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Challenges Facing Artificial Intelligence Adoption during COVID-19 Pandemic: An Investigation into the Agriculture and Agri-Food Supply Chain in India

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Abstract: The coronavirus (COVID-19) pandemic has witnessed a significant loss for farming in India due to restrictions on movement, limited social interactions and labor shortage. In this scenario, Artificial Intelligence (AI) could act as a catalyst for helping the farmers to continue with their farming. This study undertakes an analysis of the applications and benefits of AI in agri-food supply chain, while highlights the challenges facing the adoption of AI. Data were obtained from 543 farmers in Odisha (India) through a survey, and then interpreted using "Interpretive Structural Modelling (ISM)"; MICMAC; and "Step-Wise-Assessment and Ratio-Analysis (SWARA)". Response time and accuracy level; lack of standardization; availability of support for big data; big data support; implementation costs; flexibility; lack of contextual awareness; job-losses; affordability issues; shortage of infrastructure; unwillingness of farmers; and AI safety-related issues are some challenges facing the AI adoption in agri-food supply chain. Implications were drawn for farmers and policy makers.

Keywords: agriculture; agri-food supply chain; farmers; Artificial Intelligence; challenges; parameters; AI; ISM; SWARA; India

Citation: Mishra, D.; Muduli, K.; Raut, R.; Narkhede, B.E.; Shee, H.; Jana, S.K. Challenges Facing Artificial Intelligence Adoption during COVID-19 Pandemic: An Investigation into the Agriculture and Agri-Food Supply Chain in India. *Sustainability* **2023**, *15*, 6377. https://doi.org/10.3390/su15086377

Academic Editors: Zubair Baig and Francesco Contò

Received: 9 January 2023
Revised: 19 March 2023
Accepted: 4 April 2023
Published: 7 April 2023

1. Introduction

The practice of farming involves not only a number of options but also dealing with a number of unknowns. Managing the unknowns/uncertainties with farming is essential, but it can be difficult under the circumstances of shifting climates, seasonal variation of temperatures, varying costs of farming materials, unviable crops, soil degradation, crop damage caused by pests, crop suffocation caused by weeds, and so on. On the other hand, technological development has pushed various applications to the boundaries helping toward the goal of combining a natural brain with an artificial one. This has resulted in the emergence of a new field of application using "Artificial Intelligence (AI)", which refers to an intelligent machine/computer that can be made to think the way human thinks. The use of AI is becoming more common in the agricultural sector with the intention of developing innovative strategies for the continuation and enhancement of agriculture. The application of AI in agricultural sector is although evolving, it will likely be a reality with the development of other related technologies such as "big data analytics, internet-of-things, sensors and cameras, robotics, and drone technology", etc.

AI assists in providing predictive insights for agricultural activities such as "plantation- and harvesting-information" by analyzing soil management data sources [1]. These data sources include temperature, weather, soil and moisture analysis, and crop performance histories. As a result, crop yields can be increased while simultaneously reducing the amount of water, fertilizer, and pesticides used. Because of the increased use of AI technologies in agriculture, there is a potential for significant reduction in the negative impacts on natural ecosystems and on the safety of agricultural workers. This will further contribute to the maintenance of decreased food prices and increased food production thereby meeting the growing global population need. There has been interest in the field of AI [1–3] for decades and has been envisioned as a smart-machine supremacy that would take control of the planet and carry out the mundane, everyday tasks [4]. Because of its enormous benefits and improved performance, AI has emerged as a critical agenda of many companies' business models [5]. This is due to the fact that AI has evolved into a strategic system that can be applied across all industries. In the recent past, there have been a number of conceptual and empirical studies, and in many cases, the application of AI by regional and international government bodies have been demonstrated from both the academic and practitioner perspectives [6]. In addition, a number of conceptual and empirical studies have been conducted. AI has opened up a wealth of opportunities in a variety of sectors, including healthcare, agriculture, industry, and the environment [7,8].

According to Mukherjee et al. [9], most developing countries are transitioning from subsistence agriculture to commercial agriculture. This has led to a lot of use of AI, IoT, and other technologies based on information and communication in the agriculture of these countries. Consequently, the similar trend is also observed in India. Indian agriculture faces challenges such as non-uniform climatic conditions, low productivity, insect and disease infestations, market price instability, weak infrastructure, and slow agricultural growth [9,10]. Though advancements in AI technology have shifted major farmer clusters into a new competitive landscape, marginal and small farmers continue to confront challenges in adopting such new technologies, thus necessitating studies on AI implementation related issues in Indian Agriculture and allied sectors. Further, AI is transitioning into the digital era and is gradually taking over the role of intellectual resources towards economic growth [10,11]. However, the outbreak of COVID-19 pandemic in late 2019 has presented a significant risk primarily due to multiple lockdowns, curfews, social isolation, and other related restrictions. These measures were taken with the goal of slowing down the virus spread causing human deaths. Moreover, this pandemic outbreak caused problems for virtually every industry, particularly, the labor-intensive agricultural sector in India. Agricultural outputs have gone down which has a knock-on effect on national economy to a lower level. Because this has been identified as one of the most serious problems within the agricultural sector [12], finding solutions through technology applications (i.e., AI) is one of the effective ways to deal with such crisis. Although AI has not yet reached its full potential in the fight against pandemics, a noticeably higher role for AI exists during COVID-19, and it can be utilized appropriately as a tool to complement human intelligence in a variety of fields, including agriculture. Because the majority of AI systems are Internet-based, their applications in India's more remote regions are limited and constrained. The implementation of AI is contingent on the processes currently in place in an organization as well as its capacity for strategic technological planning [13]. Because of the current pandemic situation, Indian agriculture has only gradually and partially incorporated AI [14]. Since other countries have progressed with AI more rapidly to their advantage, India's slow adoption of AI has reflected on agricultural output and it's trading negatively [15]. In addition, the majority of members of the farming community in India's rural areas are less-qualified when it comes to the computers and Internet use. Therefore, the government should ideally provide assistance to farmers by designing web-services, charging lower tariffs for those working with AI systems, and providing sufficient handson training [14,15]. Although, there has been some remarkable improvement brought about for AI adoption in the agricultural sector, it still has a lesser impact on agricultural activities when compared to its impacts and potentials in other sectors. This is because the agricultural activities are more labor-intensive that allows more labor in India context and quite justified. Getting AI is not likely to replace the labor but it makes the agri-business more efficient thereby helping the farmers more productive.

The Indian agriculture supply chain faces a number of problems, such as a lack of groundwater, famine, economic hardship, resource warfare, and post-harvest losses that break nutrient cycles [16,17]. These problems have a negative effect on the availability and quality of food [18]. These post-harvest loss issues become more significant during COVID-19 because of the implementation of strict lockdowns by the state and central governments in India to restrict the spread of the virus. Studies suggest innovative technologies like AI have the potential to improve SC visibility and traceability while also addressing food quality and safety concerns [19–21]. Hence, it was realized there is a need to explore the factors those hinder AI adoption among various stake holders of agri-food supply chain in India. In addition, the use of AI can lead to significant benefits in the Indian agri-food supply chain not only during the COVID-19 outbreak period but also in the long-term, which needs to be addressed and initiated to improve the agricultural activities. An investigation is required to determine the reason why the rural areas of India have a low level of AI adoption and implementation, particularly in agri-food supply chain. What difficulties might be encountered when putting AI into practice? What challenges Indian policymakers and decision-makers encounter while resolving the issues? This research aims to identify the benefits and the challenges facing the adoption of AI in the Indian agri-food supply chain. Further, the challenges that India's developing agricultural sector need to overcome to create AI-based intelligent systems are explored.

The specific objectives are to:

- Identify the benefits of AI in agri-food supply chain, and raise awareness among Indian rural farmers for its applications in light of the current-and post-pandemic situation;
- Highlight the significant challenges associated with the implementation of AI in agri-food supply chain;
- Develop and analyze a suitable model based on the interrelationships among the challenging parameters with their ranking based on prioritization.

Rest of the paper is organized as follows. The preceding literature is examined in Section 2. Section 3 includes a full description of the research methodology. Sections 4 and 5 provide a summary of the "results" and "discussion" respectively. Implications of this research are highlighted in Section 6, followed by conclusion Section 7.

2. Literature Review

2.1. Agriculture and Artificial Intelligence (AI)

Agriculture is a sustainable foundation of the economy [15,16,22], and it plays a critical role in both long-term development of the economy and the structural transformation of societies [22–27]. Historically, the majority of agricultural activities were restricted to the growing of crops and the preparation of food [28]. On the other hand, during the past twenty years, the agricultural sector has become increasingly involved in the production, processing, and marketing of crop and livestock products, in addition to their distribution. These activities are within the agri-food supply chain. At the moment, it functions as a primary source of income and, thereby, contributes increasingly to GDP [29]. This means that it not only functions as a source of national trade but also helps in reduction of unemployment, the provision of raw materials for other industrial activities, and the overall growth of the economy of the country [30–32]. In order to satisfy the increasing food demand, agricultural and food production will need to increase by 70% by the year 2050 [33], the year the global population is estimated to surpass 9 billion. However, it is difficult to meet this target in the face of a range of challenges like resource shortages, climate changes [34], the COVID-19 pandemic, and extremely pessimistic socioeconomic projections. As a consequence, maintaining the viability of the agricultural sector is essential for ensuring food security in addition to eliminating hunger for the world's expanding population. In addition, a well-documented management solution has become a prerequisite for quality conformance in the food chain due to the emergence of food-safety issues, such as "spongiform- encephalopathy of bovines and dioxins" in poultry [35].

A systematic transition from the existing paradigm of increased production to sustainable practices in agricultural sectors is an immediate need. This can assist farmers and consumers in making more informed-choices by implementing sustainable practices to effective solutions, particularly when utilizing digital-technologies such as "Internet of Things (IoT)"; "Machine Learning (ML)"; AI; and so on. Soil management is an essential component of agriculture. An in-depth understanding of the myriad of soil types and conditions is essential for maximising crop production while simultaneously protecting the earth's natural resources. The effects of soil-borne pathogens can be controlled through proper management of the soil [36]. For example, the AI-based soil-management technique is known as "management-oriented modelling", which consists of a set of possible management options to assist in minimising nitrate-leaching. This was done to protect the environment. It included a simulator for the purpose of evaluating each alternative and an evaluator to determine the user-weighted multiple-criteria alternative [37]. Also a remote sensing device incorporated into a "higher-order neural-network" was appropriate for the characterization and assessment of the soil-moisture dynamics [38]. While the existing "coarse-resolution soil-maps" are combined with hydrographic parameters derived from a "digital elevation model", a model known as "artificial neural network (ANN)" helps predict soil-textures based on their characteristics [39].

Crop management begins with sowing and growth monitoring, followed by harvesting, storage, and distribution of crops. An agricultural management system such as "precision crop management (PCM)" is designed to focus on crops and soil-inputs in accordance with field requirements for the optimization of profitability and protection of the environment. The lack of timely as well as distributed-information on crops and soil-conditions has been reported of hampering PCM [40]. Farmers need to combine various crop management strategies to be able to deal with water shortages brought in by soils or limited irrigation [41]. This is necessary for farmers to be successful in farming. For the evaluation of the operational behaviour of a farm system and the estimation of crop production, gross-revenues, and net profits for both individual fields and the whole farm, PROLOG has been found to be effective in utilising weather data, capacities of machinery, availability of labour, and information on prioritised and permissible implements, tractors, and operators [42]. Weed is responsible for a steady decline in the anticipated yields and profits made by farmers [43]. An uncontrolled weed infestation results in a 50% yield reduction for corn crops and dried beans [43], and about a 48% loss in wheat yield [44,45]. A "global positioning-system (GPS)" controlled patch-spraying based on an AI approach can be used for weed control in agriculture [46]. A drone travelling at a speed of 1.2 km-per-h has been successfully used in weed control [47]. In most cases, the crops are laid out in rows; consequently, the application of a crop row-detection algorithm helps in properly separating the weeds and crop pixels [48]. This is something that can be utilised by an "unmanned aerial-vehicle (UAVs)" for the purpose of performing efficient weed control. In addition to this, there is a demand for the implementation of AI strategies in disease management and control [49–51].

2.2. AI Applications for Agriculture and Food Sectors Improvement

AI is a creative tool that models how human intelligence and aptitude are processed by machines, primarily by computers, robots, and digital technology [52]. The application of machine language (ML), which fosters both inventiveness and productivity, is one of the primary focuses of AI. The development of AI has paved the way for applications of the technology in the agricultural and food industries. Farmers are turning to AI tools in the hopes of discovering more efficient methods to protect their crops from being destroyed by weeds. The application of innovative AI-based techniques to the agri-food supply chain has a number of benefits, including a reduction in the cost of training, a reduction in the amount of time needed to solve problems, a reduction in the number of errors made by humans, a reduction in the amount of human intervention that is required, and intelligent decisions that are affordable, accurate, and satisfactory [53]. The application of ML algorithms to the various nodes that make up the agricultural supply chain is becoming increasingly important [54]. Numerous studies examine the significance of agricultural crop yields as a means of enhancing plant management. As a result, ML and AI algorithms can help consumers and farmers make optimal decisions for crop yield forecasting. This can lead to higher yields and greater profits for everyone involved. In recent years, various ML algorithms, such as ANN, regression, Bayesian networks, decision trees, deep learning, and others, have been utilized for the purpose of developing prediction models [55,56]. According to the findings of Arvind et al. [48], it is possible to effectively predict and manage drought by combining the use of an ML algorithm with the utilization of other sensors and systems, such as "Zigbee and Microcontroller". Further, the ANN feed-forward and ANN feed-back propagation techniques were applied in a smart farm in order to make the most of the available water resources [57]. Few examples of technology that is based on AI include UAVs and robotics, block chains [58], geographic information systems [59], and satellite navigation. Agricultural drones can now provide farmers with water, fertilizer, and pesticides, as well as filming, photographing, and creating maps of plants and fields in real time [60]. This functionality of agricultural drones could better assist farmers in making management decisions.

Adopting sustainable farming practices has been encouraged in order to safeguard natural resources and accomplish the "sustainable development goals (SDG)". Utilizing digital technologies in agriculture, notably AI, machine learning, deep learning, and the technology behind block chains, could result in potential gains. The growth of technology has resulted in an increased demand for AI, which can perform difficult jobs more quickly and efficiently, as well as at a reduced cost [61–66]. In the midst of the COVID-19 pandemic, the use of cutting-edge technology based on AI may prove to be a superior answer [67]. Moreover, AI has been used widely in the fight against the COVID-19 pandemic [68–80]. In addition, the technologies of "Industry 4.0", which take the real-time information provided by AI and IoT. Printing the necessary medical components is possible by combining cutting-edge design software with digital manufacturing technologies such as 3D printing [79,80]. According to Panpatte [81], AI enables the collection of a greater quantity of data from public websites as well as from the government, which it then analyzes and uses to give farmers solutions for a wide variety of perplexing problems [82]. In addition to this, AI has begun to play a large role in people's day-to-day lives, with the intention of modifying the environment through the extension of people's perceptions and capabilities [83–86].

2.3. AI Implementation Challenges in Agri-Food Supply Chain during COVID-19

The challenges associated with the implementation of AI in agri-food supply chain in the global level as well as Indian context are discussed in the following sub-sections.

2.3.1. AI in the Global Level

More sustainable supply chains, particularly those connected to the food sectors, are required as a result of increased globalization amidst world's population growth [87]. Moreover, an intelligent system's major attribute is considered to beits' ability in executing required tasks in a very short-time with accuracy. The majority of systems fail in achieving the required accuracy or response-time or both. However, the selection of task strategy for users gets affected by system-delay and the selection of strategy is usually a cost-function-based hypothesis that combines the factors such as: the required efforts in synchronizing the input-system's availability and the afforded accuracy-levels. Normally, people looking for minimum efforts and maximum accuracy-levels tend to choose among three-strategies: "seamless-performance, quickness, and control" features [88]. The volume of input data influences the strength of an intelligent system. An immense volume of data is required to be monitored by a real-time AI system that needs to filter-out much of the incoming data. However, to significant or unexpected events, it should remain responsive [89]. In order to improve the speed and accuracy of systems, only very relevant-data should be used with an in-depth knowledge of the task of the system. For developing an agricultural intelligent system, combined efforts of agriculture specialists from various fields are required along with the cooperation of the farmers [90]. For agricultural management, the emerging expert or intelligent systems have been useful tools in providing integrated, area-specific, and interpreted guidance. However, as the development of these intelligent systems is fairly recent for agriculture, the use of these systems in commercial-agriculture is limited [90]. In a study, a discussion has been made on various application of thermal-imaging like "pre-harvest operations, field-nursery, yield-forecasting, irrigation-scheduling, termite-attack, green-house gases, and farm-machinery" [91]. Furthermore, a distributed wireless-network has been used for controlling irrigation-process from a remote-place [92].

2.3.2. AI in the Indian Context

The AI applications need to be more robust in agriculture for exploring its enormous benefits [93,94]. The outcome of cultivation largely depends on various cognitive-solutions' reception. While, a large scale research is still in progress and the industry has been under-served, some applications are still available in the market [95]. An automated irrigation-system using GPRS-module as communicating-device was developed and it was found to result in 90% more water-savings than conventional irrigation-systems [96]. Katariya et al. [97] have suggested the use of robot in the agricultural fields for spraying of pesticides, dropping of seeds, water-supply and ploughing activities. The working of the robot was designed to follow white-linetrack of the needy tasks, while other surfaces were regarded as black/brown. Kodali and Sahu [98] have discussed the use of "Losant platform" in order to monitor the agricultural land and also, for intimating the farmers via SMS/e-mail for any variances in the system. Roopaei et al. [99] have discussed the use of cloud-based thermal-imaging system for the irrigation in agricultural sector. Since AI uses big data, thus the looking-up method and training need to be properly defined to achieve speed and accuracy [100]. Although, the AI-based systems are gradually embedded in variety of products and services, ensuring successful working of human and AI together remains a challenge. A flexible subsystems is required that will interface with an integrated environment for AI-based robotics' technology [101], and have more capabilities in accommodating a large amount of user data.

AI-based systems are unable to learn from their environment like human-being. However, the AI-based systems perform better with given parameters and rules. But the major limitations are with decision-making where context plays significant-role. The various cognitive solutions available for agriculture are very expensive, and thus the AI solutions need to be more viable to the farming-community [100]. A digital-agriculture refers to the use of "hi-tech computer-systems" for calculating a number of parameters like weed-detections, crop-predictions, yield-detections, and crop-quality by using the ML [102]. Bannerjee et al. [103] have offered a brief-overview of AI techniques by covering AI advancement in the agriculture domain from early 1980s to 2018. Jha et al. [104] have discussed different automation-practices like "wireless-communications, IoT, ML, AI, and deep-learning". Further, they discussed about a proposed system's implementation in botanical-farm for leaf and flower identification in addition to watering by using IoT. The growing demand towards the "AgTech industry" with the use of computer-vision and AI might be a path for sustainability in food-production for feeding the future [105]. Talaviya et al. [106] have discussed various methods used by drones in agriculture for spraying in addition to crop-monitoring.

3. Research Methodology

3.1. The Population and Sampling

Farmers from rural parts of Odisha (India) were the population-targets in this study. Given the social-distancing and movement restrictions, 42 villages in Khorda district of Odisha were chosen. With the assistance and direction of the respective village chiefs, a total of 1450 farmers were randomly selected from those villages. The data were collected during the mid-period of the year 2021 (i.e., during the months of March and June of 2021).

3.2. Questionnaire Design and Data Collecting

The questionnaire was designed based on existing literature along with consultation with experts in the field (Appendix A). The purpose of the questionnaire was to gather comprehensive sociodemographic data and awareness of Indian rural farmers about the use and usefulness of AI during the pandemic COVID-19. The sociodemographic data included the age, sex, education, occupations; expertise in farming; and type of farming-lands ownership. The awareness questionnaire included the knowledge levels and the benefits of AI in agriculture and agri-food supply chain in addition to its context of COVID-19. However, only 543 responses were gathered, even though all 1450 of the chosen farmers received the questionnaire personally and via farmer-to-farmer interactions. This resulted in a response rate of 37.45%.

3.3. Model Generation and Ranking of the Challenging Parameters

"Interpretive Structural Modelling (ISM)" was used to establish inter-item relationship. The direct and indirect relationships among those items help in depicting the situation more correctly in comparison to individual-item [107]. However, a collective understanding was provided by ISM for these relationships, which has been applied by various authors for different fields of applications [108–110]. The ISM was utilized in this study to determine the relationships between the challenging implementation parameters for AI in India's agricultural sectors during the COVID-19 pandemic.

With the help of thirty-two-experts having different areas of expertise (Table 1), the parameters associated with the implementation of AI in the agricultural sectors of India during COVID-19 pandemic were identified. The experts were chosen from agricultural, environmental and academic backgrounds with 25 males, 7 females, and a total 21 doctorates with remaining having master degrees. Average experiences of these experts from the three fields were with more than 23 years, 22 years, and 23 years, respectively (Table 1). Further, the interrelation among these challenging parameters in the implementation of AI was found and an ISM model was developed. In general, the beginning of ISM takes place by identifying relevant-variables to some problem that can be accomplished through extensive-review of literatures as well as experts' opinion, which extends with selection of a contextually-relevant subordinate-relation. In this study, on the basis of the judgment on element-set as well as the contextual-relation, a "structural self-interaction matrix (SSIM)" was derived from pair-wise variables' comparison. Then, the relative relationships along with the associated-direction of relations among the variables were found. The relationship-direction linking the "variables (i, j)" was represented by the following symbols: "V, A, X and O" (V: to get factor j, factor i is necessary; A: to get factor i, factor j is necessary; X: the contributions of factors i and factor j help one another; and O: factor i and factor j have no relationships). In the next-step, the SSIM was converted into a "reachability-matrix (RM)" with subsequent checking of transitivity, which is the basic assumption in ISM that states that "if variable i is related j and j is related to k, then i is necessarily related to k". After completion of the transitivity-embedding, a matrix-model was obtained, and with subsequent partitioning of the elements, the structural-model called ISM was derived. Further, the "Step-Wise-Assessment and Ratio-Analysis (SWARA)" method was utilized [109,111], for ranking of the associated parameters for AI implementation based on their preferences by the experts for prioritization.

Table 1. Experts' demographics.

Areas of Competence	Sexual Identity		Higher Education		Experience (Years)
	Male	Female	Master-Degree	Doctorate	
Agriculture	16	2	8	10	Higher than 23
Environment	5	2	1	6	Higher than 22
Academics	4	3	2	5	Higher than 23

4. Results

4.1. The Socio-Demographic Data and Awareness of Farmers

The socio-demographic data as well as awareness of farmers regarding the usefulness of Al in agriculture during COVID-19 is presented in Table 2. The majority of respondents were in the age group of 37 to 42 years (45.30%), males (60.22%), education-levels of ≤10th (37.01%), agriculture as primary-occupation (100%), none as secondary-occupation (96.31%), household-member ranging from 1 to 5 (92.26%), expertise in farming between 11 to 20 years (21.91%), and 92.63% with ownership of farming-land, respectively. Further, 520 farmers (95.76%) preferred to use traditional farming techniques. While COVID-19 outbreak was well-understood by 100% farmers, the importance, benefits and utilization of AI in agriculture or agri-food supply chain was acknowledged by only 22.83%. Only 39.59% of the farmers have the understanding that the application of AI in agriculture or agri-food supply chain will be beneficial, which revealed the unawareness among most of the farming community about the technological advancement which is supported by earlier studies [112–117].

Table 2. Sociodemographic data and awareness of farmers (*n*= 543).

Sl. No.	Variables	Category	*n* (%)
		Sociodemographic Information	
1	Age in Years	12–26	71 (13.07)
		27–36	53 (9.76)
		37–42	246 (45.30)
		43–56	134 (24.68)
		57 and more	39 (7.18)
2	Gender	Male	327 (60.22)
		Female	216 (39.78)
3	Education-level	Illiterate	95 (17.49)
		≤10th	201 (37.01)
		More than 10th and ≤12th	176 (32.41)
		More than 12th and ≤Graduation	63 (11.60)
		More than Graduation	8 (1.47)
4	Primary-occupation	Agriculture	543 (100)
		Others	0 (0)
5	Secondary-occupation	Others	20 (3.68)
		None	523 (96.31)
6	Household-member	1 to 5	501 (92.26)
		6 and more	42 (7.73)
7	Farming years of expertise	0 to 10	352 (64.82)
		11 to 20	119 (21.91)
		20 and more	72 (13.26)
8	Ownership of land by farmers	Yes	503 (92.63)
		No	40 (7.37)

Table 2. *Cont.*

Sl. No.	Variables	Category	*n* (%)
		Awareness	
9	Utilization of farming techniques	Traditional Modernized	520 (95.76) 23 (4.23)
10	Knowledge on importance, benefits and utilization of AI in agriculture or agri-food supply chain	Yes No	124 (22.83) 419 (77.16)
11	Knowledge of COVID-19 outbreak	Yes No	543 (100) 0 (0)
12	Do you think the application of AI in agriculture or agri-food supply chain will be beneficial?	Yes No	215 (39.59) 328 (60.40)

n = Total number of respondents.

4.2. Development of ISM Model

As shown in Table 3, various significant "challenging parameters (CPs)" associated with the implementation of AIin India's agri-food supply chain during this COVID-19 outbreak were identified. In the process of developing the ISM model, the identified twelve CPs were also taken into account to determine their interrelationships.

Table 3. CPs associated with implementation of AI.

Sl. No.	CPs	Symbols
1	**Response-time and accuracy-level:** Utilizing the most pertinent data and having a thorough understanding of the job at hand can help systems operate more quickly and accurately, which otherwise hinders its operation.	CP1
2	**Lack of standardization:** Lack of technical criteria and specifications for AI and other technologies to function properly, which may assist in addressing both actual and perceived issues by establishing defined boundaries and enhancing ML's ability to be reliable, predictable, and effective	CP2
3	**Requirement of big data:** In order to learn and enhance decision-making processes, AI needs a vast amount of data.	CP3
4	**Cost of big data:** Being cost-effective with big data integration and its difficulties while big data systems' scaling is expensive due to an increase in storage requirements and maintenance.	CP4
5	**Implementing method:** The unknowable nature of how deep learning models and a collection of inputs can anticipate the output and develop a solution to a problem is one of the crucial implementation issues for AI. Accuracy in AI is necessary to ensure transparency in AI-based decision-making and the underlying algorithms.	CP5
6	**Flexibility:** The inability of AI to learn-to-think creatively beyond the box is a significant drawback. With pre-fed data and prior experiences, AI is able to learn over time, but it is not capable of taking a novel method.	CP6
7	**Lack of contextual-awareness:** The outcomes of AI adoption, no matter how promising, may be impossible to reproduce, making the efforts worthlessand tough to implement in the real world owing to the absence ofcontextual-awareness.	CP7
8	**Job-losses:** One of the possible drawbacks of AI is that if computers start to take the place of human labour, there may be a rise in unemployment.	CP8
9	**Affordability issues:** High initial expenses involved in executing AI-based solutions are another possible drawback of AI.	CP9
10	**Shortage of infrastructures:** Farmers need to be aware that AI is really a more sophisticated-version of older-technology used to analyze, collect, and monitor field-data. For AI to function, the appropriate technological infrastructure is needed. Additionally, practically every phase of the ML workflow is covered by AI infrastructure. It helps the software engineers, data scientists, and data engineers to access and manage the computing resources needed to test, develop, and implement AI algorithms. Implementing AI in rural areas is challenging due to a lack of suitable infrastructure.	CP10
11	**Farmer's unwillingness:** Implementing AI is challenging because rural farmers remain reluctant to accept new technology.	CP11
12	**AI safety-related issues:** Due to the inherent difficulty of deploying AI in a transparent and secure manner, additional security measures are required. AI's internal workings make it challenging to verify the accuracy of its outputs and raise the possibility of bias. Long-term AI safety aims to ensure that cutting-edge AI-based systems are consistently in line with human-values, and continuously perform as per the preferences of their users.	CP12

On the basis of contextual-relationships, the development of SSIM for all the twelve challenging parameters from Table 3 were completed by using the symbols like "V, A, X and O" as shown in Table 4. Then, the transformation of SSIM into a "binary-matrix (B-M)", called as "initial reachability-matrix (IR-M)", was done by altering "V, A, X and O" to "0 and 1" respectively (Table 5). By displaying the driving-power and dependence of each parameter (Table 6), the "final reachability-matrix with transitivity-relation (FR-M)" was created. The driving-power of a parameter is the total number of parameters, by itself included, that it assists in achieving. The dependence also reflected the total number of criteria that it assists in achieving [118–120]. Then from the FR-M, the corresponding "reachability-set (R-S)" and "antecedent-set (A-S)" for each-element was found, where the R-S included the same parameter and other parameters that it helps to achieve, and similarly, the A-S also included the same parameter in addition to other parameters that help in achieving it. Moreover, the "intersection-set (I-S)" was derived with the positioning of top-level in ISM hierarchy for the parameter having same R-S as well as A-S. Similar strategies were followed for the identification of the elements in the subsequent levels that continued till identifying the levels of each element (shown in Tables 7–11). The identified levels were used in building the diagraph along with the ISM final-model. It may be noted that during the subsequent iteration-processes, the elimination of few parameters took-place. As illustrated in Figures 1 and 2, the ISM model for the parameters was developed first, and then the ISM final-model.

Table 4. SSIM.

CPs	CP12	CP11	CP10	CP9	CP8	CP7	CP6	CP5	CP4	CP3	CP2	CP1
CP1	O	O	O	O	O	A	X	X	O	X	X	
CP2	X	A	X	A	V	X	X	X	X	X		
CP3	O	O	O	O	O	A	O	X	X			
CP4	O	O	O	O	O	O	O	V				
CP5	V	A	X	O	V	X	X					
CP6	X	O	O	O	O	O						
CP7	V	X	X	O	V							
CP8	O	X	O	O								
CP9	O	A	A									
CP10	V	A										
CP11	X											
CP12												

Table 5. IR-M.

CPs	CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8	CP9	CP10	CP11	CP12
CP1	1	1	1	0	1	1	0	0	0	0	0	0
CP2	1	1	1	1	1	1	1	1	0	1	0	1
CP3	1	1	1	1	1	0	1	0	0	0	0	0
CP4	0	1	1	1	1	0	0	0	0	0	0	0
CP5	1	1	1	0	1	1	1	1	0	1	0	1
CP6	1	1	0	0	1	1	0	0	0	0	0	1
CP7	1	1	0	0	1	0	1	1	0	1	1	1
CP8	0	0	0	0	0	0	0	1	0	0	1	0
CP9	0	1	0	0	0	0	0	0	1	0	0	0
CP10	0	1	0	0	1	0	1	0	1	1	0	1
CP11	0	1	0	0	1	0	1	1	1	1	1	1
CP12	0	1	0	0	0	1	0	0	0	0	1	1

Table 6. FR-M.

CPs	CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8	CP9	CP10	CP11	CP12	Drive-Power
CP1	1	1	1	0	1	1	0	0	0	0	0	0	5
CP2	1	1	1	1	1	1 *	1	1	0	1	0	1	10
CP3	1	1	1	1 *	1	0	1	0	0	0	0	0	6
CP4	0	1	1 *	1	1	0	0	0	0	0	0	0	4
CP5	1	1	1	0	1	1	1	1	0	1	0	1	9
CP6	1	1 *	0	0	1	1	0	0	0	0	0	1	5
CP7	1	1	0	0	1	0	1	1	0	1	1	1	8
CP8	0	0	0	0	0	0	0	1	0	0	1	0	2
CP9	0	1	0	0	0	0	0	0	1	0	0	0	2
CP10	0	1	0	0	1	0	1	0	1	1	0	1	6
CP11	0	1	0	0	1	0	1	1	1	1	1	1	8
CP12	0	1	0	0	0	1	0	0	0	0	1	1	4
Dependence	6	11	5	3	9	5	6	5	3	5	5	7	

* Transitivity-relationships.

Table 7. Iteration-1.

CPs	R-S	A-S	I-S	Level
CP1	1, 2, 3, 5, 6	1, 2, 3, 5, 6, 7	1, 2, 3, 5, 6	**I**
CP2	1, 2, 3, 4, 5, 6, 7, 8, 10, 12	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12	1, 2, 3, 4, 5, 6, 7, 10, 12	
CP3	1, 2, 3, 4, 5, 7	1, 2, 3, 4, 5	1, 2, 3, 4, 5	
CP4	2, 3, 4, 5	2, 3, 4	2, 3, 4	
CP5	1, 2, 3, 5, 6, 7, 8, 10, 12	1, 2, 3, 4, 5, 6, 7, 10, 11	1, 2, 3, 5, 6, 7, 10	
CP6	1, 2, 5, 6, 12	1, 2, 5, 6, 12	1, 2, 5, 6, 12	**I**
CP7	1, 2, 5, 7, 8, 10, 11, 12	2, 3, 5, 7, 10, 11	2, 5, 7, 10, 11	
CP8	8, 11	2, 5, 7, 8, 11	8, 11	**I**
CP9	2, 9	9, 10, 11	9	
CP10	2, 5, 7, 9, 10, 12	2, 5, 7, 10, 11	2, 5, 7, 10	
CP11	2, 5, 7, 8, 9, 10, 11, 12	7, 8, 11, 12	7, 8, 11, 12	
CP12	2, 6, 11, 12	2, 5, 6, 7, 10, 11, 12	2, 6, 11, 12	**I**

Table 8. Iteration-2.

CPs	R-S	A-S	I-S	Level
CP2	2, 3, 4, 5, 7, 10	2, 3, 4, 5, 7, 9, 10, 11	2, 3, 4, 5, 7, 10	**II**
CP3	2, 3, 4, 5, 7	2, 3, 4, 5	2, 3, 4, 5	
CP4	2, 3, 4, 5	2, 3, 4	2, 3, 4	
CP5	2, 3, 5, 7, 10	2, 3, 4, 5, 7, 10, 11	2, 3, 5, 7, 10	**II**
CP7	2, 5, 7, 10, 11	2, 3, 5, 7, 10, 11	2, 5, 7, 10, 11	**II**
CP9	2, 9	9, 10, 11	9	
CP10	2, 5, 7, 9, 10	2, 5, 7, 10, 11	2, 5, 7, 10	
CP11	2, 5, 7, 9, 10, 11	7, 11	7, 11	

Table 9. Iteration-3.

CPs	R-S	A-S	I-S	Level
CP3	3, 4	3, 4	3, 4	**III**
CP4	3, 4	3, 4	3, 4	**III**
CP9	9	9, 10, 11	9	**III**
CP10	9, 10	10, 11	10	
CP11	9, 10, 11	11	11	

Table 10. Iteration-4.

CPs	R-S	A-S	I-S	Level
CP10	10	10, 11	10	**IV**
CP11	10, 11	11	11	

Table 11. Iteration-5.

CPs	R-S	A-S	I-S	Level
CP11	11	11	11	**V**

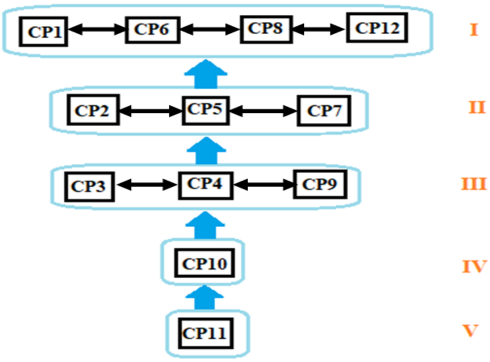

Figure 1. ISM model for CPs.

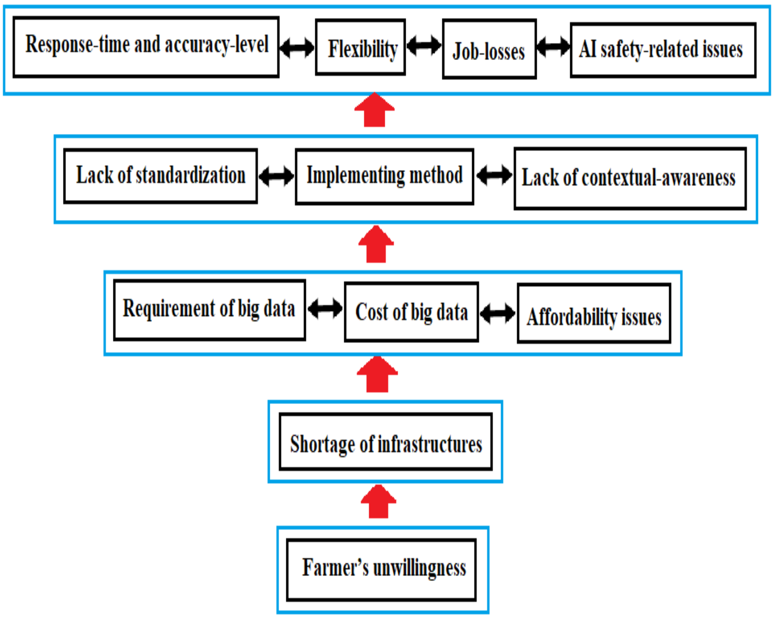

Figure 2. ISM final-model.

4.3. MICMAC Analysis

In the MICMAC (Matriced'ImpactsCroisés Multiplication Appliquée á un Classement) analysis, four categories, such as, "excluded, dependent, relay, and influential", were applied to the parameters so as to classify them of the influence of driving-power and dependence on such parameters. For the MICMAC analysis, the dependence was plotted on "X-axis", while the drive-power on "Y-axis", as shown in Figure 3. Given that any changes to one cluster's parameters might have caused equal changes to occur in another cluster's parameters, the system is presumed to be stable. The following is how the cluster was classified in the MICMAC analysis along with its typical meanings:

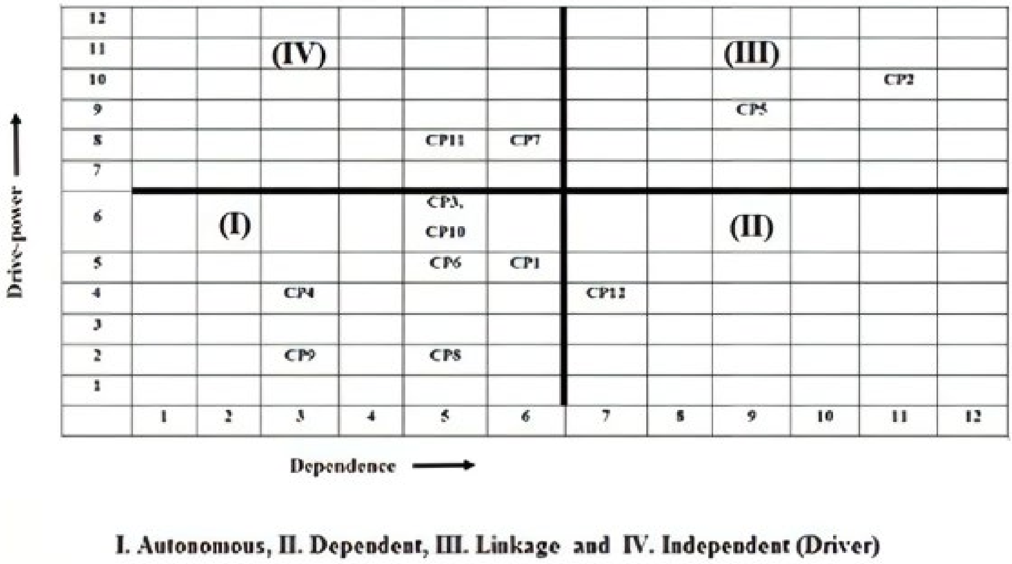

Figure 3. Diagraph of MICMAC analysis.

(a) Cluster-I

This segment is referred as the "excluded-enablers" or "autonomous", with "weak driving-power as well as weak dependence", which look rather out-of-line just with minimal ties with the system. In this study, CP1, CP3, CP4, CP6, CP8, CP9 and CP10 such as "Response-time and accuracy-level; Requirement of big data; Cost of big data; Flexibility; Job-losses; Affordability issues; and Shortage of infrastructures" were recognized in this cluster.

(b) Cluster-II

These are characterized as being "result-enablers", having "weak driving-power in addition to strong dependency", and even being "little-influent in addition to very-dependent". The CPs "AI safety-related issues (CP12)" was found in this cluster.

(c) Cluster-III

These are characterized as being "very-influent". Other terms for them include "relay or linkage enablers" that are "unstable" and having "strong driving-power other than strong-dependency". CP2 and CP5 (e.g., "Lack of standardization; and Implementing method") were in this cluster.

(d) Cluster-IV

These are characterized as being "very-influent and little-dependent", which regulate the system's remaining components and are sometimes referred to "determinant-enablers" or "independent", with "strong driving-power in addition to weak-dependency". In the system, these are also referred to as "entry-enablers". The parameters CP7 i.e., "Lack of contextual-awareness" and CP11 i.e., "Farmer's unwillingness" were recognized in this cluster.

4.4. The Associated Parameters for the CPs in AI Implementation and Their Ranking

The "associated parameters (APs)" for the CPs in AI implementation were illustrated in Table 12.

The stages recommended by Keršuliene et al. [121] served as the foundation for the SWARA method's ranking of the most and least significant criteria i.e., the associated challenges, at higher- and lower-levels. As shown in Table 12, the associated major-parameters and corresponding sub-parameters for AI implementation in agriculture were taken into consideration as criteria and sub-criteria for further ranking using the SWARA method. The three-criteria that were identified in this study included: "Performance (AP1); Costs and methods associated (AP2); and Farming-community oriented (AP3)", respectively. Under the criteria AP1,the recognized five sub-criteria included: "Response-time and accuracy-level (CP1); Lack of standardization (CP2); Requirement of big data (CP3); Flexibility (CP6); AI safety-related issues (CP12)".Under the criteria AP2, the recognized four sub-criteria included: "Cost of big data (CP4); Implementing method (CP5); Affordability issues (CP9); and Shortage of infrastructures (CP10)".Correspondingly, the two sub-criteria, under the criteria AP3 included: "Lack of contextual-awareness (CP7); Job-losses (CP8); and Farmer's unwillingness (CP11)"; respectively.

Table 12. APs for AI implementation.

Sl. No.	APs	Associated Sub-Parameters (i.e., CPs)
1	Performance (AP1)	Response-time and accuracy-level (CP1) Lack of standardization (CP2) Requirement of big data (CP3) Flexibility (CP6) AI safety-related issues (CP12)
2	Costs and methods associated (AP2)	Cost of big data (CP4) Implementing method (CP5) Affordability issues (CP9) Shortage of infrastructures (CP10)
3	Farming-community oriented (AP3)	Lack of contextual-awareness (CP7) Job-losses (CP8) Farmer's unwillingness (CP11)

Following the calculation of the associated criteria along with sub-criteria weights by the use of SWARA approach, their ranking was completed. Tables 13–16 reflected the weights of the various criterion and sub-criteria, accordingly. The participating 32 experts' assistance was used to determine the relative relevance of "average-values (s_j)" for both criterion and sub-criteria as well. The final-weights of the relevant sub-criteria were calculated by using the criteria's weights. Moreover, the calculation's evaluation scale was based on 5% increments, with the experts indicating a comparison and value differences based on 5% increments (like 5%, 10%, 15%, and so forth). The final figures in this section, however, were computed using the "arithmetic-average" of the judgments of the experts.

Table 13. Final-weights of AP1, AP2, and AP3.

Criteria	Relative Relevance of s_j	k_j	q_j	w_j
AP2		1	1	0.402
AP1	0.24	1.24	0.806	0.324
AP3	0.19	1.19	0.677	0.272

Table 14. Final revised-weight's of CPs under AP1.

Sub-Criteria	Relative Relevance of s_j	k_j	q_j	w_j	Final Revised w_j
CP1		1	1	0.264	0.085
CP3	0.18	1.18	0.847	0.224	0.072
CP2	0.14	1.14	0.743	0.196	0.063
CP6	0.16	1.16	0.640	0.169	0.054
CP12	0.17	1.17	0.547	0.144	0.046

Final revised w_j of sub-criteria, CP5 = 0.267 × 0.402 = 0.107; CP7 = 0.388 × 0.272 = 0.105; and so on.

Table 15. Final revised-weight's of CPs under AP2.

Sub-Criteria	Relative Relevance of s_j	k_j	q_j	w_j	Final Revised w_j
CP4		1	1	0.309	0.124
CP5	0.16	1.16	0.862	0.267	0.107
CP9	0.19	1.19	0.724	0.224	0.090
CP10	0.13	1.13	0.641	0.198	0.079

Table 16. Final revised-weight's of CPs under AP3.

Sub-Criteria	Relative Relevance of s_j	k_j	q_j	w_j	Final Revised w_j
CP7		1	1	0.388	0.105
CP8	0.17	1.17	0.854	0.332	0.090
CP11	0.19	1.19	0.718	0.279	0.075

***Step-A:** Priority-based classification of the criteria.

On the basis of the relative relevance of each criterion, experts ranked the criteria in this phase. Initial placement of the most significant criterion came first, and was followed by the placement of the least significant criteria in the final position.

Step-B: Choosing the "average-values (s_j)" that are most important.

Starting with the criterion that was placed second, the relative relevance of average-values (s_j) was calculated depending on how important criterion (c_j) was compared to criterion (c_{j+1}).

Step-C: Performing the "coefficients (k_j)" calculation as represented in Equation (1):

$$k_j = \begin{cases} 1, j = 1 \\ s_j + 1, j > 1 \end{cases} \tag{1}$$

Step-D: Performing the "revised-weights (q_j)" calculation as represented in Equation (2):

$$q_j = \begin{cases} 1, j = 1 \\ \frac{q_{j-1}}{k_j}, j > 1 \end{cases} \tag{2}$$

Step-E: Performing the "comparative-weights (w_j)" calculation as represented in Equation (3) for the evaluation-criteria:

$$w_j = \frac{q_j}{\sum_{k=1}^{n} q_k} \tag{3}$$

where "n" is the number of criterion

Table 17 provided a summary of the weights of all relevant criteria and sub-criteria along with their respective rankings in relation to the final weights' values.

From the Table 17, it was found that the associated major-parameters for AI implementation in agriculture, such as "Costs and methods associated" ranked first followed by "Performance"; and "Farming-community oriented", respectively. Similarly, other associated sub-parameters ranking were: cost of big data; implementing method; lack of contextual-awareness; both "job-losses" and "affordability issues"; response-time and accuracy-level; shortage of infrastructures; farmer's unwillingness; requirement of big data; lack of standardization; flexibility; and AI safety-related issues, respectively.

Table 17. Weighted summarization of criterion as well as sub-criteria.

Criteria and Corresponding Sub-Criteria	Final-Weights	w_j Based Criteria Rank	Final Revised w_j Based Sub-Criteria Rank
AP1	0.324	**2**	–
CP1	0.085	–	**5**
CP2	0.063	–	**9**
CP3	0.072	–	**8**
CP6	0.054	–	**10**
CP12	0.046	–	**11**
AP2	0.402	**1**	–
CP4	0.124	–	**1**
CP5	0.107	–	**2**
CP9	0.090	–	**4**
CP10	0.079	–	**6**
AP3	0.272	**3**	–
CP7	0.105	–	**3**
CP8	0.090	–	**4**
CP11	0.075	–	**7**

Final revised w_j of sub-criteria, CP5 = 0.267 × 0.402 = 0.107; CP7 = 0.388 × 0.272 = 0.105; and so on.

5. Discussion

India's agricultural sector sustainability is essential for continued economic growth. AI adoption is perceived to have a positive effect on the growth and development of agricultural practices in India. It has the potential to offer effective and workable solutions to the majority of the challenges such as rising labour costs, cultivation costs, crop's failures due to diseases with unpredictable yields, rainfall uncertainties, climatic alterations, soil fertility degradation, and the fluctuating market prices for agricultural products. Under the circumstances, AI can offer advanced farming practices to beat the challenges. The challenging parameters identified include response-time and accuracy-level, lack of standardization, requirement of big data, flexibility, AI safety-related issues, cost of big data, implementing method, affordability issues, shortage of infrastructures, lack of contextual-awareness, job-losses, and farmer's unwillingness, respectively. The parameters determine how they interacted with one another to develop the ISM model, which was then followed by a MICMAC analysis for possible mitigation measures. Based on the cluster's categorization in the MICMAC analysis, the challenging parameters such as "response-time and accuracy-level; requirement of big data; cost of big data; flexibility; job losses; affordability issues; and shortage of infrastructure" were identified in the autonomous category. These parameters appear problematic for a number of reasons, including concerns regarding the AI's level of safety. The parameters such as "lack of standardization", and "Implementing approach" are revealed as influential factors. On the other hand, "lack of contextual-awareness" and "Farmer's unwillingness" are two more CPs in its list of possible explanations. However, when the SWARA method was used to rank all of the criteria, i.e., for the associated major parameters for AI implementation in agriculture, it was discovered that "Costs and methods associated" ranked first, followed by "Performance" and "Farming-community-oriented", respectively. Similarly, depending on the ranking of corresponding sub-parameters, the descending priorities were: cost of big data; implementing method; lack of contextual-awareness; both "job-losses" and "affordability issues"; response-time and accuracy-level; shortage of infrastructure; farmer's unwillingness; requirement of big data; lack of standardization; flexibility; and AI safety-related issues, respectively.

Farmers may be able to resolve the complex problems facing the industry by making use of AI platforms, which can be done with the available resources. However, the rural farmers must approach the government since they cannot afford to invest in the proposed process due to the high expense of building agricultural infrastructures. The number of initiatives suggested and completely supported by the government was significantly affected by the income level of the rural farmers. High-income farmers may fund the construction of agricultural infrastructures on their own without putting a financial burden on the government [122], while the low-income farmers usually avoid of taking such initiatives. The application of AI is highly beneficial and has the potential to bring about technological improvement in diverse areas. In the context of COVID-19, AI-based systems are still in an early stage, and it may take some time before it becomes visible [123]. Additionally, very few AI systems have reached an operationally mature state at this point. Despite this, the farmers have been facing lot of difficulties in carrying out agricultural tasks during this COVID-19 pandemic. Although there are significant variations in the rate of AI adoption between countries [124], developing countries are just now beginning to experiment with the technology. There has been growing interest from the academic and research communities in developing AI methods [125]. Over twenty percent of the jobs that are currently held in developed nations such as the United Kingdom are expected to be considerably impacted by AI-driven technology, according to a report published by the "World Economic Forum" [126]. It is anticipated that adoption of AI-driven digitalization will contribute around $15.7 trillion to the global financial system by the year 2030 [127], and countries all over the world are working to implement it. In addition, a number of other countries are rapidly allocating public funding for AI-allied initiatives [128], but they also encounter obstacles in their efforts to successfully employ these monies [129]. These challenges are around ethical considerations, and value creation for the public sector and the community [130]. It is believed that the use of AI would result in a competitive edge because it would increase productivity to some degree.

There have only been a limited number of studies that have sought to explain the use and thereby the obstacles in AI adoption [131,132]. Despite the fact that AI and ML are very popular as a predictive interdisciplinary approach to improve the food and agriculture practices, there are some limitations that stakeholders need to understand [133]. The possibility of there being too few jobs requirement is by far the most significant societal issue. As robots and intelligent machines take over the majority of repetitive tasks, there will be a significant drop in human engagement. The skills requirement will rather shift from the front-end activities to the back-office operations in the event of AI adoption. Other technological challenges like the robots that can only complete the occupations or tasks for which they were programmed, otherwise they frequently fail or produce irrelevant outputs. The expensive cost of constructing and maintaining intelligent devices and computers is another technological limitation. This is especially true when it comes to regular updates of hardware and software in order to stay up with shifting requirements. Repairing and maintaining machines is an expensive endeavour. The relatively expensive price of these applications may cause an increase in the overall price of the agricultural product. In addition, there may be risks and issues related to sustainability that go beyond the advantages offered by intelligent and automated technology. It includes things like enormous energy utilisation, issues with e-waste, competitive intensity, job losses, and even moral guidelines [134–137]. It is crucial to keep in mind that most rural farmers have limited landholdings and a constrained resource base when using AI technology. In order to employ AI technology to enhance their profitability sustainably, farmers must be encouraged to see agriculture as a business. Additionally, farmers' interest in employing the already-available AI model has to be piqued. Farmers must receive the proper training and demonstrations on how to use certain AI-based technologies. Therefore, AI technology is needed to tackle problems in the actual world. For AI to be extensively used, it must be adaptable, inexpensive, accessible, realistic, and sustainable. In the coming years, AI has a huge potential, especially in developing nations. AI tools might help with accurate crop monitoring and, to a significant part, solve the labour shortage problem in agriculture. With advancements in the IT infrastructure [138,139], the potential of AI technology in agriculture adds to greater agricultural growth.

A fundamental obstacle to the broad use of AI in agriculture is the absence of straightforward solutions that smoothly integrate and embed AI in agriculture. The bulk of farmers lack the resources and digital abilities to study AI options on their own. These new AI technologies must be linked into farmers' established and systems and infrastructure in order to integrate AI seamlessly throughout the agriculture and agri-food supply chain. AI is not fully capable of supporting agriculture since it cannot function outside of its training. Farmers lack technical understanding and are ignorant of such technology, especially those in rural regions. Agriculture may become semi-autonomous when knowledge is increased, and technologies are made more available to the typical farmer, with AI paving the way.

6. Implications

Due to farming's reliance on natural forces for the majority of its output, the rural farmers are under a great deal of stress. The unpredictable nature of rain, a labour shortage, and a yearly requirement for higher yields all contribute to this stress. This means that the agricultural sectors as well as the agri-food supply chain network will need to expand up significantly over the next several years, and farm efficiency would need to be doubled. AI offers farm automation while taking all of these difficulties into consideration. This article gives the targeted academics, readers, and researchers a thorough compilation of challenges associated in implementing AI in India's agri-food supply chain during COVID-19 pandemic and beyond. The untapped challenges and potential opportunities in adopting AI to improve the agri-food supply chain are also brought to the readers' attention. It also has the potential to more streamlined approaches to develop AI-based relevant studies in this specific subject area.

Future AI-powered technologies will cause a huge change in the agriculture industry. AI and other cognitive technologies may be used by farms all over the world to enhance decision-making, automate tedious processes, and increase productivity. The farmers must also realize that AI is really a more developed form of earlier, less-complex technology to process, collect, and monitor field data. For AI to function, a proper technological base is required. Additionally, when farmers become acclimated to a simpler solution, it will be acceptable to step up and offer more AI functions.

7. Concluding Remarks

AI will have solutions for practically everything related to agricultural activities including labour support and many other dimensions. It will directly help the Indian farming community in the years to come. AI implementation can help in developing smart farming for improved agricultural quality and productivity with reduced resource consumption. The technical breakthroughs will benefit companies that are interested in enhancing AI-based goods and/or services. This will allow better manage food supply challenges for a growing population. The future of AI in agriculture will require a strong focus on accessibility to rural Indian farming community because the majority of cutting-edge technology is presently being employed on large farms producing high-quality crops.

This study has revealed the difficult aspects of applying AI in India's agricultural sectors, such as response-time and accuracy-level, lack of standardization, requirement of big data, flexibility, AI safety-related issues, cost of big data, implementing method, affordability issues, shortage of infrastructures, lack of contextual-awareness, job-losses, and farmer's unwillingness, respectively. Given the sector highly affected due to COVID-19 pandemic, this study has revealed the challenges of AI adoption. The proposed framework in this study puts the different potential barriers to AI adoption in the Indian agri-food supply chain into hierarchical order and groups them by type so that policymakers can think about them. Policymakers and academics could find out how much each barrier affects the use of AI in the agri-food supply chain in India, especially in rural areas, by paying attention to and analyzing each one separately. This could help them develop new skills and policies to reduce the effects of the barriers. The provision of infrastructure, the creation of a knowledge base for farmer organizations, holding training sessions, and the provision of low-interest bank loans are all examples of what the government could do to aid.

Future AI technologies will provide creative and accurate answers to the main agricultural problems that farmers throughout the nation are now facing. The agri-food supply chain is being streamlined by AI as it assists farmers in automating their operations and moving toward precision cultivation for increased crop production and quality while employing fewer resources. Due to the fact that the bulk of cutting-edge technology is now being used on large, well-connected farms, the future of AI in agriculture will necessitate a strong focus on accessibility. AI will be beneficial and efficient in the agricultural sectors and the agri-food supply chain since it maximizes resource usage and efficiency and, to a great extent, overcomes the resources and labour deficit.

As this study is limited to the information gathered from 543 farmers, considering 42 villages in Khorda district of Odisha (India), this can be further extended to other different village farmers throughout India for more reliable analysis and interpretation. Moreover, the identified CPs and APs were limited to very few, which may increase if the other farming communities throughout the nation will be considered.

Author Contributions: Conceptualization and methodology, D.M. and K.M.; Original draft preparation, D.M. and K.M.; Review and editing, R.R., B.E.N., H.S. and S.K.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Table A1. Questionnaire on the farmers' sociodemographics and awareness.

Sl. No.	Variables	Category	Put $\surd$ Marks, Wherever Applicable	
		Sociodemographic Information		
1	What is your age in years?	12–26	**Yes ( )**	**No ( )**
		27–36	**Yes ( )**	**No ( )**
		37–42	**Yes ( )**	**No ( )**
		43–56	**Yes ( )**	**No ( )**
		57and more	**Yes ( )**	**No ( )**
2	What is your gender?	Male	**Yes ( )**	**No ( )**
		Female	**Yes ( )**	**No ( )**
3	What is your education-level?	Illiterate	**Yes ( )**	**No ( )**
		$\leq$10th	**Yes ( )**	**No ( )**
		More than 10th and $\leq$12th	**Yes ( )**	**No ( )**
		More than 12th and $\leq$Graduation	**Yes ( )**	**No ( )**
		More than Graduation	**Yes ( )**	**No ( )**
4	What is your primary-occupation?	Agriculture	**Yes ( )**	**No ( )**
		Others	**Yes ( )**	**No ( )**
5	What is your secondary-occupation?	Others	**Yes ( )**	**No ( )**
		None	**Yes ( )**	**No ( )**
6	What is the number of household-member in your home?	1 to 5	**Yes ( )**	**No ( )**
		6 and more	**Yes ( )**	**No ( )**
7	How many years of farming expertise you have?	0 to 10	**Yes ( )**	**No ( )**
		11 to 20	**Yes ( )**	**No ( )**
		20 and more	**Yes ( )**	**No ( )**
8	Do you own any farming land?	Yes	**Yes ( )**	**No ( )**
		No	**Yes ( )**	**No ( )**

Table A1. *Cont.*

Sl. No.	Variables	Category	Put √ Marks, Wherever Applicable	
		Awareness		
9	Which of the farming techniques you utilize?	Traditional Modernized	**Yes ( )** **Yes ( )**	**No ( )** **No ( )**
10	Do you have any prior knowledge on importance, benefits and utilization of AI in agriculture or agri-food supply chain?	Yes No	**( )** **( )**	
11	Do you have any prior knowledge of COVID-19 outbreak?	Yes No	**( )** **( )**	
12	Do you think the application of AI in agriculture or agri-food supply chain will be beneficial?	Yes No	**( )** **( )**	

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