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Analyzing the Relationship between Agricultural AI Adoption and Government-Subsidized Insurance

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Abstract: Due to the increased unpredictability and severity of weather patterns caused by climate change, traditional farming practices and risk management strategies are becoming increasingly inadequate. In this paper, we explore the literature to understand the potential of artificial intelligence (AI) in mitigating climate-related agricultural risks and the pivotal role that public institutions play in encouraging farmers to adopt such technologies. We propose a framework to integrate AI into government-subsidized insurance structures, focusing on reduced premiums through government intervention. We argue that AI's potential to reduce the uncertainty and severity of climate-induced damages could lower the overall risk profile of insured farmers, thereby justifying lower premiums in the long run. We further discuss the implications of such policies on insurance markets, agricultural sustainability, and global food security. Our initial exploration contributes to the literature by addressing a relatively underexplored intersection of two critical fields—agricultural insurance and artificial intelligence—suggesting directions for future research.

Keywords: agricultural insurance; artificial intelligence; subsidy system

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1. Introduction

Agricultural insurance has emerged as a cornerstone of modern agriculture, playing a crucial role in helping stabilize the income of farmers and securing food supply chains globally [1]. In an era where climate change and environmental uncertainties pose significant risks to agricultural productivity, the importance of agricultural insurance cannot be overstated [2,3]. Agricultural insurance can provide a safety net for farmers against losses due to adverse weather conditions, pests, diseases, and other unforeseen events, ensuring that they can continue their operations despite such setbacks [4]. Furthermore, agricultural insurance can act as a mechanism to encourage investment in agriculture by mitigating the risks associated with it. This is particularly vital for sustaining innovation and the adoption of new technologies in farming, which are essential for enhancing productivity and meeting the food demands of a growing global population [5]. Additionally, agricultural insurance supports rural economies by providing a measure of protection to farmers' expected incomes, which can prevent migration to urban areas and maintain the social fabric of rural communities. Ultimately, agricultural insurance can not only help secure the livelihoods of those directly involved in agriculture but also contribute to global food security and economic stability, highlighting its critical role in the sustainability of agriculture and resilience of food systems worldwide.

There have been many strategies employed to foster the adoption of agricultural insurance among farmers and stakeholders, encompassing education, financial incentives, and policy support. Awareness and education campaigns stand out as fundamental techniques, considering that inadequate knowledge about agricultural insurance drives non-adoption [6,7]. By hosting workshops and seminars and leveraging media, these awareness initiatives strive to enhance the understanding and trust in insurance mechanisms, illustrating their critical role in comprehensive risk management strategies.

Secondly, the subsidization of premiums emerges as a potent financial incentive. Governments and financial institutions often implement subsidy programs to lower the cost barrier, making agricultural insurance more accessible and appealing to a broader demographic of farmers [8]. This approach not only alleviates the immediate financial burden on farmers but also serves as a tangible demonstration of the value and feasibility of insurance as a risk mitigation tool.

In conjunction with financial incentives, the integration of insurance into credit offerings presents another potentially effective technique [9]. Financial institutions and lenders may require or incentivize insurance as a condition for agricultural loans, thereby naturally integrating insurance into the farmers' financial planning and lending processes. This integration not only promotes the adoption of insurance but also ensures that loans are safeguarded against agricultural risks, creating a more secure environment for both lenders and borrowers.

Policy support and regulatory frameworks form the backbone of a supportive environment for agricultural insurance. Governments play a pivotal role in enacting policies that encourage insurance uptake through regulatory incentives, streamlined processes, and ensuring a competitive marketplace [10]. Additionally, public–private partnerships can catalyze the development and distribution of innovative insurance products tailored to meet the specific needs of diverse agricultural sectors [11,12].

Alongside the challenge of increased adoption of agricultural insurance is the challenge of improving its outcomes. Even in cases when agricultural insurance has been adopted, questions arise on how to optimize its implementation for better efficiency. Doing so necessitates exploring various socioeconomic incentives for all stakeholders to ensure that agricultural insurance meets its goals.

With the broadening appeal of agricultural insurance, new agricultural technologies have been developing [13–16]. There is much literature on how increases in index insurance adoption coincide with the increase in the adoption of technology-driven agricultural solutions [17]. These include such technologies as satellite imagery, remote sensing, and mobile platforms, among others. One of them is artificial intelligence (AI).

AI technologies have the potential to significantly enhance agricultural productivity and sustainability [18]. These technologies can help optimize resource use, predict crop yields with greater accuracy, and enable more effective management of pests and diseases. Supporting insurance for farmers who adopt AI through both existing and new subsidy frameworks aligns with governmental goals of promoting agricultural innovation and efficiency. This is also beneficial in improving AI models. More uptake on the part of agriculture stakeholders and allowing AI models access to their data can significantly benefit from the enhancement of both the quality and quantity of data available for analysis. The improvement in data acquisition directly translates to the refinement of AI models' performance. High-quality data ensure that AI algorithms can learn from accurate, clean, and relevant datasets, leading to more reliable and precise predictions and decisions. This access to a larger quantity of data broadens the scope of AI models' learning, enabling them to recognize patterns and nuances across a more extensive range of scenarios. This combination of quality and quantity in data acquisition not only enriches the training environment for AI models but also enhances their adaptability and applicability to real-world situations. Consequently, this progression plays a crucial role in advancing the capabilities of AI technologies, driving innovation, and optimizing outcomes across various applications in agriculture.

However, the adoption of AI in agriculture often requires substantial initial investment and presents a learning curve, factors that can deter farmers from integrating these technologies into their operations. Realigning existing governmental subsidies on insurance towards incentivizing technology utilization could serve as a financial incentive, reducing the perceived financial risks associated with the adoption of AI technologies [19]. This, in turn, could accelerate the uptake of AI in agriculture, leading to broader economic and environmental benefits. This integration of AI with agricultural insurance can subsequently lead to more data-driven and precise risk assessment models, potentially lowering the overall risk and cost of insurance [20]. This could create a more sustainable and resilient agricultural insurance sector, benefiting not just individual farmers but the agricultural economy at large. In essence, such a policy could foster an environment where innovation is rewarded and supported, leading to advancements in agricultural practices that benefit society as a whole.

In light of the above, the focus of this research is understanding to what extent the peer-reviewed literature has discussed agricultural insurance in conjunction with artificial intelligence. We contribute to this literature by addressing a relatively underexplored intersection of two critical fields—agricultural insurance and artificial intelligence. By mapping the extent of current discussions, we aim to identify existing knowledge gaps, offering directions for future research. Fostering an interdisciplinary understanding and encouraging collaboration between different fields, our research includes perspectives from computer science and artificial intelligence, the agricultural sciences, law and policy, and economics and finance. Such cross-disciplinary insights are essential for developing holistic and effective solutions to complex challenges in agriculture. Additionally, our research seeks to highlight how AI can transform traditional sectors like agriculture insurance through improving subsidization processes, helping push forth the evolution and potential future directions of AI in enhancing agricultural practice. As part of our broader research goals, we aim to have a direct impact not only on policy development and insurance company strategies but also on farmers' livelihoods, agricultural sustainability, and greater food security.

2. Materials and Methods

2.1. Research Scheme

In the following Research Scheme (Figure 1), we highlight the relationship between AI, agriculture, and insurance, taking into account the role that a system of subsidies can play.

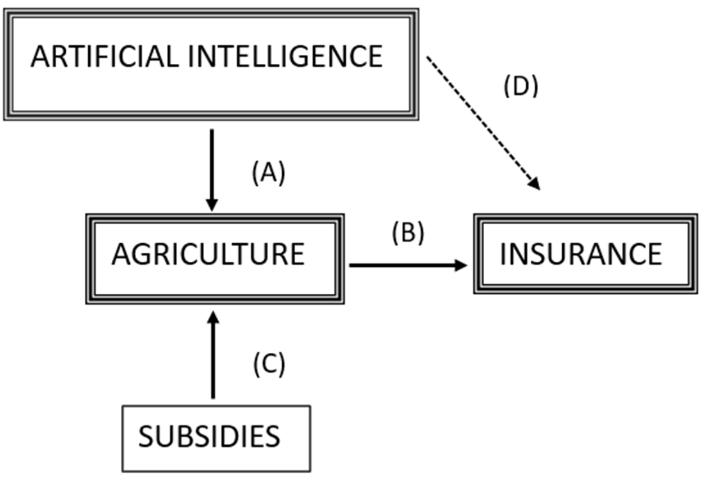

Figure 1. Research Scheme.

In the Research Scheme (Figure 1), the keywords of the literature research (ARTIFICIAL INTELLIGENCE, AGRICULTURE, INSURANCE) are outlined. Their relationship was analyzed with a particular focus on the following:

- The relationship between (A) ARTIFICIAL INTELLIGENCE and AGRICULTURE in terms of analyzing the effects of this new kind of technologies on the agricultural activities. (This is different from the concept of "climate smart agriculture"; see Fusco et al. [21]).
- The relationship between (B) AGRICULTURE and INSURANCE in terms of analyzing the effects of the new technologies in agriculture on the insurance system.
- The effects of (C) SUBSIDIES on AGRICULTURE to incentivize the adoption of ARTIFICIAL INTELLIGENCE.

The direct relationship between ARTIFICIAL INTELLIGENCE and INSURANCE, meaning the effects of AI on the insurance companies' activities, indicated in Figure 1 with (D), is not addressed in this article. For a literature review on this topic, see Eiling et al. [22].

2.2. Literature Review

This literature review seeks to elucidate the integration and implications of AI within the contexts of agriculture and insurance. The review systematically identifies, examines, and synthesizes existing research articles that encompass all three domains to outline current trends, methodologies, and outcomes of integrating AI in the agricultural sector and the effects on insurance.

2.2.1. Data Sources and Search Strategy

The primary data sources for this literature review included peer-reviewed journal articles indexed in Web of Science and Scopus. The search strategy employed a combination of keywords related to our research domains. Specifically, the keywords "agriculture" AND "insurance" AND "artificial intelligence" were used.

We devised our inclusion and exclusion criteria to sieve through the literature for studies explicitly exploring the application and implications of AI within the agriculture and insurance sectors. The selection process honed in on articles that satisfied several key conditions to ensure a focused and relevant review. For inclusion, articles needed to be published in peer-reviewed journals indexed by Web of Science or Scopus, a measure ensuring the credibility and scholarly merit of the sources. Furthermore, the presence of all three pivotal terms—"artificial intelligence", "agriculture", and "insurance"—within the body of the publication was imperative, pinpointing the specific intersection of interests. We narrowed the scope further to pieces written in English, aiming to capture the contemporary developments and applications of AI that are most relevant to today's technological landscape and regulatory environments.

Conversely, the exclusion criteria were set to filter out articles that did not directly address the integration of AI across both agricultural and insurance domains, thus maintaining the review's thematic integrity. Inaccessibility to the full text of studies resulted in exclusion, as complete content analysis was paramount. We removed duplicated studies across the searched databases. Lastly, to concentrate exclusively on original research, conference proceedings, editorials, book chapters, commentaries, and review articles were excluded. This rigorous approach was designed to distill a body of literature that precisely reflects the current state and potential of AI in revolutionizing agriculture and insurance, providing a solid foundation for analysis and future research directions.

We acknowledge the potential limitations of our study design. For one, we acknowledge potential biases in the selection of articles, particularly those published in peer-reviewed journals indexed in Web of Science and Scopus, potentially overlooking relevant research published elsewhere. The exclusion of certain key relationships, such as the direct impact of AI on insurance company activities, also narrows the scope of the study. Lastly, the language focus of the literature reviewed may limit the generalizability of findings to diverse agricultural contexts globally. However, we believe that despite these limitations, our study still provides relevant and important insights into the state of AI adoption in the context of agricultural insurance.

2.2.2. Data Extraction and Synthesis

Eligible articles identified through the search strategy were downloaded and compiled into a digital folder for detailed examination. The abstract of each paper was then assessed and categorized based on their primary focus within the intersection of AI, agriculture, and insurance:

1. Technological innovations and developments: articles focusing on new AI technologies, models, or methodologies developed for use in agriculture and insurance.
2. Application and case studies: papers detailing specific applications of existing AI technologies in agriculture and insurance, including case studies, pilot projects, and implementation reports.
3. Impact and policy analysis: studies analyzing the broader implications, challenges, and policy considerations of integrating AI into agriculture and insurance sectors.

A set of analysis criteria was established to guide the synthesis of the categorized articles. Guided by a questionnaire, we took note of each paper's methodology, field and focus, geographical scope, assessment of technological novelty, applicability and scalability, accessibility and impact on stakeholders, and policy recommendations. All identified articles and relevant data were stored in a shared digital folder. This repository facilitated the collaborative review and synthesis of the research team's findings. This methodology provided a structured approach to systematically review the literature at the nexus of AI, agriculture, and insurance. By categorizing the articles and applying a uniform set of analysis criteria, our review aims to uncover trends, identify gaps in the literature, and suggest directions for future research in this still-developing field.

In the following Table 1, a list of the articles selected is provided together with the number used in this review to refer to each of them, the title, the keywords, the journal of publication, the year of publication, the countries where the authors come from, and the index source.

Table 1. List of the articles analyzed.

	Title	Keywords	Journal	Year Published	Author Countries	Indexed Where?
1	*RetIS: Unique Identification System of Goats through Retinal Analysis*	goat fundus imaging; biometric authentication; active contouring; hamming distance; retinal recognition	*Computers and Electronics in Agriculture*	2021	India	Scopus Journal
2	*A mix-method model for adaptation to climate change in the agricultural sector: A case study for Italian wine farms*	climate change; adaptation strategy; complex system; metaheuristic model; decision support system; wine farm accounting	*Journal of Cleaner Production*	2017	Italy	Scopus Journal
3	*AI-Driven Livestock Identification and Insurance Management System*	machine learning; transfer learning; deep learning; artificial intelligence	*Egyptian Informatics Journal*	2023	Egypt	Scopus Journal
4	*Climate-Agriculture-Modeling and Decision Tool (CAMDT): A software framework for climate risk management in agriculture*	camdt; dssat; seasonal climate forecasts; downscaling; decision support system tool	*Environmental Modelling and Software*	2017	USA	Scopus Journal
5	*Big Data and Actual Science*	big data; data mining; actuary; insurance; risk; cyber security	*Big Data and Cognitive Computing*	2020	Iran; Austria; USA; Greece	WOS Journal

Table 1. *Cont.*

	Title	Keywords	Journal	Year Published	Author Countries	Indexed Where?
6	*Methodological evolution of potato yield prediction: a comprehensive review*	yield prediction; potato; precision agriculture; remote sensing; crop growth model	*Frontiers in Plant Science*	2023	China	WOS Journal
7	*Deep Learning at the Interface of Agricultural Insurance Risk and Spatio-Temporal Uncertainty in Weather Extremes*	deep learning; agricultural insurance risk; weather extremes	*North American Actuarial Journal*	2019	US; Canada	WOS; Scopus Journal Not available
8	*Prospects for financial technology for health in Africa*	technology health; financial institutions; insurance; cryptocurrency; mobile banking	*Digital Health*	2022	UK; Philippines; Thailand; Nigeria; Ghana; Sierra Leone; Congo; China; Sudan	WOS; Scopus Journal
9	*Artificial neural networks for automated year-round temperature prediction*	artificial intelligence; neural network; temperature prediction; frost protection; fruit crops; vegetable crops	*Computers and Electronics in Agriculture*	2009	US	WOS Journal
10	*Evaluation of Deep Learning for Automatic Multi-View Face Detection in Cattle*	cattle face detection; retina net; deep learning; precision livestock	*Agriculture*	2021	China; the Netherlands	WOS Journal
11	*Nondestructive methods for determining the firmness of apple fruit flesh*	apple firmness; internal quality; nondestructive	*Information Processing In Agriculture*	2021	Iran	WOS Journal
12	*Late-spring frost risk between 1959 and 2017 decreased in North America but increased in Europe and Asia*	climate change phenology; spring leaf-out; late frost; freezing damage	*PNAS Biological Sciences*	2020	Various	WOS Journal
13	*Crop Insurance Premium Recommendation System Using Artificial Intelligence Techniques*	ada boost regressor; agriculture; artificial intelligence (AI); crop insurance premium; gradient boosting regressor extra trees regressor; machine learning (ml); right farming practices	*International Journal of Professional Business Review*	2023	India	Scopus Journal
14	*MenGO: A Novel Cloud-Based Digital Healthcare Platform For Andrology Powered By Artificial Intelligence*	andrology; artificial intelligence; bioinformatics; blockchain; cloud; deep learning; digital healthcare; genomics; machine learning; natural language processing	*Biomedical Sciences Instrumentation*	2021	US; India	Scopus Journal

3. Results

In this section, we provide a brief outline of the 14 papers (see Table 1), as well as commonalities between them and their different features in terms of the definition of AI, the use of AI in agriculture, the methodology, the geographical scope, the assessment of technological novelty, and the benefits of AI to agriculture. Moreover, we finally analyze their contents in terms of empirical research to provide valuable insights into the practical implications of the findings.

3.1. The Definition of AI in Agriculture

There is no singular definition of AI in the papers selected. They often assumed a working knowledge of the term among their audience. However, a few papers offered insights into how AI is perceived or utilized within the context of their research, reflecting a broad understanding of AI as encompassing technologies and methodologies capable of performing tasks that typically require human intelligence.

For example, "*Deep Learning at the interface of Agricultural insurance risks and spatio-intertemporal uncertainty in Weather Extremes*" [23] and "*Evaluation of Deep Learning for Automatic Multi-View Cattle Face Detection in cattle*" [24] implicitly define AI through the application of deep learning techniques, suggesting AI involves the use of sophisticated algorithms (like deep belief networks and RetinaNet) that could analyze data, recognize patterns, and make predictions with high levels of accuracy. "*Artificial neural networks for Automated Year-Round Temperature Prediction*" [25] also indirectly defines AI by discussing the use of artificial neural networks for temperature prediction, implying AI's capability to model complex relationships and perform predictions based on vast datasets. "*Potato Yield Prediction Using Machine Learning Techniques and Sentinel 2 Data*" [26] also does not provide a direct definition of AI, but it references the use of machine learning models and data fusion techniques in agricultural yield prediction.

In essence, the definitions and applications of AI across these papers highlight its role in automating complex analytical tasks, improving decision-making processes, and enhancing predictive models in various domains, particularly in agriculture and related fields. AI is portrayed as capable of leveraging large datasets to unearth insights and patterns that are not readily apparent through traditional methods but have no singular definition.

Some of the studies focused on scoping reviews that were not directly related to AI in agriculture. For example, "*Big Data and Actual Science*" [27] discusses the role of big data in enhancing the accuracy and efficiency of insurance actuarial practices. The paper "*MenGO: A Novel Cloud-Based Digital Healthcare Platform For Andrology Powered By Artificial Intelligence, Data Science & Analytics, Bio-Informatics And Blockchain*" [28] introduces a pioneering digital healthcare platform integrating AI, bioinformatics, and blockchain to revolutionize andrology healthcare. "*Prospects for Financial Technology for Health in Africa*" [29] explores the application of FinTech in healthcare services in Africa. These studies mention agriculture only tangentially as a potential field of application but focus on other fields.

On the other hand, others did not directly mention "artificial intelligence". One study, "*Late-spring frost risk between 1959 and 2017 decreased in North America but increased in Europe and Asia*" [30], uses advanced statistical and modeling techniques to provide a comprehensive analysis of historical climate data. It revealed diverging trends in late-spring frost risks across different regions in North America, Europe, and Asia, impacting agriculture and biodiversity conservation strategies. While these computational methods are akin to machine learning, AI is only mentioned as a footnote. Another example is "*A Mix-Method Model for Climate Adaptation*" [31], which focuses on developing a decision system using the Chianti region's production, combining climate adaptation strategies with advanced technological tools, but not mentioning AI specifically.

Others were more direct in their application of AI in agriculture. The paper "*RetIS: Retinal Analysis of Goats*" [32] provides an innovative approach to livestock identification using analysis of the retina to uniquely identify individual goats. Similarly, "*AI-Driven Livestock Identification*" [33] showcases a novel AI-driven system for livestock identification and insurance management, highlighting the integration of technology in agriculture and insurance. The same principle is discussed in "*Evaluation of Deep Learning for Automatic Multi-View Face Detection in Cattle*" [24], which showcases the potential of AI, specifically deep learning, in enhancing livestock identification and management through automatic multi-view face detection in cattle. "*Nondestructive Methods for Determining the Firmness of Apple Fruit Flesh*" [34] offers an in-depth review of current nondestructive technologies for assessing apple firmness, emphasizing the potential of AI and data fusion techniques.

3.2. The Use of AI in Agriculture

Based on this limited literature, AI has also been used to improve decision-making in agriculture, with the goal of lessening future risks. For example, the "*Climate-Agriculture-Modeling and Decision Tool (CAMDT)*" paper [35] presents a novel software implementation for weather forecasting to improve agricultural activities, using a case study from the Philippines. "*Deep Learning at the Interface of Agricultural Insurance Risk and Spatio-Temporal Uncertainty in Weather Extremes*" [23] demonstrates how deep learning can enhance predictions of climate-induced risks in agriculture, offering a significant improvement over traditional approaches. "*Artificial Neural Networks for Automated Year-round Temperature Prediction*" [25] describes the development of neural network models for precise temperature prediction throughout the year, which is vital for agricultural planning and climate modeling. "*Potato Yield Prediction Using Machine Learning Techniques and Sentinel 2 Data*" [26] provides a comprehensive review of the advancements in potato yield prediction, discussing the integration of AI and multisource data fusion for enhanced prediction accuracy. The study "*Crop Insurance Premium Recommendation System using artificial intelligence techniques*" [36] introduces a model that employs various AI techniques for accurate predictions of crop insurance premiums, enhancing fairness for both insurers and farmers.

The primary theme that emerged across the 14 papers is the integration and application of AI within the context of agriculture. By applying AI technologies—ranging from machine learning models and deep learning to neural networks and data analytics—researchers and practitioners aim to address pressing challenges in agriculture, such as yield prediction, disease detection, climate impact assessment, and livestock management. This interdisciplinary approach often extends to include implications for insurance, particularly agricultural insurance, and how AI can contribute to managing and mitigating risks associated with climate change and other uncertainties in agriculture. This theme reflects a broader scholarly and practical interest in leveraging AI to enhance agricultural productivity, sustainability, and resilience. Simultaneously, these AI-driven advancements are shown to reduce risks and uncertainties, thus potentially transforming agricultural insurance by making it more efficient, predictive, and aligned with the evolving needs of the agricultural sector.

3.3. Methodology and Geographical Scope

Among the papers reviewed, the most frequently employed methodology is experimental. In general, this methodology is prominently used in studies where AI technologies are developed, tested, or applied to address specific challenges in agriculture and related fields. These experimental methodologies allow researchers to systematically investigate the effects and efficacy of AI models in controlled settings, offering tangible evidence of their impact and potential applications in agriculture and insurance. Experimental studies, such as those focusing on the application of deep learning for weather prediction [23], face detection in cattle [24], and automated temperature forecasting Smith, Hoogenboom and McClendon [25], provide crucial insights into how AI can be leveraged to enhance agricultural productivity, manage risks, and adapt to climate change.

Additionally, several of the studies discussed are focused on specific geographical or cultural regions, highlighting how the application of AI in agriculture and insurance is shaped by and tailored to the unique characteristics of different locales. These regional foci allow for a more detailed understanding of how AI solutions can be adapted to various environmental, economic, and cultural contexts. "*Late-spring frost risk 1959–2017 decreased in North America but increased in Europe and Asia*" [30] took a broad regional approach, comparing late-spring frost risks across North America, Europe, and Asia. "*Deep Learning at the Interface of Agricultural Insurance Risk and Spatio-Temporal Uncertainty in Weather Extremes*" [23] focused on Manitoba, Canada. It examines the application of deep learning to predict climate-induced risks in agriculture. The specific focus on Manitoba underscores the regional applicability of AI in understanding and mitigating agricultural risks unique to this area. The "*Climate-Agriculture-Modeling and Decision Tool (CAMDT)*" study [35] presents a case study from Bicol, Philippines, illustrating the use of a software tool for weather forecasting to support agricultural activities. The focus on the Philippines highlights the role of AI in addressing the agricultural challenges specific to tropical climates. "*A Mix-Method Model for Climate Adaptation*" [31] focuses on the Chianti region, exploring a decision system for agricultural production in response to climate change. The regional focus provides insights into how AI and data-driven models can support agriculture in specific wine-producing areas, taking into account local climatic and cultural nuances. These examples show that while the application of AI in agriculture and insurance has universal aspects, many studies emphasize regional specifics to address localized challenges effectively. The focus on particular regions allows researchers to account for local environmental conditions, agricultural practices, and risk profiles, ensuring that AI solutions are relevant and effective for the target populations.

3.4. Assessment of Technological Novelty

The papers reviewed also cover a range of approaches regarding the introduction of novel techniques versus the analysis of the existing status quo. For the first one, examples include "*Deep Learning in Weather Extremes*" [23], which introduces novel deep learning methodologies to improve the prediction of climate-induced risks in agriculture; "*Automatic Multi-View Cattle Face Detection*" [24], which demonstrates the application of a cutting-edge object detection algorithm, RetinaNet, for identifying cattle; and "*Artificial Intelligence Neural Network for Automated Year-Round Temperature Prediction*" [25], which explores the use of artificial neural networks for precise year-round temperature forecasting.

On the other hand, some papers merely analyze the current status of how technology is being used. "*Potato Yield Prediction Using Machine Learning Techniques and Sentinel 2 Data*" [26] provides a comprehensive review of the progress in potato yield prediction studies, comparing various strategies and discussing uncertainties of models and multi-source data fusion, thereby focusing on the analysis of the existing methodologies rather than introducing new ones. While the "*Climate-Agriculture-Modeling and Decision Tool (CAMDT)*" [35] indeed presents an implementation of a software tool for weather forecasting to improve agricultural activities, it does not necessarily introduce a novel AI technique but rather applies existing technologies to a specific context. Lastly, "*Nondestructive Methods for Determining the Firmness of Apple Fruit Flesh*" [34] offers an analysis of current nondestructive testing methods for evaluating apple firmness, including the potential application of AI, without introducing new AI methodologies.

Overall, the collection of papers showcases a balance between introducing innovative AI techniques to address specific agricultural challenges and conducting thorough analyses of the current status quo in the application of AI in agriculture. This blend underscores the vibrant and dynamic nature of research at the intersection of AI and agriculture, highlighting both groundbreaking advancements and critical evaluations of existing practices.

3.5. The Benefits of AI to Agriculture

Among the papers discussed, several explicitly highlight how AI is a pivotal tool for improving agricultural practices and, in particular, how AI can aid agriculture in addressing the consequences of climate change.

There are a number of examples in our dataset. The "*Late-spring frost risk 1959–2017 decreased in North America but increased in Europe and Asia*" [30] study does not directly mention AI but involves an extensive analysis of climate data to investigate changes in late-spring frost risks, which have significant implications for agriculture. The methodologies employed suggest that AI techniques could be utilized for predictive modeling and data analysis, making a case for AI's role in adapting agricultural practices to changing climatic conditions.

"*Deep Learning for Automatic Multi-View Cattle Face Detection*" [24] specifically discusses the application of deep learning methodologies to improve predictions of climate-induced risks in agriculture. It illustrates AI's potential in creating more accurate, speedy, and scalable models for predicting climate impacts. This directly showcases AI's capability to help agriculture adapt to climate change consequences by enhancing risk assessment and management.

Although focused on temperature prediction, the paper "*Artificial Neural Networks for Automated Year-Round Temperature Prediction*" [25] provides a clear example of how AI, through neural networks, can be used for precise climate modeling, which is crucial for agriculture. By improving the accuracy of temperature forecasts, AI enables farmers to make better-informed decisions regarding crop selection, planting schedules, and water management, which are all critical in the face of climate variability.

While not explicitly focused on AI, the "*Climate-Agriculture-Modeling and Decision Tool (CAMDT)*" [35] discussion on a software tool for weather forecasting to improve agricultural activities touches on the application of AI technologies. Tools like CAMDT, potentially integrated with AI for enhanced prediction capabilities, exemplify how AI can support agriculture by providing actionable insights for coping with climate change.

The literature review in "*Potato Yield Prediction Using Machine Learning Techniques and Sentinel 2 Data*" [26] highlights the progression of methodologies for potato yield prediction, emphasizing the growing role of AI. By comparing various strategies for yield prediction, the paper argues for AI's superiority in handling complex data and providing accurate forecasts, which is crucial for adjusting agricultural practices to climate change impacts.

3.6. Contribution to Empirical Research

Moreover, we finally analyzed their contents to determine what concerns the empirical research to provide valuable insights into the practical implications of the findings.

Not all the articles analyzed provide for empirical research.

Particularly, "*Big Data and Actual Science*" [27] discusses the role of big data in enhancing the accuracy and efficiency of insurance actuarial practices without any empirical implementation. Also, the "*Potato Yield Prediction Using Machine Learning Techniques and Sentinel 2 Data*" [26] does not provide any empirics but a discussion of the advancements in yield prediction methodologies, including AI applications that can predict potato yields with higher accuracy. "*Prospects for Financial Technology for Health in Africa*" [29] explores only theoretically the application of FinTech in healthcare services in Africa. "*Nondestructive Methods for Determining the Firmness of Apple Fruit Flesh*" [34] offers an in-depth review of current nondestructive technologies for assessing apple firmness, emphasizing the potential of AI but without an empirical part. The paper "*MenGO: A Novel Cloud-Based Digital Healthcare Platform For Andrology Powered By Artificial Intelligence, Data Science & Analytics, Bio-Informatics And Blockchain*" [28] introduces a pioneering digital healthcare platform integrating AI, bioinformatics, and blockchain to revolutionize andrology healthcare, but it does not provide any empirical results.

On the other hand, we find that the following selected papers include an empirical section to demonstrate their results.

The paper "*RetIS: Retinal Analysis of Goats*" [32] implemented an innovative approach to livestock identification by an analysis of the retina to uniquely identify individual goats. Using a database consisting of the retinal images of goats captured from the farm of the

Indian Veterinary Research Institute in West Bengal, India, the authors demonstrate the validity of the approach proposed.

"*A Mix-Method Model for Climate Adaptation*" [31] empirically tested a decision system for agricultural production in response to climate change in the Chianti region. As a result, in this specific case, it has been proved that AI and data-driven models can support agriculture in specific wine-producing areas with effects on the insurance system.

In "*AI-Driven Livestock Identification*" [33], the accuracy of an AI-driven system for livestock identification with relevant consequences on insurance management was proved, highlighting the integration of technology in agriculture and insurance.

"*Climate-Agriculture-Modeling and Decision Tool (CAMDT)*" [35] demonstrates that the use of a software tool integrated with AI for enhanced prediction capabilities can support agriculture by providing actionable insights, and coping with climate change may improve the insurance market.

"*Deep Learning at the Interface of Agricultural Insurance Risk and Spatio-Temporal Uncertainty in Weather Extremes*" [23] empirically demonstrates how deep learning can enhance predictions of climate-induced risks in agriculture, offering a significant improvement over traditional approaches.

"*Artificial Neural Network for Year-Round Temperature Prediction*" [25] demonstrates AI's role in improving the predictability of environmental conditions that directly impact agricultural productivity and risk, contributing to more reliable risk assessment models for agricultural insurance.

"*Evaluation of Deep Learning for Automatic Multi-View Cattle Face Detection*" [24] demonstrates the potential for AI to contribute to improving management by tracking livestock health. And, indirectly, it shows the possibility of reducing fraudulent claims and improving risk assessment.

"*Late-spring frost risk between 1959 and 2017 decreased in North America but increased in Europe and Asia*" [30] uses advanced statistical and modeling techniques to provide a comprehensive analysis of historical climate data. Proving the diverging trends in late-spring frost risks across different regions in North America, Europe, and Asia reveals possible effects on the managing of risk.

The study "*Crop Insurance Premium Recommendation System using artificial intelligence techniques*" [36] estimated a model that employs various AI techniques for accurate predictions of crop insurance premiums, enhancing fairness for both insurers and farmers.

In Table 2, we summarized the content of the empirical part, the data used, and the results obtained for each article selected.

Table 2. The contribution of articles analyzed to empirical research.

	Title	Empirical Part	Data	Results
1	*RetIS: Unique Identification System of Goats through Retinal Analysis* (2021)	A novel identification technology was implemented to identify and recognize individual goat through retinal image analysis	A database was created consisting of the retinal images of goats captured from the farm of the Indian Veterinary Research Institute, ERS Kalyani, West Bengal, India	The images identified the maximal mismatching in the case of inter-class matching. Also, the lowest quality image just fitting the quality for selection standards for "RetIS" helps in finding the minimal matching in case of intra-class matching problem
2	*A mix-method model for adaptation to climate change in the agricultural sector: A case study for Italian wine farms* (2017)	A metaheuristic model solved by an evolutionary genetic algorithm applied strategies that would minimize expected economic losses	Case study located in central Italy production of very high-quality wine (Chianti Classico)	The results show that high-quality wines have a higher potential for the adoption of adaptation strategies. The good rating of Chianti Classico also suggests that maintaining a specific level of production seems to be preferable to insurance unless favorable conditions for farmers are met, e.g., a low percentage of deductibles proposed by insurance companies

Table 2. *Cont.*

	Title	Empirical Part	Data	Results
3	*AI-Driven Livestock Identification and Insurance Management System* (2023)	A Yolov7 technique of object detection was used to detect objects accurately and swiftly	The dataset includes 9400 images. Total annotated dataset comprises 15,416 class labels representing all four classes: face, nose, dirty nose and not cow. Then, it had to be split into training ~94%, validation ~5%, and testing 1%. Finally, images of a total of 500 animals were used.	Images of animals were used to evaluate the recognition algorithm, and it recognized all the animals with 100% accuracy. The authors discussed the implications for the insurance market
4	*Climate-Agriculture-Modeling and Decision Tool (CAMDT): A software framework for climate risk management in agriculture* (2017)	A software framework, CAMDT (Climate Agriculture Modeling and Decision Tool), was used to take a seasonal climate forecast released with one to three months of lead-time and link it to the DSSAT-CSM-Rice model by downscaling to daily sequences of weather data	Two rice cultivars (PSB Rc82 and Mestiso 20) were calibrated based on field experiments by the Philippine Rice Research Institute (PhilRice). The experiments were conducted during the dry (sowing in December) and wet (sowing in July) seasons in 2012 with different fertilizer applications	The results demonstrate that the use of the software framework CAMDT can inform decision-making when selecting agricultural management practices before or during the growing seasons. Effects are also expected on the supply of insurance products.
5	*Big Data and Actual Science* (2020)	No	No	No
6	*Potato Yield Prediction Using Machine Learning Techniques and Sentinel 2 Data* (2019)	No.	No	No
7	*Deep Learning at the Interface of Agricultural Insurance Risk and Spatio-Temporal Uncertainty in Weather Extremes* (2019)	The paper provides a pilot study of deep learning algorithms, specifically deep belief networks	The paper uses historical crop yields, weather station–based records, and gridded weather reanalysis data for Manitoba, Canada, from 1996 to 2011	The findings show that deep learning can attain higher prediction accuracy, specifically weather index crop insurance plans, as the indemnities paid to producers depend on how accurately the weather index relates the realizations of a weather variable over a prespecified period at a specified weather station to the yield losses incurred by the producers
8	*Prospects for financial technology for health in Africa* (2022)	No	No	No
9	*Artificial neural networks for automated year-round temperature prediction* (2009)	This paper provides for the application of artificial neural networks (ANNs) for the prediction of air temperature during the entire year based on near real-time data	Ward-style ANNs were developed using detailed weather data collected by the Georgia Automated Environmental Monitoring Network (AEMN)	The results show that accurate cloud-cover predictions might aid in the prediction of associated cooling events, especially during the summer
10	*Evaluation of Deep Learning for Automatic Multi-View Face Detection in Cattle* (2021)	Using the cutting-edge object detection algorithm, RetinaNet, multi-view cattle face detection in housing farms was performed with fluctuating illumination, overlapping, and occlusion.	Datasets collected from two housing farms located in Jiangxi Province, China: 85 healthy scalpers and Simmental ranging in age from 6 to 20.	Experimental results showed that RetinaNet incorporating the ResNet 50 was superior in accuracy and speed through performance evaluation, which yielded an average precision score of 99.8% and an average processing time of 0.0438 s per image.
11	*Nondestructive methods for determining the firmness of apple fruit flesh* (2021)	No	No	No

Table 2. *Cont.*

	Title	Empirical Part	Data	Results
12	*Late-spring frost risk between 1959 and 2017 decreased in North America but increased in Europe and Asia* (2020)	LSFs were put in relation with the resistance strategies of Northern Hemisphere woody species to infer trees' adaptations for minimizing frost damage to their leaves and to forecast forest vulnerability under the ongoing changes in frost frequencies	Historical data between 1959 and 2017	It measures diverging trends in late-spring frost risks across different regions in North America, Europe, and Asia
13	*Crop Insurance Premium Recommendation System Using Artificial Intelligence Techniques* (2023)	A descriptive research method is used to represent the characteristics of a group of items	A dataset consisting of secondary data (nature of data) given by Non-Banking Financial Companies (NBFCs) in Coimbatore was used. The entire dataset (population) was chosen for this study. It contains 943 respondents' details and six variables.	The results indicate that farmers should concentrate most on the regional risk or chances of crop failure in a particular region in which they are focusing on agriculture and least on the cultivation time period of a crop or the season in which a crop is cultivated.
14	*MenGO: A Novel Cloud-Based Digital Healthcare Platform For Andrology Powered By Artificial Intelligence, Data Science & Analytics, Bio-Informatics And Blockchain* (2021)	No	No	No

4. Discussion

All of these papers collectively underscored AI's transformative potential in agriculture, especially in mitigating and adapting to the consequences of climate change. AI's ability to process vast amounts of data, identify patterns, and predict outcomes makes it an invaluable tool for enhancing resilience and sustainability in agricultural practices [37].

However, among the papers selected, there still remains a research gap between AI and agricultural insurance per se: those that illustrate how insurance can aid agriculture and present a case for why such insurance might be subsidized were more implicit in their discussion of the role of insurance in agriculture. For example, "*Deep Learning at the Interface of Agricultural Insurance Risk and Spatio-Temporal Uncertainty in Weather Extremes*" [23] demonstrates the potential of deep learning to enhance predictions of climate-induced risks, which could significantly benefit agricultural insurance by making it more accurate and tailored to specific climatic events. The improved risk assessment models could justify the need for (or, as the case may be, the continuous implementation of) subsidies as they help in precisely determining insurance premiums and coverage needs, thereby making insurance more accessible and affordable for farmers. While primarily focused on livestock identification through AI, "*Deep Learning for Automatic Multi-View Cattle Face Detection*" [24] indirectly supports the case for agricultural insurance by highlighting the potential for AI to contribute to improved management and tracking of livestock health and productivity. Accurate livestock identification can reduce fraudulent claims and improve risk assessment, presenting a case for subsidizing insurance as it becomes more efficient and aligned with actual risks. The same can be held true for "*RetIS: Retinal Analysis of Goats through Retinal Analysis*" [32] and "*AI-Driven Livestock Identification and Insurance Management System*" [33]. The "*Potato Yield Prediction Using Machine Learning Techniques and Sentinel 2 Data*" [26] discusses advancements in yield prediction methodologies, including AI applications that can predict potato yields with higher accuracy. Such predictive capabilities are crucial for crop insurance, as they enable better assessment of production risks. By demonstrating the effectiveness of AI in yield prediction, the paper indirectly supports the argument for subsidizing agricultural insurance, as it can lead to more precisely calculated premiums based on actual risk levels.

While these papers primarily focus on the technological advancements that can support agricultural practices, they indirectly suggest the importance of agricultural insurance in providing a safety net against various risks, including those exacerbated by climate change.

Among the papers discussed, a few also illustrated how AI can make agricultural insurance less risky, thereby incentivizing insurance companies to support AI applications in agriculture and farmers who utilize them. "*Deep Learning at the Interface of Agricultural Insurance Risk and Spatio-Temporal Uncertainty in Weather Extremes*" [23] shows how AI can significantly improve the prediction of climate-induced risks in agriculture through more accurate and timely predictions of weather extremes, thereby reducing the uncertainty associated with agricultural insurance risk assessment. This reduction in risk can make agricultural insurance more attractive to insurers, providing a strong case for insurance companies to invest in and support AI technologies in agriculture. While focused on temperature prediction using artificial neural networks, the "*Artificial Neural Network for Automated Year-Round Temperature Prediction*" [25] highlights AI's role in improving the predictability of environmental conditions that directly impact agricultural productivity and risk. By enhancing the accuracy of temperature forecasts, AI technologies could contribute to more reliable risk assessment models for agricultural insurance, potentially lowering the perceived risk for insurance companies and promoting their support for AI-driven agricultural practices.

The use of AI in agricultural insurance addresses information asymmetry by providing insurers with more accurate and timely data about agricultural conditions, crop yields, and risks. This helps insurers make better-informed decisions and offer more appropriate insurance policies to farmers [38]. However, none of the papers mentioned discussed the various ways that AI can help improve agricultural insurance, particularly its subsidization, to which our paper seeks to contribute.

Hazell and Varangis [8] highlighted the various challenges that agricultural insurance faces, as well as enumerated a number of good practices in existing subsidies provided for agricultural insurance. This includes improved risk assessment mechanisms, targeted subsidies, proper documentation of the purpose of the subsidy, selection of capable insurance institutions and pushing for competition amongst them, and a proper monitoring and evaluation system, among others.

A primary challenge that faces the subsidization of agricultural insurance is the lack of quantitative studies that illustrate whether doing so yields positive results [8]. AI can help address this by leveraging advanced data analytics and predictive modeling techniques. One approach is to utilize AI algorithms to analyze large datasets encompassing information on crop yields, weather patterns, insurance claims, and socioeconomic indicators [37]. By applying machine learning algorithms, AI can identify correlations and causal relationships between the subsidization of agricultural insurance and various outcomes such as increased farmer resilience, improved agricultural productivity, and reduced financial losses. Additionally, AI-driven predictive modeling can simulate different scenarios and assess the potential impact of subsidization on key performance indicators, allowing policymakers and stakeholders to make evidence-based decisions [39]. Natural language processing (NLP) techniques can also be employed to analyze textual data from research papers, policy documents, and expert opinions to identify trends, insights, and best practices related to the subsidization of agricultural insurance. By harnessing AI's analytical capabilities, quantitative studies can be conducted more efficiently and comprehensively, providing policymakers with valuable insights into the effectiveness of subsidization efforts and informing future policy design and implementation strategies, such as whether to continue these existing subsidies or realign funds towards alternative measures.

At the same time, there is a gap in the impact assessment of insurance laws and policies, which AI can help improve through advanced data analytics and risk modeling [40–42]. One significant way AI can contribute is by leveraging big data analytics to assess the effectiveness of subsidized insurance programs in mitigating risks for farmers and enhancing their resilience to various hazards [43]. By analyzing vast datasets encompassing historical weather patterns, crop yields, socioeconomic indicators, and insurance claims, AI algorithms can identify trends, predict future risks, and evaluate the impact of insurance interventions on agricultural outcomes. For example, a number of research institutes, including the International Research Institute for Climate and Society (IRI) and the US Climate Prediction Center, employ AI techniques to analyze climate data and assess the effectiveness of subsidized weather index insurance programs in different regions, helping policymakers refine insurance policies and target interventions more effectively [44]. Furthermore, AI-driven predictive modeling can simulate different scenarios and assess the potential impact of policy changes or investment decisions on farmers' welfare and insurance coverage, facilitating evidence-based policymaking and resource allocation. By harnessing AI's analytical power, policymakers and insurance providers can gain valuable insights into the performance of subsidized agricultural insurance programs, identify areas for improvement, and ensure that these initiatives effectively support farmers in managing risks and building sustainable livelihoods.

To further minimize risks, AI can also be utilized in the assessment of agricultural conditions through satellite imagery and remote sensing data agricultural conditions [45]. AI algorithms can analyze these vast amounts of data to detect patterns, predict crop yields, and assess risks such as weather-related disasters or crop diseases, as well as analyze satellite imagery for monitoring crop health and predicting yield fluctuations. This helps enable insurers to assess potential losses more accurately. Additionally, Javaid et al. [46] note how AI-powered predictive modeling can integrate diverse datasets, including historical weather patterns, soil quality, and market trends, to forecast risks and optimize insurance policies accordingly. By leveraging AI-driven analytics, agricultural insurers can improve their understanding of the factors influencing crop production, enhance risk assessment, and ultimately offer more tailored and cost-effective insurance solutions to farmers, thereby contributing to the resilience of agricultural communities worldwide.

Agriculture is indeed a risky business [47]. Transforming risk management in agriculture using AI makes the sector more insurable and attractive to insurance companies. By leveraging AI for better risk assessment and management, agricultural insurance can become more efficient and effective, prompting insurers to support the integration of AI technologies in agricultural practices. At the same time, the implication is that by making insurance more effective and aligned with technological advancements, there is a stronger case for the government or other entities to subsidize such insurance, making it more accessible to farmers and thus supporting agricultural stability and sustainability.

On a second level of analysis, it is necessary to explore potential efficient solutions for a system of public incentives, particularly in how governments can subsidize insurance premiums for farmers who use AI in agriculture. While integrating AI into agricultural insurance can offer benefits, it also poses several potential drawbacks. One major concern is the increased costs associated with implementing AI technologies, such as the need for advanced infrastructure, training, and maintenance, which may ultimately drive up premiums for farmers. Energy and upkeep costs are also important to address [48]. Additionally, digital disparities, particularly among rural farmers with limited access to reliable internet or the necessary technical skills, could further widen the gap between those who can fully benefit from AI-powered insurance and those who cannot [49]. This uneven access may exacerbate existing inequalities in agricultural support, leaving smaller or more isolated farmers at a disadvantage. An efficient public incentives approach takes these considerations into account and combines insights from AI advancements in agricultural risk assessment with governmental support mechanisms to promote the adoption of AI technologies. This can be performed through a variety of strategies, including designing incentives and disincentives for stakeholders, targeted subsidies based on AI implementation, data-driven policy making, improving competition, insurance premium discounts for AI adoption, and public–private partnerships.

AI can play a pivotal role in addressing challenges in subsidized agricultural insurance by designing incentives and disincentives for all stakeholders involved, as is currently being explored in taxation policy, considering both utilitarian social welfare and trade-offs between equality and productivity [50]. Utilitarian social welfare aims to maximize overall benefits for society, while trade-offs between equality and productivity involve finding a balance between ensuring fair support for all farmers and encouraging efficient, high-yield farming practices. Policy design assisted by insights gleaned through AI can help foster the effectiveness of agricultural insurance programs, as well as the sustainability of subsidies. One technical approach to achieve this could be to utilize AI-powered predictive analytics to assess risk factors comprehensively and tailor insurance premiums and payouts accordingly [51]. For example, by analyzing historical data on weather patterns, crop performance, and insurance claims, AI algorithms can identify high-risk areas and incentivize farmers in these regions to adopt risk-mitigation practices through discounted premiums or timely payouts. For instance, the Index-Based Livestock Insurance (IBLI) program can utilize AI-driven models to calculate insurance payouts based on satellite data on forage availability, incentivizing pastoralists to invest in herd management practices and reduce livestock losses during droughts. Additionally, AI can facilitate the design of incentive structures that promote data-sharing and collaboration among stakeholders, such as insurers, governments, and agricultural extension services, to improve risk management practices and resilience at the community level [52]. By analyzing socioeconomic data and behavioral patterns, AI algorithms can help identify effective communication strategies and incentive mechanisms, including data sharing agreements (DSAs), to encourage farmers' participation in insurance programs and adoption of sustainable agricultural practices.

Governments can also allocate already-existing subsidies for insurance premiums to target farmers who implement AI technologies in their agricultural practices. This incentivization can be based on the degree to which AI is integrated into their operations, such as precision farming, predictive analytics for crop yield, and livestock monitoring. By specifically targeting subsidies towards AI adopters, governments encourage the uptake of AI, recognizing its potential to reduce risks associated with climate change, pests, and diseases. With more uptake by farmers and the generation of better-quality data, the use of AI in agriculture can be leveraged to make better-informed policy decisions [53]. Governments can utilize AI-generated insights to identify areas where subsidies would have the most significant impact, such as regions prone to extreme weather conditions or crops that require precise water management. By adopting a data-driven approach, subsidies can be more accurately allocated. This strategy can help ensure that they support the most vulnerable farmers and the adoption of AI technologies that directly contribute to mitigating agricultural risks.

Insurance companies, supported by these government policies, can also offer premium discounts to farmers who use AI technologies. This system serves as a direct incentive for farmers to invest in AI, as it lowers their insurance costs. The rationale is that AI adoption leads to better risk management and potentially lowers the incidence of insurance claims, making it a viable option for insurers to offer such incentives.

When it comes to the insurance market, AI can play a crucial role in enhancing competition among insurance companies to offer subsidized agricultural insurance to farmers by streamlining processes, reducing costs, and improving risk assessment accuracy [54–56]. One way AI achieves this is by optimizing underwriting processes through predictive modeling and data analytics. By analyzing a wide range of data sources, including satellite imagery, weather patterns, soil quality, and historical crop performance, AI algorithms can assess risk factors more accurately and enable insurance companies to offer competitive premiums tailored to farmers' specific needs and risk profiles. AI-driven risk models can be leveraged to provide innovative insurance products tailored to smallholder farmers in developing countries. This can enhance competition by offering more affordable and accessible coverage options. Furthermore, AI-powered automation can streamline administrative tasks, such as policy issuance, claims processing, and customer service, reducing operational costs and enabling insurers to offer more competitive pricing to farmers. By leveraging these AI technologies, insurance companies can enhance their efficiency, expand their reach to underserved markets, and foster healthy competition in the provision of subsidized agricultural insurance. This ultimately benefits farmers by improving access to affordable risk management solutions.

Lastly, creating partnerships between the government, insurance companies, and technology providers can foster an ecosystem that supports the adoption of AI in agriculture. These partnerships can facilitate the development of insurance products specifically designed for AI-enhanced farming practices. Governments can subsidize part of the insurance premiums or provide grants to farmers for purchasing AI technologies, with insurance companies adjusting their products to reflect the reduced risks thanks to AI.

In summary, the integration of AI in agriculture, supported by strategic governmental incentives and partnerships, establishes a virtuous cycle that enhances agricultural sustainability and economic stability. By subsidizing insurance premiums for AI adoption among farmers, governments catalyze the initial step in this cycle, encouraging the use of technologies that mitigate the risks of climate change, pests, and diseases. As more farmers implement AI, the resultant data-rich environment not only improves agricultural practices but also informs better policy and subsidy allocation through a data-driven approach. This, in turn, attracts further investment in AI from the agricultural community, bolstered by insurance premium discounts and the development of tailored insurance products. The cycle is completed as public–private partnerships ensure the continuous advancement and integration of AI technologies in agriculture. This ecosystem not only fosters innovation and reduces risks but also supports the resilience of the agricultural sector against future challenges, thereby securing food supply chains and supporting rural economies.

5. Conclusions

Based on the information provided, none of the papers in our literature review directly addressed how AI in agriculture makes the sector less risky for insurance companies, nor did they discuss insurance companies supporting AI in agriculture due to reduced risks. The focus of the reviewed papers primarily centered on the application and integration of AI within the agricultural sector for various purposes, including productivity enhancement, risk management related to climate change, and improving the accuracy of agricultural practices through technology.

However, the underlying theme across some papers hints at the potential for AI to significantly impact risk assessment and management in agriculture. By improving predictive accuracy and enabling more precise risk modeling, AI technologies could inherently make agricultural insurance less risky for providers. This improved risk management could encourage insurance companies to more actively support and invest in AI-driven agricultural practices, recognizing the benefits of reduced uncertainty and more tailored insurance products.

In essence, while the direct discussion on insurance companies supporting AI in agriculture due to reduced risks was not explicitly covered in the summaries provided, the applications and implications of AI discussed in the papers suggest a pathway toward this outcome. The enhancement of predictive models through AI, as demonstrated in these studies, points to a future where agricultural insurance is more closely aligned with technological advancements, potentially leading to greater support from insurance companies.

The most efficient solution to integrate more AI adoption into agricultural insurance involves a holistic approach that combines targeted subsidies, data-driven policymaking, direct incentives through premium discounts, and the establishment of PPPs. This multifaceted strategy ensures that subsidies are not only provided but are done so in a manner that maximizes the benefits of AI in agriculture, promotes sustainable farming practices, and supports economic stability in the farming community.

Finally, the approach followed in this article recognizes the transformative potential of AI in agriculture and aligns governmental support mechanisms with the goal of fostering innovation and resilience in the agricultural sector. More empirical research is needed especially to answer specific questions in this area to help the implementation of government-subsidized insurance that supports AI adoption.

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