result in unintended damage to crops or equipment.
- Deployment and Integration Issues: Integrating generative AI with existing IT systems and operational processes in agriculture and food processing can be challenging. For example, legacy irrigation controllers may not be compatible with AI models without upgrades. Thus, ensuring seamless deployment and integration requires careful planning and consideration of the specific needs and constraints of agricultural and food manufacturing operations [155].
- Evaluation and Testing: Rigorous evaluation and testing of generative models are essential to ensure their accuracy and reliability in real-world applications [156]. It is necessary to evaluate the outcome comprehensively before, during, and post-deployment. For instance, without thorough testing, predictions could fail to detect spoilage risks and cause outbreaks.
- Lack of Trust: There is often a lack of trust in AI-based systems among farmers, particularly regarding their reliability and the accuracy of their predictions [157]. Building this trust is crucial for the widespread adoption of generative AI in sustainable farming. If the system's predictions are inaccurate or inconsistent, farmers may hesitate to rely on AI, favoring traditional methods.
- Data Processing: Generative AI services use traditional cloud computing for large computational needs but face high latency due to data transmission and numerous user requests [158]. Data transmission delays between cloud servers and remote farms can hinder timely decision-making, especially in regions with limited internet infrastructure. Therefore, efficiently processing large volumes of agricultural data is a challenge that needs to be addressed for the successful implementation of generative AI.

5.5. Responsible use and governance in generative AI

Generative AI and the use of existing machinery like robots and drones are significantly changing agricultural and food manufacturing work. However, using this new technology also brings challenges and opportunities related to safety, sustainability, and understanding technical needs. Mallinger and Baeza-Yates looked at how environmental, social, and technological factors affect farmers' adoption of AI [93]. They proposed a framework for creating reliable AI that supports farmer autonomy and emphasizes the importance of responsible AI tools from a broader perspective. Ensuring data governance and ownership is crucial, with policies needed to make sure farmers keep control over their proprietary information and benefit fully from AI advancements [159]. At the same time, as AI technologies change the agricultural labor landscape, proactive measures should support workforce transitions, upskilling, and re-skilling to prevent job displacement. Pursuing global equity is essential; access to AI tools must help bridge the digital divide, enabling farmers from diverse socio-economic backgrounds to use these innovations, and ensuring an inclusive and fair advancement towards a technologically advanced agri-food future. Engaging the stakeholders and end-users to understand concerns and requirements is fundamental for the responsible deployment of generative AI in agriculture and food production. This includes actively involving farmers, agricultural workers, food manufacturers, and rural communities in the development and implementation processes to ensure the technology addresses real-world challenges with user acceptance.

5.6. Unbiased and fair outcome

The effectiveness of generative AI systems relies heavily on using real and unbiased data. Systems trained on biased datasets can perpetuate and even worsen biases [160], leading to poor decisions that affect crop yields, livestock health, and ultimately, food sources. The consequences of biased AI decisions in agriculture are extensive, impacting economic stability, food security, and resource distribution. Inaccurate predictions and analyses can result in misallocated investments, ineffective farming practices, and skewed market dynamics, disproportionately affecting small-scale farmers and vulnerable communities. It is crucial to curate diverse and representative datasets and develop algorithms that can detect and correct biases in their training data [161]. This requires continuous auditing of generative systems to evaluate their decisions critically and iteratively improve their learning processes. Comprehensive testing and evaluation are vital solutions for identifying and mitigating biases as they can emerge from any phases related to algorithm building, parameter setting, and improper evaluation. Engaging stakeholders and end-users throughout the development process ensures that generative AI systems are designed with a deep understanding of the diverse needs and challenges within the agricultural sector. This requires continuous auditing of generative models to evaluate their decisions critically and iteratively improve their learning processes.

5.7. Transparency

In AI-driven solutions within the agri-food sector, transparency is crucial for building trust between technology and its users. Following strict data regulations, like the General Data Protection Regulation (GDPR) [162] and other regulations (e.g. EU Data Act) is essential to ensure transparency in data usage and processing. However, Generative AI models often source data from various origins, sometimes bypassing the strict compliance required by these regulations. Transparency helps build trust among users and stakeholders and ensures accountability in how AI systems handle and process data. To bridge the trust gap, efforts must be made to clarify generative AI operations, making sure data sources are clear and compliant with regulatory standards [163]. Integrating strong transparency measures in generative AI will be essential to maintaining ethical standards and user confidence. For example, transparency can be achieved in generative AI that simulate crop yield forecasts by clearly indicating the types of data sources used, such as satellite imagery, historical yield data, and weather patterns, along with their origin and compliance with data protection regulations. Engaging stakeholders and end-users throughout the development process is significant for understanding their concerns and ensuring that AI solutions meet their needs.

5.8. Explainability

Explainability is a key ethical requirement in deploying AI-based solutions in the agri-food sector, emphasizing the need to make methodologies, frameworks, and datasets understandable. However, many current generative AI solutions lack full adherence to this principle. To address this, incorporating tools and methods from Explainable AI (XAI) [164] can be instrumental. Techniques such as Shapley additive explanations (SHAP) [165] and Local Interpretable Model-agnostic

Explanations (LIME) [166] provide insights into the decision-making processes of complex models and allow users to understand the rationale behind AI-generated outputs. The deployment of XAI methodologies can clarify the often opaque nature of Generative AI and allow stakeholders to better understand, trust, and use these technologies effectively. It is essential for developers and researchers to integrate these XAI approaches into generative AI systems [164]. For example, in predicting optimal planting times for specific crops, using techniques like SHAP or LIME can clarify how factors such as soil type, weather patterns, and crop variety contribute to the final recommendation.

5.9. Privacy and security

Privacy concerns are especially important when using generative AI in the agri-food sector because of the sensitive and proprietary nature of the data involved. Generative AI models often collect detailed information about farming practices, crop yields, and livestock health, which requires strong privacy protections. There is a risk that data used to train these AI systems could be exposed or misused, compromising the privacy and competitive advantage of farmers and agri-businesses. Privacy-preserving techniques like differential privacy and federated learning can protect individual data points while still allowing for the benefits of aggregated insights [165,166]. Additionally, encrypting data both in transit and at rest, along with strict access controls, can help keep sensitive information secure [167,168].

The security of generative AI systems in the agri-food sector is crucial, especially as these systems become more important to agricultural and food manufacturing operations. The potential for malicious entities to disrupt or manipulate AI-driven processes could have serious consequences [169], such as altering crop management strategies or corrupting supply chain logistics. Therefore, security measures must be thorough and proactive to protect against threats that could undermine the integrity of agri-food systems and the trust placed in them. To build secure generative AI frameworks, it is essential to consider the entire lifecycle of the data and the AI models [170]. Additionally, the systems must be resilient to adversarial attacks designed to deceive or confuse generative models, a field known as adversarial machine learning. Generative AI systems in the agri-food sector often involve a network of interconnected devices and platforms, from sensors in the field to cloud-based data analytics. Therefore, a holistic approach to security is necessary. This approach should include not only digital security but also the physical security of hardware and the human elements of the system. Training farm staff in best cybersecurity practices can help mitigate risks from human error or oversight. Regular assessments and updates of security measures, along with industry-wide collaboration on security standards and practices, will be essential to safeguard the agri-food ecosystem relying on generative AI.

5.10. Reliability and robustness

Reliability and robustness are fundamental aspects of deploying generative AI in the agri-food sector. Robust AI models can handle diverse and unexpected inputs without failing or producing inaccurate outputs, which is crucial in dynamic agricultural environments. Techniques such as robust training [171], redundancy [172], and fault tolerance [173] can be implemented to enhance the reliability of these systems. Comprehensive testing and evaluation with end-users are essential to validate the robustness of AI models under real-world conditions. This involves simulating various scenarios, including edge cases and potential system failures, to ensure that the generative models can maintain performance and provide reliable results [174]. For instance, in crop disease prediction, a robust generative AI model should reliably detect early signs of disease across varying crop conditions and unforeseen environmental shifts. Engaging stakeholders and end-users throughout the development process helps in identifying practical issues and refining the models to meet the specific needs and challenges of the agri-food sector.

6. Conclusion

Generative AI's capability to process and analyze extensive datasets can help address global challenges such as food security and climate change resilience. This paper reviewed the applications of generative AI in the agri-food sector, highlighting its role across various domains such as crop management, food quality, safety and sustainability, supply chain optimization, and beyond. Moreover, exploring potential use cases highlights the benefits of generative AI in the agri-food sector, including enhancing animal welfare, optimizing pest management, combating climate change, and ensuring food sustainability. The potential roles of artificial general intelligence (AGI) and quantum computing were also discussed as future directions for generative AI in the agri-food sector. Deploying generative AI on a larger scale requires focusing on ethical considerations, including data privacy, security, and reducing bias in AI decisions. Generative AI should be developed and implemented with a framework that prioritizes technological advancement alongside the social, ethical, and environmental integrity of global food systems.

6.1. Ethical approval

Ethical approval was not required because no personal data was used. Any analysis presented were aggregated.

CRediT authorship contribution statement

Sakib Shahriar: Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Maria G. Corradini:** Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization. **Shayan Sharif:** Writing – review & editing, Validation, Methodology, Formal analysis. **Medhat Moussa:** Writing – review & editing, Validation, Methodology, Formal analysis. **Rozita Dara:** Writing – review & editing, Validation, Supervision, Funding acquisition, Conceptualization.

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Declaration of competing interest

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

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Data availability

No data was used for the research described in the article.

References

[1] I.P. on C. Change, Special report on climate change and land: chapter 5 - food security [Online], https://www.ipcc.ch/srccl/chapter/chapter-5/, 2019.

[2] K. Pawlak, M. Kołodziejczak, The role of agriculture in ensuring food security in developing countries: considerations in the context of the problem of sustainable food production, Sustainability 12 (13) (2020) 5488.
[3] M. Javaid, A. Haleem, I.H. Khan, R. Suman, Understanding the potential applications of artificial intelligence in agriculture sector, Adv. Agrochem 2 (1) (Mar. 2023) 15–30, https://doi.org/10.1016/j.aac.2022.10.001.
[4] A. Taneja, et al., Artificial intelligence: implications for the agri-food sector, Agronomy 13 (5) (2023) 1397.
[5] V. Sahni, S. Srivastava, R. Khan, Modelling techniques to improve the quality of food using artificial intelligence, J. Food Qual. 2021 (1) (2021) 2140010, https://doi.org/10.1155/2021/2140010.
[6] C. Yaiprasert, A.N. Hidayanto, AI-powered in the digital age: ensemble innovation personalizes the food recommendations, J Open Innov. Technol. Mark. Complex. 10 (2) (Jun. 2024) 100261, https://doi.org/10.1016/j.joitmc.2024.100261.
[7] K.-B. Ooi et al., "The potential of generative artificial intelligence across disciplines: perspectives and future directions," J. Comput. Inf. Syst., vol. 0, no. 0, pp. 1–32, doi: 10.1080/08874417.2023.2261010.
[8] J. Brédy, J. Gallichand, P. Celicourt, S.J. Gumiere, Water table depth forecasting in cranberry fields using two decision-tree-modeling approaches, Agric. Water Manag. 233 (Apr. 2020) 106090, https://doi.org/10.1016/j.agwat.2020.106090.
[9] K. Lepenioti, A. Bousdekis, D. Apostolou, G. Mentzas, Prescriptive analytics: literature review and research challenges, Int. J. Inf. Manag. 50 (Feb. 2020) 57–70, https://doi.org/10.1016/j.ijinfomgt.2019.04.003.
[10] A. Ibrahim, K. Senthilkumar, K. Saito, Evaluating responses by ChatGPT to farmers' questions on irrigated lowland rice cultivation in Nigeria, Sci. Rep. 14 (1) (Feb. 2024) 3407, https://doi.org/10.1038/s41598-024-53916-1.
[11] L.P. Thiele, Sustainability, John Wiley & Sons, 2024.
[12] J. Morales-García, A. Bueno-Crespo, F. Terroso-Sáenz, F. Arcas-Túnez, R. Martínez-España, J.M. Cecilia, Evaluation of synthetic data generation for intelligent climate control in greenhouses, Appl. Intell. 53 (21) (Nov. 2023) 24765–24781, https://doi.org/10.1007/s10489-023-04783-2.
[13] M. Xu, et al., Generative AI-Empowered simulation for autonomous driving in vehicular mixed reality metaverses, IEEE J. Sel. Top. Signal Process 17 (5) (2023) 1064–1079, https://doi.org/10.1109/JSTSP.2023.3293650.
[14] V. Kakani, V.H. Nguyen, B.P. Kumar, H. Kim, V.R. Pasupuleti, A critical review on computer vision and artificial intelligence in food industry, J. Agric. Food Res. 2 (Dec. 2020) 100033, https://doi.org/10.1016/j.jafr.2020.100033.
[15] P.P. Ray, Generative AI and its impact on sugarcane industry: an insight into modern agricultural practices, Sugar Tech 26 (2) (Apr. 2024) 325–332, https://doi.org/10.1007/s12355-023-01358-w.
[16] T. Jebara, Machine Learning: Discriminative and Generative vol. 755, Springer Science & Business Media, 2012.
[17] S. Shahriar, A.-R. Al-Ali, A.H. Osman, S. Dhou, M. Nijim, Machine learning approaches for EV charging behavior: a review, IEEE Access Pract. Innov. Open Solut. 8 (2020) 168980–168993.
[18] K. Hayawi, S. Shahriar, S.S. Mathew, The imitation game: detecting human and AI-generated texts in the era of ChatGPT and BARD, J. Inf. Sci. (2024) 01655515241227531.
[19] J.D.M.-W.C. Kenton, L.K. Toutanova, BERT: pre-training of deep bidirectional transformers for language understanding, in: Proceedings of NAACL-HLT, 2019, pp. 4171–4186.
[20] A. Rahali, M.A. Akhloufi, End-to-end transformer-based models in textual-based NLP, Acta Iran. Encycl. Perm. Études Iran. 4 (1) (2023) 54–110.
[21] K. Han, et al., A survey on vision transformer, IEEE Trans. Pattern Anal. Mach. Intell. 45 (1) (Jan. 2023) 87–110, https://doi.org/10.1109/TPAMI.2022.3152247.
[22] A. Vaswani, et al., Attention is all you need, Adv. Neural Inf. Process. Syst. 30 (2017).
[23] N.Q.K. Le, Leveraging transformers-based language models in proteome bioinformatics, Proteomics 23 (23–24) (2023) 2300011.
[24] K.A. Nfor, T.P. Theodore Armand, K.P. Ismaylovna, M.-I. Joo, H.-C. Kim, An explainable CNN and vision transformer-based approach for real-time food recognition, Nutrients 17 (2) (Jan. 2025) 362, https://doi.org/10.3390/nu17020362.
[25] M. Zaheer, et al., Big bird: transformers for longer sequences, in: Advances in Neural Information Processing Systems, Curran Associates, Inc., 2020, pp. 17283–17297. Accessed: Jul. 01, 2024. [Online]. Available: https://proceedings.neurips.cc/paper/2020/hash/c8512d142a2d849725f31a9a7a361ab9-Abstract.html.
[26] T. Brown, et al., Language models are few-shot learners, Adv. Neural Inf. Process. Syst. 33 (2020) 1877–1901.
[27] E.J. Topol, As artificial intelligence goes multimodal, medical applications multiply, Science 381 (6663) (Sep. 2023) eadk6139, https://doi.org/10.1126/science.adk6139.
[28] J. Yang, et al., Harnessing the power of LLMs in practice: a survey on ChatGPT and beyond, ACM Trans. Knowl. Discov. Data 18 (6) (Apr. 2024) 160:1–160:32, https://doi.org/10.1145/3649506.
[29] I. Goodfellow, et al., Generative adversarial nets, Adv. Neural Inf. Process. Syst. 27 (2014).
[30] S. Shahriar, GAN computers generate arts? A survey on visual arts, music, and literary text generation using generative adversarial network, Displays 73 (2022) 102237.
[31] Y. Lu, D. Chen, E. Olaniyi, Y. Huang, Generative adversarial networks (GANs) for image augmentation in agriculture: a systematic review, Comput. Electron. Agric. 200 (Sep. 2022) 107208, https://doi.org/10.1016/j.compag.2022.107208.
[32] D. Saxena, J. Cao, Generative adversarial networks (GANs): challenges, solutions, and future directions, ACM Comput. Surv. 54 (3) (May 2021) 63:1–63:42, https://doi.org/10.1145/3446374.
[33] J. Ho, A. Jain, P. Abbeel, Denoising diffusion probabilistic models, Adv. Neural Inf. Process. Syst. 33 (2020) 6840–6851.
[34] A. Kazerouni, et al., Diffusion models in medical imaging: a comprehensive survey, Med. Image Anal. (2023) 102846.
[35] M.N. Pham, Understanding Human Imagination through Diffusion Model, Virginia Tech, 2023 [Online], https://hdl.handle.net/10919/117279. (Accessed 13 May 2024).
[36] G.E. Box, G.M. Jenkins, G.C. Reinsel, G.M. Ljung, Time Series Analysis: Forecasting and Control, John Wiley & Sons, 2015.
[37] A. Karpathy, J. Johnson, L. Fei-Fei, Visualizing and Understanding Recurrent Networks, 2015. ArXiv Prepr. ArXiv150602078.
[38] C.-C. Lin, A. Jaech, X. Li, M.R. Gormley, J. Eisner, Limitations of autoregressive models and their alternatives, in: K. Toutanova, A. Rumshisky, L. Zettlemoyer, D. Hakkani-Tur, I. Beltagy, S. Bethard, R. Cotterell, T. Chakraborty, Y. Zhou (Eds.), Proceedings of the 2021 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Association for Computational Linguistics, Jun. 2021, pp. 5147–5173, https://doi.org/10.18653/v1/2021.naacl-main.405. Online.
[39] B. Biggio, F. Roli, Wild patterns: ten years after the rise of adversarial machine learning, in: Proceedings of the 2018 ACM SIGSAC Conference on Computer and Communications Security, 2018, pp. 2154–2156.
[40] N. Papernot, P. McDaniel, I. Goodfellow, S. Jha, Z.B. Celik, A. Swami, Practical black-box attacks against machine learning, in: Proceedings of the 2017 ACM on Asia Conference on Computer and Communications Security, 2017, pp. 506–519.
[41] A. Shafahi, et al., Adversarial training for free, in: Advances in Neural Information Processing Systems, Curran Associates, Inc., 2019. Accessed: Jul. 01, 2024. [Online]. Available: https://proceedings.neurips.cc/paper_files/paper/2019/hash/7503cfacd12053d309b6bed5c89de212-Abstract.html.
[42] M. Grieves, J. Vickers, Digital twin: mitigating unpredictable, undesirable emergent behavior in complex systems, in: F.-J. Kahlen, S. Flumerfelt, A. Alves (Eds.), Transdisciplinary Perspectives on Complex Systems: New Findings and Approaches, Springer International Publishing, Cham, 2017, pp. 85–113, https://doi.org/10.1007/978-3-319-38756-7_4.
[43] F. Corradini, A. Marcelletti, A. Morichetta, B. Re, L. Ruschioni, A digital twin approach for blockchain smart contracts, in: 2024 IEEE International Conference on Software Analysis, Evolution and Reengineering - Companion (SANER-C), Mar. 2024, pp. 1–11, https://doi.org/10.1109/SANER-C62648.2024.00007.
[44] A. Rasheed, O. San, T. Kvamsdal, Digital twin: values, challenges and enablers from a modeling perspective, IEEE Access 8 (2020) 21980–22012, https://doi.org/10.1109/ACCESS.2020.2970143.
[45] P. Eigenschink, T. Reutterer, S. Vamosi, R. Vamosi, C. Sun, K. Kalcher, Deep generative models for synthetic data: a survey, IEEE Access 11 (2023) 47304–47320, https://doi.org/10.1109/ACCESS.2023.3275134.
[46] M. Weiss, F. Jacob, G. Duveiller, Remote sensing for agricultural applications: a meta-review, Remote Sens. Environ. 236 (2020) 111402.
[47] D. Chen, X. Qi, Y. Zheng, Y. Lu, Y. Huang, Z. Li, Synthetic data augmentation by diffusion probabilistic models to enhance weed recognition, Comput. Electron. Agric. 216 (Jan. 2024) 108517, https://doi.org/10.1016/j.compag.2023.108517.
[48] K.A. Patyk, et al., Modelling the domestic poultry population in the United States: a novel approach leveraging remote sensing and synthetic data methods, Geospatial Health 15 (2) (Dec. 2020) 2, https://doi.org/10.4081/gh.2020.913.
[49] A. Wang, R. Dara, S. Yousefinaghani, E. Maier, S. Sharif, A review of social media data utilization for the prediction of disease outbreaks and understanding public perception, Big Data Cogn. Comput. 7 (2) (Jun. 2023) 2, https://doi.org/10.3390/bdcc7020072.
[50] A. Recio-Román, M. Recio-Menéndez, M.V. Román-González, The future of retail: harnessing generative AI for disruptive innovation and sector transformation, in: Reshaping Marketing Science in Wholesaling and Retailing, IGI Global Scientific Publishing, 2024, pp. 309–333, https://doi.org/10.4018/979-8-3693-6145-0.ch013.
[51] Y. Akkem, S.K. Biswas, A. Varanasi, A comprehensive review of synthetic data generation in smart farming by using variational autoencoder and generative adversarial network, Eng. Appl. Artif. Intell. 131 (May 2024) 107881, https://doi.org/10.1016/j.engappai.2024.107881.
[52] Y. Cao, et al., A Comprehensive Survey of Ai-Generated Content (Aigc): A History of Generative Ai from gan to Chatgpt, 2023. ArXiv Prepr. ArXiv230304226.
[53] P. Batz, T. Will, S. Thiel, T.M. Ziesche, C. Joachim, From identification to forecasting: the potential of image recognition and artificial intelligence for aphid pest monitoring, Front. Plant Sci. 14 (Jul) (2023), https://doi.org/10.3389/fpls.2023.1150748.
[54] V. Kumar, A.R. Ashraf, W. Nadeem, AI-powered marketing: what, where, and how? Int. J. Inf. Manag. (2024) 102783.
[55] B. Tang, J. Ewalt, H.-L. Ng, Generative AI models for drug discovery, in: Biophysical and Computational Tools in Drug Discovery, Springer, 2021, pp. 221–243.
[56] X. Tang, H. Chen, D. Lin, K. Li, Harnessing LLMs for multi-dimensional writing assessment: reliability and alignment with human judgments, Heliyon 10 (14) (2024) e34262, https://doi.org/10.1016/j.heliyon.2024.e34262.
[57] D. Baidoo-Anu, L.O. Ansah, Education in the era of generative artificial intelligence (AI): understanding the potential benefits of ChatGPT in promoting teaching and learning, J. AI 7 (1) (2023) 52–62.

[58] T. van Klompenburg, A. Kassahun, C. Catal, Crop yield prediction using machine learning: a systematic literature review, Comput. Electron. Agric. 177 (Oct. 2020) 105709, https://doi.org/10.1016/j.compag.2020.105709.
[59] X. Wang, Y. Bouzembrak, A.O. Lansink, H.J. van der Fels-Klerx, Application of machine learning to the monitoring and prediction of food safety: a review, Compr. Rev. Food Sci. Food Saf. 21 (1) (2022) 416–434, https://doi.org/10.1111/1541-4337.12868.
[60] M. Abdollahzadeh, T. Malekzadeh, C.T.H. Teo, K. Chandrasegaran, G. Liu, N.-M. Cheung, A Survey on Generative Modeling with Limited Data, Few Shots, and Zero Shot, 2023, https://doi.org/10.48550/arXiv.2307.14397. Jul. 26, *arXiv*: arXiv:2307.14397.
[61] Y. Pan, Y. Zhang, X. Wang, X.X. Gao, Z. Hou, Low-cost livestock sorting information management system based on deep learning, Artif. Intell. Agric. 9 (Sep. 2023) 110–126, https://doi.org/10.1016/j.aiia.2023.08.007.
[62] B. Decardi-Nelson, A.S. Alshehri, A. Ajagekar, F. You, Generative AI and Process Systems Engineering: the Next Frontier, 2024. ArXiv Prepr. ArXiv240210977.
[63] S.P.H. Boroujeni, et al., A comprehensive survey of research towards AI-enabled unmanned aerial systems in pre-, active-, and post-wildfire management, Inf. Fusion (2024) 102369.
[64] S. Liu, J. Chen, Y. Feng, Z. Xie, T. Pan, J. Xie, Generative artificial intelligence and data augmentation for prognostic and health management: taxonomy, progress, and prospects, Expert Syst. Appl. 255 (Dec. 2024) 124511, https://doi.org/10.1016/j.eswa.2024.124511.
[65] A. Mao, E. Huang, X. Wang, K. Liu, Deep learning-based animal activity recognition with wearable sensors: overview, challenges, and future directions, Comput. Electron. Agric. 211 (Aug. 2023) 108043, https://doi.org/10.1016/j.compag.2023.108043.
[66] T.-H. Dang, J. Park, V.-T. Tran, W.Y. Chung, VAE-LSTM data augmentation for cattle behavior classification using a wearable inertial sensor, IEEE Sens. Lett. 8 (5) (May 2024) 1–4, https://doi.org/10.1109/LSENS.2024.3385418.
[67] K.B. Chhetri, Applications of artificial intelligence and machine learning in food quality control and safety assessment, Food Eng. Rev. 16 (1) (Mar. 2024) 1–21, https://doi.org/10.1007/s12393-023-09363-1.
[68] M. Raisul Islam, et al., Deep learning and computer vision techniques for enhanced quality control in manufacturing processes, IEEE Access 12 (2024) 121449–121479, https://doi.org/10.1109/ACCESS.2024.3453664.
[69] M.R. Molitor, The united Nations climate change agreements, in: The Global Environment, Routledge, 1999.
[70] A. Tzachor, et al., Large language models and agricultural extension services, Nat. Food 4 (11) (Nov. 2023) 941–948, https://doi.org/10.1038/s43016-023-00867-x.
[71] A.C. Tricco, et al., PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation, Ann. Intern. Med. 169 (7) (Oct. 2018) 467–473, https://doi.org/10.7326/M18-0850.
[72] M.S. Razzaq, F. Maqbool, M. Ilyas, H. Jabeen, EvoRecipes: a generative approach for evolving context-aware recipes, IEEE Access Pract. Innov. Open Solut. 11 (2023) 74148–74164, https://doi.org/10.1109/ACCESS.2023.3296144.
[73] P. Niszczota, I. Rybicka, The credibility of dietary advice formulated by ChatGPT: robo-diets for people with food allergies, Nutrition 112 (Aug. 2023) 112076, https://doi.org/10.1016/j.nut.2023.112076.
[74] J.M. Rodríguez-de-Vera, et al., Dining on details: LLM-guided expert networks for fine-grained food recognition, in: Proceedings of the 8th International Workshop on Multimedia Assisted Dietary Management, in MADiMa '23, Association for Computing Machinery, New York, NY, USA, Oct. 2023, pp. 43–52, https://doi.org/10.1145/3607828.3617797.
[75] T. Yang, Y. Mei, L. Xu, H. Yu, Y. Chen, Application of question answering systems for intelligent agriculture production and sustainable management: a review, Resour. Conserv. Recycl. 204 (May 2024) 107497, https://doi.org/10.1016/j.resconrec.2024.107497.
[76] M.T. Kuska, M. Wahabzada, S. Paulus, AI for crop production – where can large language models (LLMs) provide substantial value? Comput. Electron. Agric. 221 (Jun. 2024) 108924 https://doi.org/10.1016/j.compag.2024.108924.
[77] S. Stoyanov, M. Kumurdjieva, V. Tabakova-Komsalova, L. Doukovska, Using LLMs in cyber-physical systems for agriculture-ZEMELA, in: 2023 International Conference on Big Data, Knowledge and Control Systems Engineering (BdKCSE), IEEE, 2023, pp. 1–6.
[78] D. De Clercq, E. Nehring, H. Mayne, A. Mahdi, Large language models can help boost food production, but be mindful of their risks, Front. Artif. Intell. 7 (Oct) (2024), https://doi.org/10.3389/frai.2024.1326153.
[79] C. Maraveas, C.-S. Karavas, D. Loukatos, T. Bartzanas, K.G. Arvanitis, E. Symeonaki, Agricultural greenhouses: resource management technologies and perspectives for zero greenhouse gas emissions, Agriculture 13 (7) (Jul. 2023) 7, https://doi.org/10.3390/agriculture13071464.
[80] A. Ajagekar, N.S. Mattson, F. You, Energy-efficient AI-based control of semi-closed greenhouses leveraging robust optimization in deep reinforcement learning, Adv. Appl. Energy 9 (Feb. 2023) 100119, https://doi.org/10.1016/j.adapen.2022.100119.
[81] P. Hosseini Monjezi, M. Taki, S. Abdanan Mehdizadeh, A. Rohani, M.S. Ahamed, Prediction of greenhouse indoor air temperature using artificial intelligence (AI) combined with sensitivity analysis, Horticulturae 9 (8) (Aug. 2023) 8, https://doi.org/10.3390/horticulturae9080853.
[82] S. Bose, S. Banerjee, S. Kumar, A. Saha, D. Nandy, S. Hazra, Review of applications of artificial intelligence (AI) methods in crop research, J. Appl. Genet. (Jan. 2024), https://doi.org/10.1007/s13353-023-00826-z.
[83] W. Min, et al., From Plate to Production: Artificial Intelligence in Modern Consumer-Driven Food Systems, Nov. 04, 2023, https://doi.org/10.48550/arXiv.2311.02400 *arXiv*: arXiv:2311.02400.
[84] M. Kang, X. Wang, H. Wang, J. Hua, P. de Reffye, F.-Y. Wang, The development of AgriVerse: past, present, and future, IEEE Trans. Syst. Man Cybern. Syst. 53 (6) (Jun. 2023) 3718–3727, https://doi.org/10.1109/TSMC.2022.3230830.
[85] G. Sara, G. Todde, D. Pinna, M. Caria, Investigating the Intention to Use Augmented Reality Technologies in Agriculture: Will Smart Glasses Be Part of the Digital Farming Revolution?, Feb. 14, 2024, https://doi.org/10.2139/ssrn.4726136. Rochester, NY: 4726136.
[86] J.J.K. Chai, C. O'Sullivan, A.A. Gowen, B. Rooney, J.-L. Xu, Augmented/mixed reality technologies for food: a review, Trends Food Sci. Technol. 124 (Jun. 2022) 182–194, https://doi.org/10.1016/j.tifs.2022.04.021.
[87] R.M. Ellahi, L.C. Wood, A.E.-D.A. Bekhit, Blockchain-based frameworks for food traceability: a systematic review, Foods Basel Switz. 12 (16) (2023) 3026.
[88] F. Büyükakin, Ö.B. Soylu, Metaverse: transformation and future of agriculture, in: F.S. Esen, H. Tinmaz, M. Singh (Eds.), Metaverse: Technologies, Opportunities and Threats, Springer Nature, Singapore, 2023, pp. 333–355, https://doi.org/10.1007/978-981-99-4641-9_23.
[89] Q. Yang, X. Du, Z. Wang, Z. Meng, Z. Ma, Q. Zhang, A review of core agricultural robot technologies for crop productions, Comput. Electron. Agric. 206 (Mar. 2023) 107701, https://doi.org/10.1016/j.compag.2023.107701.
[90] C. Cheng, J. Fu, H. Su, L. Ren, Recent advancements in agriculture robots: benefits and challenges, Machines 11 (1) (2023) 48.
[91] S. Agarwal, S.P. Chinchali, Synthesizing adversarial visual scenarios for model-based robotic control, in: Proceedings of the 6th Conference on Robot Learning, PMLR, Mar. 2023, pp. 800–811. Accessed: Aug. 01, 2024. [Online]. Available: https://proceedings.mlr.press/v205/agarwal23b.html.
[92] M. Wakchaure, B.K. Patle, A.K. Mahindrakar, Application of AI techniques and robotics in agriculture: a review, Artif. Intell. Life Sci. 3 (Dec. 2023) 100057, https://doi.org/10.1016/j.ailsci.2023.100057.
[93] K. Mallinger, R. Baeza-Yates, Responsible AI in farming: a multi-criteria framework for sustainable technology design, Appl. Sci. 14 (1) (Jan. 2024) 1, https://doi.org/10.3390/app14010437.
[94] V. Balaska, Z. Adamidou, Z. Vryzas, A. Gasteratos, Sustainable crop protection via robotics and artificial intelligence solutions, Machines 11 (8) (Aug. 2023) 8, https://doi.org/10.3390/machines11080774.
[95] C.-L. Chang, H.-W. Chen, J.-Y. Ke, Robust guidance and selective spraying based on deep learning for an advanced four-wheeled farming robot, Agric. Nitra Slovak. 14 (1) (2023) 57.
[96] F.E. Nasir, M. Tufail, M. Haris, J. Iqbal, S. Khan, M.T. Khan, Precision agricultural robotic sprayer with real-time Tobacco recognition and spraying system based on deep learning, PLoS One 18 (3) (2023) e0283801.
[97] S. Kumar, S. Mohan, V. Skitova, Designing and implementing a versatile agricultural robot: a vehicle manipulator system for efficient multitasking in farming operations, Machines 11 (8) (2023) 776.
[98] S. Arellano, B. Otero, T.P. Kucner, R. Canal, A 3D terrain generator: enhancing robotics simulations with GANs, in: G. Nicosia, V. Ojha, E. La Malfa, G. La Malfa, P.M. Pardalos, R. Umeton (Eds.), Machine Learning, Optimization, and Data Science, Springer Nature Switzerland, Cham, 2024, pp. 212–226, https://doi.org/10.1007/978-3-031-53969-5_17.
[99] P. Mishra, et al., Footstep planning of humanoid robot in ROS environment using Generative Adversarial Networks (GANs) deep learning, Robot. Auton. Syst. 158 (Dec. 2022) 104269, https://doi.org/10.1016/j.robot.2022.104269.
[100] N.A. Ubina, et al., Digital twin-based intelligent fish farming with artificial intelligence internet of Things (AIoT), Smart Agric. Technol. 5 (Oct. 2023) 100285, https://doi.org/10.1016/j.atech.2023.100285.
[101] J. Liu, et al., Exploring the integration of digital twin and generative AI in agriculture, in: 2023 15th International Conference on Intelligent Human-Machine Systems and Cybernetics (IHMSC), 2023, pp. 223–228, https://doi.org/10.1109/IHMSC58761.2023.00059.
[102] M.G. Corradini, A.K. Homez-Jara, C. Chen, Virtualization and digital twins of the food supply chain for enhanced food safety, Adv. Food Nutr. Res. 111 (2024) 71–91, https://doi.org/10.1016/bs.afnr.2024.06.001.
[103] S. Subudhi, R.G. Dabhade, R. Shastri, V. Gundu, G.D. Vignesh, A. Chaturvedi, Empowering sustainable farming practices with AI-enabled interactive visualization of hyperspectral imaging data, Meas. Sens. 30 (Dec. 2023) 100935, https://doi.org/10.1016/j.measen.2023.100935.
[104] S. Debnath, A. Preetham, S. Vuppu, S.N.P. Kumar, Optimal weighted GAN and U-Net based segmentation for phenotypic trait estimation of crops using Taylor Coot algorithm, Appl. Soft Comput. 144 (Sep. 2023) 110396, https://doi.org/10.1016/j.asoc.2023.110396.
[105] J.U.M. Akbar, S.F. Kamarulzaman, A.J.M. Muzahid, Md A. Rahman, M. Uddin, A comprehensive review on deep learning assisted computer vision techniques for smart greenhouse agriculture, IEEE Access 12 (2024) 4485–4522, https://doi.org/10.1109/ACCESS.2024.3349418.
[106] S. Haggag, M. Veres, C. Tarry, M. Moussa, Object detection in tomato greenhouses: a study on model generalization, Agriculture 14 (2) (Feb. 2024) 2, https://doi.org/10.3390/agriculture14020173.
[107] A.A. Baniya, T.-K. Glory, Lee, P.W. Eklund, S. Aryal, Current state, data requirements and generative AI solution for learning-based computer vision in horticulture, Preprints Jun. 26 (2023) 2023061738, https://doi.org/10.20944/preprints202306.1738.v1.
[108] B.B. Sapkota, et al., Use of synthetic images for training a deep learning model for weed detection and biomass estimation in cotton, Sci. Rep. 12 (1) (Nov. 2022) 19580, https://doi.org/10.1038/s41598-022-23399-z.

[109] M. Veres, C. Tarry, K. Grigg-McGuffin, W. McFadden-Smith, M. Moussa, An evaluation of multi-channel sensors and density estimation learning for detecting fire blight disease in pear orchards, Sensors 24 (16) (Jan. 2024) 16, https://doi.org/10.3390/s24165387.
[110] M. Al-Sarayreh, M. Gomes Reis, A. Carr, M.M. dos Reis, Inverse design and AI/ Deep generative networks in food design: a comprehensive review, Trends Food Sci. Technol. 138 (Aug. 2023) 215–228, https://doi.org/10.1016/j.tifs.2023.06.005.
[111] M.G. Bedoya, D.R. Montoya, G. Tabilo-Munizaga, M. Pérez-Won, R. Lemus-Mondaca, Promising perspectives on novel protein food sources combining artificial intelligence and 3D food printing for food industry, Trends Food Sci. Technol. 128 (Oct. 2022) 38–52, https://doi.org/10.1016/j.tifs.2022.05.013.
[112] B.A. Galitsky, LLM- Based Personalized Recommendations in Health, Feb. 29, 2024, https://doi.org/10.20944/preprints202402.1709.v1. Preprints: 2024021709.
[113] B. Baillif, J. Cole, P. McCabe, A. Bender, Deep generative models for 3D molecular structure, Curr. Opin. Struct. Biol. 80 (Jun. 2023) 102566, https://doi.org/10.1016/j.sbi.2023.102566.
[114] Gemini Team, et al., Gemini: A Family of Highly Capable Multimodal Models, Apr. 02, 2024, https://doi.org/10.48550/arXiv.2312.11805 *arXiv*: arXiv:2312.11805.
[115] K. Hayawi, S. Shahriar, AI Agents from Copilots to Coworkers: Historical Context, Challenges, Limitations, Implications, and Practical Guidelines, Apr. 10, 2024, https://doi.org/10.20944/preprints202404.0709.v1. Preprints: 2024040709.
[116] O. Mujahid, I. Contreras, A. Beneyto, J. Vehi, Generative deep learning for the development of a type 1 diabetes simulator, Commun. Med. 4 (1) (Mar. 2024) 1–13, https://doi.org/10.1038/s43856-024-00476-0.
[117] S. Neethirajan, The significance and ethics of digital livestock farming, AgriEngineering 5 (1) (Mar. 2023) 1, https://doi.org/10.3390/agriengineering5010032.
[118] L. Zhang, et al., Advancements in artificial intelligence technology for improving animal welfare: current applications and research progress, Anim. Res. One Health 2 (1) (2024) 93–109, https://doi.org/10.1002/aro2.44.
[119] K. Ezzameli, H. Mahersia, Emotion recognition from unimodal to multimodal analysis: a review, Inf. Fusion 99 (Nov. 2023) 101847, https://doi.org/10.1016/j.inffus.2023.101847.
[120] Y. Matsuo, et al., Deep learning, reinforcement learning, and world models, Neural Netw. 152 (Aug. 2022) 267–275, https://doi.org/10.1016/j.neunet.2022.03.037.
[121] N. Vakitbilir, et al., Time-series modeling and forecasting of cerebral pressure–flow physiology: a scoping systematic review of the human and animal literature, Sensors 24 (5) (Jan. 2024) 5, https://doi.org/10.3390/s24051453.
[122] J. Zhao, D. Liu, R. Huang, A review of climate-smart agriculture: recent advancements, challenges, and future directions, Sustainability 15 (4) (Jan. 2023) 4, https://doi.org/10.3390/su15043404.
[123] I. Malik, et al., Estimation of the extent of the vulnerability of agriculture to climate change using analytical and deep-learning methods: a case study in Jammu, Kashmir, and Ladakh, Sustainability 15 (14) (2023) 11465.
[124] C.T. Nguyen, et al., Generative AI-Enabled Blockchain Networks: Fundamentals, Applications, and Case Study, 2024, https://doi.org/10.48550/arXiv.2401.15625. Jan. 28, *arXiv*: arXiv:2401.15625.
[125] R.A. Ahmed, E.E.-D. Hemdan, W. El-Shafai, Z.A. Ahmed, E.-S.M. El-Rabaie, F. E. Abd El-Samie, Climate-smart agriculture using intelligent techniques, blockchain and Internet of Things: concepts, challenges, and opportunities, Trans. Emerg. Telecommun. Technol. 33 (11) (2022) e4607.
[126] A. Holzinger, K. Keiblinger, P. Holub, K. Zatloukal, H. Müller, AI for life: trends in artificial intelligence for biotechnology, New Biotechnol 74 (May 2023) 16–24, https://doi.org/10.1016/j.nbt.2023.02.001.
[127] B. Obrenovic, X. Gu, G. Wang, D. Godinic, I. Jakhongirov, Generative AI and human–robot interaction: implications and future agenda for business, society and ethics, AI Soc. (2024) 1–14.
[128] H.O. Demirel, M.H. Goldstein, X. Li, Z. Sha, Human-Centered Generative Design Framework: An Early Design Framework to Support Concept Creation and Evaluation, International Journal of Human–Computer Interaction 40 (4) (2023) 933–944. https://doi.org/10.1080/10447318.2023.2171489.
[129] A. Režek Jambrak, M. Nutrizio, I. Djekić, S. Pleslić, F. Chemat, Internet of nonthermal food processing technologies (IoNTP): food industry 4.0 and sustainability, Appl. Sci. 11 (2) (Jan. 2021) 2, https://doi.org/10.3390/app11020686.
[130] N. Pillai, M. Ramkumar, B. Nanduri, Artificial intelligence models for zoonotic pathogens: a survey, Microorganisms 10 (10) (Oct. 2022), https://doi.org/10.3390/microorganisms10101911. Art. no. 10.
[131] S. Yousefinaghani, R.A. Dara, Z. Poljak, S. Sharif, A decision support framework for prediction of avian influenza, Sci. Rep. 10 (1) (Nov. 2020) 19011, https://doi.org/10.1038/s41598-020-75889-7.
[132] M. Soleymani, M. Bonyani, C. Wang, Simulation of autonomous resource allocation through deep reinforcement learning-based portfolio-project integration, Autom. Constr. 162 (2024) 105381.
[133] C.T. Teo, M. Abdollahzadeh, N.-M. Cheung, Fair generative models via transfer learning, in: Proceedings of the AAAI Conference on Artificial Intelligence, 2023, pp. 2429–2437.
[134] S. Fosso Wamba, M.M. Queiroz, C.J. Chiappetta Jabbour, C. Victor Shi, Are both generative AI and ChatGPT game changers for 21st-Century operations and supply chain excellence? Int. J. Prod. Econ. 265 (Nov. 2023) 109015 https://doi.org/10.1016/j.ijpe.2023.109015.
[135] H. Feng, X. Wang, Y. Duan, J. Zhang, X. Zhang, Applying blockchain technology to improve agri-food traceability: a review of development methods, benefits and challenges, J. Clean. Prod. 260 (2020) 121031.
[136] R. Bhandal, R. Meriton, R.E. Kavanagh, A. Brown, The application of digital twin technology in operations and supply chain management: a bibliometric review, Supply Chain Manag. Int. J. 27 (2) (2022) 182–206.
[137] G.E. Gignac, E.T. Szodorai, Defining intelligence: bridging the gap between human and artificial perspectives, Intelligence 104 (May 2024) 101832, https://doi.org/10.1016/j.intell.2024.101832.
[138] G. Lu, et al., AGI for Agriculture, Apr. 12, 2023, https://doi.org/10.48550/arXiv.2304.06136 *arXiv*: arXiv:2304.06136.
[139] A.P. Kirubakaran, J. Midhunchakkaravarthy, A hybrid application of quantum computing methodologies to AI techniques for paddy crop leaf disease identification, in: S. Goundar, R. Anandan (Eds.), Integrating Blockchain and Artificial Intelligence for Industry 4.0 Innovations, Springer International Publishing, Cham, 2024, pp. 69–83, https://doi.org/10.1007/978-3-031-35751-0_4.
[140] A. Ajagekar, F. You, Quantum computing and quantum artificial intelligence for renewable and sustainable energy: a emerging prospect towards climate neutrality, Renew. Sustain. Energy Rev. 165 (Sep. 2022) 112493, https://doi.org/10.1016/j.rser.2022.112493.
[141] C. Karam, M. Awad, Y. Abou Jawdah, N. Ezzeddine, A. Fardoun, GAN-based semi-automated augmentation online tool for agricultural pest detection: a case study on whiteflies, Front. Plant Sci. 13 (Sep) (2022), https://doi.org/10.3389/fpls.2022.813050.
[142] R. Chandra, Farmbeats: empowering farmers with affordable digital agriculture solutions. Presented at the ASA, CSSA and SSSA International Annual Meetings (2019), ASA-CSSA-SSSA, Nov. 2019 [Online], https://scisoc.confex.com/scisoc/2019am/meetingapp.cgi/Paper/122179. (Accessed 13 February 2025).
[143] R. Calone, et al., Analysing the potential of ChatGPT to support plant disease risk forecasting systems, Smart Agric. Technol. (Feb. 2025) 100824, https://doi.org/10.1016/j.atech.2025.100824.
[144] F. Osorio, R. Vallejos, W. Barraza, S.M. Ojeda, M.A. Landi, Statistical estimation of the structural similarity index for image quality assessment, Signal Image Video Process 16 (4) (Jun. 2022) 1035–1042, https://doi.org/10.1007/s11760-021-02051-9.
[145] A. Bandi, P.V.S.R. Adapa, Y.E.V.P.K. Kuchi, The power of generative AI: a review of requirements, models, input–output formats, evaluation metrics, and challenges, Future Internet 15 (8) (Aug. 2023) 8, https://doi.org/10.3390/fi15080260.
[146] A. Carraro, G. Saurio, F. Marinello, Towards rigorous dataset quality standards for deep learning tasks in precision agriculture: a case study exploration, Smart Agric. Technol. 10 (Mar. 2025) 100721, https://doi.org/10.1016/j.atech.2024.100721.
[147] M. Al-kfairy, Strategic integration of generative AI in organizational settings: applications, challenges and adoption requirements, IEEE Eng. Manag. Rev. (2025) 1–14, https://doi.org/10.1109/EMR.2025.3534034.
[148] N.R. Mannuru, et al., Artificial intelligence in developing countries: the impact of generative artificial intelligence (AI) technologies for development, Inf. Dev. (Sep. 2023) 02666669231200628, https://doi.org/10.1177/02666669231200628.
[149] K. Mallinger, L. Corpaci, T. Neubauer, I.E. Tikász, G. Goldenits, T. Banhazi, Breaking the barriers of technology adoption: explainable AI for requirement analysis and technology design in smart farming, Smart Agric. Technol. 9 (Dec. 2024) 100658, https://doi.org/10.1016/j.atech.2024.100658.
[150] A. Berthelot, E. Caron, M. Jay, L. Lefèvre, Estimating the environmental impact of Generative-AI services using an LCA-based methodology, Procedia CIRP 122 (Jan. 2024) 707–712, https://doi.org/10.1016/j.procir.2024.01.098.
[151] L. Ale, N. Zhang, S.A. King, D. Chen, Empowering generative AI through mobile edge computing, Nat. Rev. Electr. Eng. 1 (7) (Jul. 2024) 478–486, https://doi.org/10.1038/s44287-024-00053-6.
[152] J. Wen, et al., Generative AI for low-carbon artificial intelligence of Things with Large Language Models, IEEE Internet Things Mag 8 (1) (Jan. 2025) 82–91, https://doi.org/10.1109/IOTM.001.2400074.
[153] M. Kusak, Quality of data sets that feed AI and big data applications for law enforcement, ERA Forum 23 (2) (Oct. 2022) 209–219, https://doi.org/10.1007/s12027-022-00719-4.
[154] R. Dara, S.M. Hazrati Fard, J. Kaur, Recommendations for ethical and responsible use of artificial intelligence in digital agriculture, Front. Artif. Intell. 5 (2022) 884192.
[155] S.O. Araújo, R.S. Peres, J. Barata, F. Lidon, J.C. Ramalho, Characterising the agriculture 4.0 landscape—emerging trends, challenges and opportunities, Agronomy 11 (4) (Apr. 2021) 4, https://doi.org/10.3390/agronomy11040667.
[156] A.S. Albahri, et al., A systematic review of trustworthy and explainable artificial intelligence in healthcare: assessment of quality, bias risk, and data fusion, Inf. Fusion 96 (Aug. 2023) 156–191, https://doi.org/10.1016/j.inffus.2023.03.008.
[157] M. McCaig, R. Dara, D. Rezania, Farmer-centric design thinking principles for smart farming technologies, Internet Things 23 (Oct. 2023) 100898, https://doi.org/10.1016/j.iot.2023.100898.
[158] Y.-C. Wang, J. Xue, C. Wei, C.-C.J. Kuo, An overview on generative AI at scale with edge–cloud computing, IEEE Open J. Commun. Soc. 4 (2023) 2952–2971, https://doi.org/10.1109/OJCOMS.2023.3320646.
[159] J. Kaur, R. Dara, Analysis of farm data license agreements: do data agreements adequately reflect on farm data practices and farmers' data rights? Agric. Nitra Slovak. 13 (11) (2023) 2170.
[160] N. Pagan, J. Baumann, E. Elokda, G. De Pasquale, S. Bolognani, A. Hannák, A classification of feedback loops and their relation to biases in automated

decision-making systems, in: Proceedings of the 3rd ACM Conference on Equity and Access in Algorithms, Mechanisms, and Optimization, 2023, pp. 1–14.
[161] W. Liang, et al., Advances, challenges and opportunities in creating data for trustworthy AI, Nat. Mach. Intell. 4 (8) (2022) 669–677.
[162] I.G.P. Team, Eu General Data Protection Regulation (Gdpr)–an Implementation and Compliance Guide, IT Governance Ltd, 2020.
[163] N. Díaz-Rodríguez, J. Del Ser, M. Coeckelbergh, M.L. de Prado, E. Herrera-Viedma, F. Herrera, Connecting the dots in trustworthy Artificial Intelligence: from AI principles, ethics, and key requirements to responsible AI systems and regulation, Inf. Fusion 99 (2023) 101896.
[164] R. Dwivedi, et al., Explainable AI (XAI): core ideas, techniques, and solutions, ACM Comput. Surv. 55 (9) (2023) 1–33.
[165] S.M. Lundberg, S.-I. Lee, A unified approach to interpreting model predictions, Adv. Neural Inf. Process. Syst. 30 (2017).
[166] M.T. Ribeiro, S. Singh, C. Guestrin, "' Why should i trust you?' Explaining the predictions of any classifier,", in: Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, 2016, pp. 1135–1144.
[167] M. Amiri-Zarandi, R.A. Dara, E. Duncan, E.D. Fraser, Big data privacy in smart farming: a review, Sustainability 14 (15) (2022) 9120.
[168] S. Shahriar, R. Dara, R. Akalu, A comprehensive review of current trends, challenges, and opportunities in text data privacy, Comput. Secur. 151 (Apr. 2025) 104358, https://doi.org/10.1016/j.cose.2025.104358.
[169] T.C. King, N. Aggarwal, M. Taddeo, L. Floridi, Artificial intelligence crime: an interdisciplinary analysis of foreseeable threats and solutions, Sci. Eng. Ethics 26 (2020) 89–120.
[170] S. Shahriar, S. Allana, S.M. Hazratifard, R. Dara, A Survey of Privacy Risks and Mitigation Strategies in the Artificial Intelligence Life Cycle, IEEE Access 11 (2023) 61829–61854, https://doi.org/10.1109/ACCESS.2023.3287195.
[171] M.A. Hanif, F. Khalid, R.V.W. Putra, S. Rehman, M. Shafique, Robust machine learning systems: reliability and security for deep neural networks, in: 2018 IEEE 24th International Symposium on On-Line Testing and Robust System Design (IOLTS), Jul. 2018, pp. 257–260, https://doi.org/10.1109/IOLTS.2018.8474192.
[172] A. Ruospo, E. Sanchez, On the reliability assessment of artificial neural networks running on AI-oriented MPSoCs, Appl. Sci. 11 (14) (Jan. 2021) 14, https://doi.org/10.3390/app11146455.
[173] V.K. Menaria, S. Jain, N. Raju, R. Kumari, A. Nayyar, E. Hosain, NLFFT: a novel fault tolerance model using artificial intelligence to improve performance in wireless sensor networks, IEEE Access Pract. Innov. Open Solut. 8 (2020) 149231–149254.
[174] R. Hamon, H. Junklewitz, I. Sanchez, Robustness and explainability of artificial intelligence, Publ. Off. Eur. Union 207 (2020) 2020, and others.