

Digitalisation and sustainability convergence: leveraging artificial intelligence capabilities to enhance agri-food value chains' sustainability in Africa

*Digitalização e convergência da sustentabilidade:
aplicação da inteligência artificial para melhorar
a sustentabilidade das cadeias de valor
agroalimentares na África*

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ABSTRACT

The convergence of digitalisation and sustainability offers transformative potential for Africa's agri-food value chains. By employing structural equation modelling, this paper investigates the convergence of digitalisation and sustainability in Africa's agri-food value chains, including the mediating role of agri-food supply chain resilience. The critical role that Artificial Intelligence plays in enhancing food supply chain resilience in Africa is at the core of this study. This study employs a deductive research approach to achieve the research objective, drawing on established theories to guide the development of the conceptual model and hypotheses. The results underline the importance of AI-driven initiatives such as Farmers' Yield Optimization, Food Retail Demand Prediction, Real-time Data Analysis, and Enhanced Supply Chain Administration in strengthening the resilience of agri-food supply chains. These findings suggest that investing in resilience-building measures can generate long-term benefits for the stability and sustainability of agri-food systems.

Keywords: Agri-food supply chain. Value chains. Artificial Intelligence. Resilience. Sustainability. SDGs.

RESUMO

A convergência entre digitalização e sustentabilidade oferece um potencial transformador para as cadeias de valor agroalimentares na África. Aplicando modelagem de equações estruturais, este artigo

analisa a convergência entre digitalização e sustentabilidade nas cadeias de valor agroalimentares da África, incluindo o papel mediador da resiliência da cadeia de suprimentos agroalimentar. O papel crítico que a Inteligência Artificial desempenha no fortalecimento da resiliência da cadeia de suprimentos de alimentos na África está no centro deste estudo. Esta pesquisa segue uma abordagem dedutiva para alcançar seu objetivo, apoiando-se em teorias consolidadas para orientar o desenvolvimento do modelo conceitual e das hipóteses. Os resultados destacam a importância de iniciativas impulsionadas por IA, tais como Farmers' Yield Optimization (Otimização do Rendimento Agrícola), Food Retail Demand Prediction (Previsão de Demanda no Varejo de Alimentos), Real-time Data Analysis (Análise de Dados em Tempo Real) e Enhanced Supply Chain Administration (Gestão Aprimorada da Cadeia de Suprimentos) na consolidação da resiliência das cadeias de suprimentos agroalimentares. Essas descobertas sugerem que investir em medidas de construção de resiliência pode gerar benefícios de longo prazo para a estabilidade e sustentabilidade dos sistemas agroalimentares.

Palavras-chave: Cadeia de abastecimento agroalimentar. Cadeias de valor. Inteligência Artificial. Resiliência. Sustentabilidade. SDGs.

1 INTRODUCTION

The African continent has remained engulfed in the search for means to elevate agriculture into a viable business activity capable of creating wealth, providing an adequate food supply, and transforming rural communities, thereby reducing poverty. One of the fundamental goals of the United Nations is to eliminate hunger by 2030, a goal underscored by the projected global population growth to 9 billion by 2050 and 11 billion by 2100, which highlights the urgent need for a more sustainable and efficient food production system (Pathan *et al.*, 2020). The continent is making significant strides to attain the United Nations Sustainable Development Goals (SDGs) of no poverty (SDG-1) and food and nutrition security (SDG-2) by 2030. Agricultural sector growth is three to five times more effective in reducing poverty and achieving food security compared to other sectors (Osabohien *et al.*, 2022). However, challenges such as socioeconomic shocks and land grabbing are slowing agricultural productivity, making it crucial to enhance efficiency through value chain development to improve the livelihoods of poor households and achieve key UN Sustainable Development Goals, particularly SDG-1 and SDG-2 (Afesorgbor *et al.*, 2024; Msomi, Zenda, 2024).

Moreover, agri-food value chains (AFVCs) are gaining increasing importance in both developing and developed countries due to their role in advancing environmentally sustainable consumption and production practices, enhancing social welfare, boosting business competitiveness, and driving economic growth (Braun *et al.*, 2023; Joshi *et al.*, 2023).

Over the past two decades, there has been a global increase in AFVCs, and the capacity of these value chains to recuperate from the disruptions has increasingly attracted the attention of scholars and practitioners (Kazancoglu *et al.*, 2024; Lee *et al.*, 2023). Especially in today's vulnerable business environment, where disruptions may occur, and the continuity of operations needs to be guaranteed, supply chain resilience becomes critical (Gaudenzi *et al.*, 2023). The inability to develop the agricultural sector and enhance the value of its products could lead many underdeveloped economies to face the risk of producing low-value commodities, continuing to struggle to secure a significant share of value-added goods in the global market (Harsono *et al.*, 2024; Raji *et al.*, 2024). Agri-food supply chains are crucial for ensuring that food is produced, processed, transported, and distributed safely, efficiently, and sustainably. Moreover, poor AFVCs that do not have the capacity to add value to commodities are highly likely to put many African countries in danger of producing low-value agricultural commodities that cannot compete on the global market hence find it difficult to occupy a meaningful value-added proportion in the global market (Raji *et al.*, 2024). The widespread adoption of technology is essential for increasing employment opportunities and enabling farmers to extend their activities beyond the farmgate (Aldosari *et al.*, 2019). For instance, mobile financial services

such as Kenya's Mobile Money platform M-PESA assist farmers in ordering and paying for services, enhancing their agribusiness operations.

Artificial Intelligence (AI) has emerged as a powerful tool, offering advanced data analytics, predictive modelling, and decision-making capabilities necessary to achieve value addition to commodities and build resilience (Belhadi *et al.*, 2021; Rane, J.; Choudhary; Rane, N., 2024). According to Elufioye *et al.* (2024), AI can significantly enhance various stages of the food supply chain, from production and harvesting to logistics and retail. By integrating AI technologies, stakeholders can achieve greater efficiency, reduce waste, and improve the overall sustainability of the food system while revolutionising agricultural practices through precision agriculture (Javaid *et al.*, 2023). According to Gawande *et al.* (2023), precision agriculture involves using information and communication technology (ICT) to manage spatial and temporal field variability, enabling the identification of management zones with similar field and crop characteristics. Although significant research has been conducted on the fourth industrial revolution and supply chain management, the specific challenges faced by Africa's AFVCs in vulnerable regions still need to be explored. This gap requires attention, especially considering the urgent issues of population growth and climate change in African countries.

2 THEORETICAL FOUNDING

2.1 INFORMATION PROCESSING THEORY (IPT)

According to information processing theory (IPT), utilising IT is an effective strategy for enhancing information sharing and processing capabilities, which are essential for recovering from disruptions (Dubey *et al.*, 2019; Galbraith, 1974). In particular, IT standardises information formats to improve processing capabilities, enabling rapid decision-making and immediate action in response to supply chain disruptions. Additionally, IPT emphasises that an organisation's information processing capabilities must align with the information demands of its operational environment (Galbraith, 1974; Foerstl *et al.*, 2018). In the supply chain realm, IPT stresses that in the event of risky occurrences, supply chain information processing capability will come in handy to allow a firm to meet its information needs, particularly relating to related collaboration among supply chain partners, thereby promoting supply chain resilience (Huang *et al.*, 2021; Li *et al.*, 2021). Most commonly, IPT is commonly used to illustrate the importance of information processing capability in executing supply chain management practices. These practices encompass resilience (Wong *et al.*, 2020; Gu *et al.*, 2021), information integration (Huang *et al.*, 2021), finance (Yu *et al.*, 2021; Yuan & Li, 2022), and decision-making (Cao *et al.*, 2015).

3 LITERATURE REVIEW

3.1 UNDERSTANDING ARTIFICIAL INTELLIGENCE (AI)

AI relates to the computer systems' capabilities to undertake tasks, such as learning, reasoning, problem-solving, and decision-making, that ordinarily require human intelligence (Belhadi *et al.*, 2021; Rane, N.; Choudhary; Rane, J., 2024). AI in agriculture, also known as smart farming, involves using software applications, sensing technologies, and communication systems to gather land-specific data (Beecham, 2014; Javaid *et al.*, 2023). AI is revolutionising agriculture by promoting precision farming, crop monitoring, and supply chain optimisation, including drones and precision techniques for efficient water and nutrient management (Gupta *et al.*, 2023). The benefits of precision farming include enhanced productivity, reduced use of agrochemicals, minimised soil degradation, and more efficient water usage (Bigliardi *et al.*, 2023). Furthermore, the application of artificial neural networks and genetic algorithms in agricultural systems highlights the advanced use of AI in this domain (Maraveas

et al., 2023). Deep learning, physical robots, computer vision, machine learning, experiential systems, and software robots contribute to efficient farming by precisely assessing soil, water, crops, humidity, temperature, and livestock conditions, enabling resource optimisation (Di Vaio *et al.*, 2020; Li *et al.*, 2025). By integrating the supply chain, facilitating information sharing, and ensuring transparency, adopting Industry 4.0 technologies is expected to significantly improve supply chain management performance (Fatorachian; Kazemi, 2021).

3.2 AGRIC-FOOD VALUE CHAINS (AFVCS)

The growth of globalisation and increased competition have led to longer and more complex agri-food supply chains. Critical challenges in these supply chains include traceability issues, ensuring the safety and quality of products, maintaining consumer trust, and managing inefficiencies (Kazancoglu *et al.*, 2024). These challenges pose significant economic and social risks, particularly as they directly impact public health. AFVCS have become a significant component of Africa's food system, contributing significantly to global food security, poverty alleviation, and international trade (Opoku *et al.*, 2023). The value chains have attracted the attention of diverse stakeholders who continuously analyse and discuss the dynamics and roles that the value chain plays in value addition and value creation for sustainable agriculture. The agricultural value chain comprises the activities undertaken by value chain nodes to ensure that agricultural produce moves from the producer to the final consumers (Trienekens, 2011). Momentous collaborative efforts are essential to introduce, adopt, and adhere to sustainable practices within global agricultural value chains, which face challenges such as environmental constraints, rural poverty, and inequality—issues that severely affect rural regions in developing countries (Dasgupta; Robinson, 2022; Meier; Pinto, 2020).

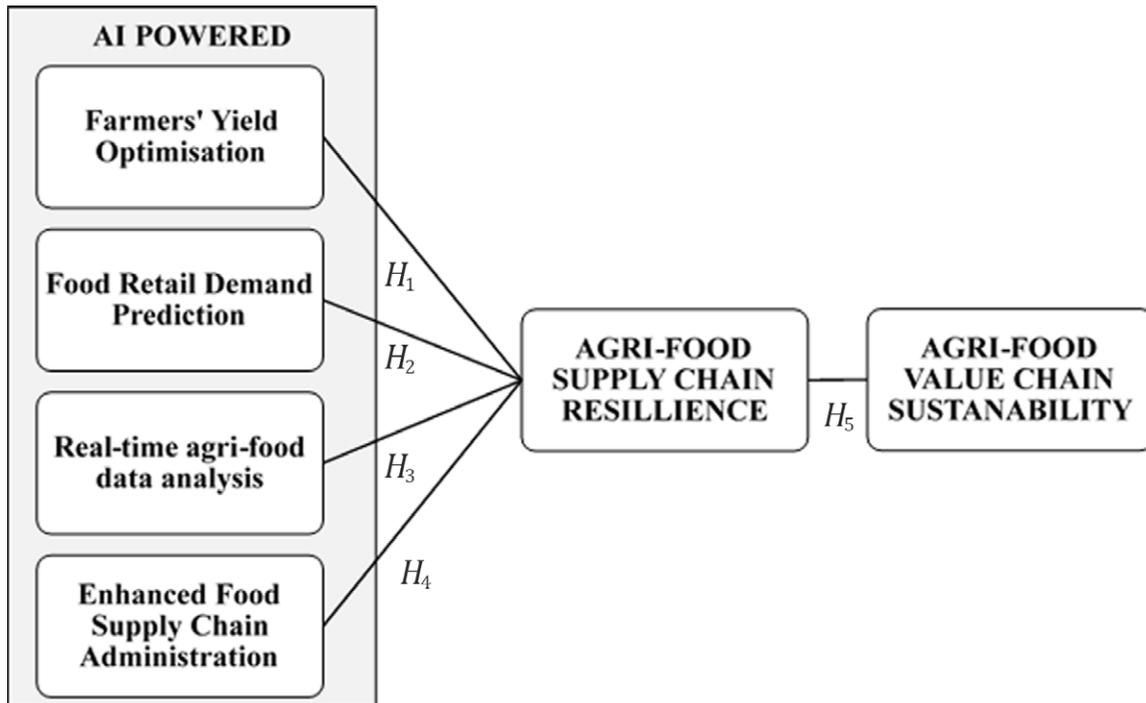
3.3 AGRI-FOOD SUPPLY CHAIN RESILIENCE

Supply chain resilience is defined as the capability of the supply chain to recover from disruptions and maintain the continuity of material, information, and cash flow (Belhadi *et al.*, 2021; Hendry *et al.*, 2019). In the era of unprecedented technological advancements, emerging technologies offer transformative potential, particularly within food supply chains, often considered highly distributed, heterogeneous, and diverse. It requires an agri-business to work with its suppliers and customers to guarantee the integrity of cooperative structures and processes (Corallo *et al.*, 2024). Food supply chains in Africa face challenges, such as a lack of transparency and trust, food scandals, and inefficient information flow, hindering the attainment of several sustainable development goals. In 2020, the lean, agile, and resilient supply chains were severely challenged by the disruptions caused by the Covid-19 global pandemic, which highlighted the need for an entirely new decision-making framework for supply chain practitioners (Belhadi *et al.*, 2021). Covid-19 triggered a negative supply shock that led to the disruption of the global supply chain network, especially the agricultural and food supply chains (Wood *et al.*, 2023; Zurek *et al.*, 2022).

4 CONCEPTUAL MODEL AND HYPOTHESES DEVELOPMENT

4.1 CONCEPTUAL MODEL

Based on the review of the literature and the influence of IPT, which emphasises the role of information processing capabilities in enhancing organisational effectiveness, the following conceptual model has been developed to explore the impact of AI on agricultural value chain sustainability¹.



4.2 HYPOTHESIS DEVELOPMENT

4.2.1 AI-POWERED FARMERS' YIELD OPTIMISATION AND AGRI-FOOD SUPPLY CHAIN RESILIENCE

Traditionally, boosting production demanded higher agricultural input usage, which often led to negative environmental consequences. According to Lee *et al.* (2017), approximately 33% of the total food produced annually is wasted. However, AI enables site-specific input applications, allowing for reduced input usage without compromising agricultural sustainability (Reardon *et al.*, 2020). Modern practices such as precision farming are boosting yield quality and quantity, lowering production costs, and elevating the socio-economic status of farmers (Mehta, 2019). With the turn of the millennium, embedded technology such as sensors and actuators has propagated precision agriculture, and today, these technological advances, combined with new equipment such as drones and robots, promote accuracy and efficiency in food production (Gawande *et al.*, 2023; Javaid *et al.*, 2023). Self-driving tractors mark a significant advancement in agricultural automation, functioning independently without human control. Equipped with sensors like radar, lasers, and cameras, these tractors can navigate fields, adjust speeds, avoid obstacles, and carry out tasks such as seeding, planting, and tillage autonomously (Ayaz *et al.*, 2019). Also, autonomous equipment and robots are rapidly contributing to precision farming, exploiting positioning data from sensors to perform routine agriculture tasks like seeding and weed independently (Pandey *et al.*, 2021). By leveraging AI technologies, stakeholders can achieve greater efficiency, reduce waste, and ensure equitable access to food, aligning with both environmental goals and social equity. This gives rise to the following hypothesis pertinent to this study.

H₁ There is a positive and significant relationship between AI-powered Farmers' Yield Optimisation and Agri-Food Supply Chain Resilience in Africa.

4.2.2 AI-POWERED FOOD RETAIL DEMAND PREDICTION AND AGRI-FOOD SUPPLY CHAIN RESILIENCE

Industry 4.0 enables greater integration among stakeholders, promoting collaboration, transparency, and responsiveness to changing consumer needs (Ayaz *et al.*, 2019; Elufioye *et al.*, 2024). The application of Industry 4.0 concepts in agri-food supply chains offers significant potential to address challenges related to food safety, sustainability, and resource optimisation, ultimately creating more resilient and sustainable food systems (Bigliardi *et al.*, 2023). Several machine learning algorithms, such as linear regression and k-means clustering, are generally used in supply chain management to predict demand for products. Leveraging AI-powered demand prediction platforms can significantly facilitate and expedite the decision-making process, which results in the improved overall performance of the agri-food supply chain (Olan *et al.*, 2024; Sarker, 2024). At the retail level, AI-driven analytics can help businesses understand consumer behavior and preferences, enabling more accurate demand forecasting and inventory management. The primary advantage of employing an AI-powered food retail demand prediction process is its real-time optimisation and automation across complex, interconnected supply chain networks. This enhances efficiency, resilience, and responsiveness throughout the entire supply chain. By utilising these technologies, organisations can streamline processes, enhance real-time decision-making, and develop more agile, customer-focused supply chains in the Industry 4.0 era. Building on this argument, this study makes the following hypothesis.

H_2 There is a positive and significant relationship between AI-powered food retail demand prediction and agri-food supply chain resilience in Africa.

4.2.3 AI-POWERED REAL-TIME AGRI-FOOD DATA ANALYSIS AND AGRI-FOOD SUPPLY CHAIN RESILIENCE

Karunathilake, Chung, and Mansoor (2023) highlight that systems utilising GPS technology are now available to deliver real-time location data for farm equipment and livestock, enabling farmers to improve processes such as planting, harvesting, and herding. AI examines a wide range of environmental data and historical farming records stored in extensive data repositories, revealing hidden patterns vital for identifying pests, detecting diseases, forecasting yields, and optimising fertiliser strategies within agricultural decision support systems (Elufioye *et al.*, 2024; Sarker, 2024). These insights are critical for enhancing the precision and efficiency of agricultural practices, supporting well-informed decisions through comprehensive data analysis. Wireless Sensor Networks (WSNs) consist of stationary or mobile sensor nodes strategically placed across extensive areas to gather vital data needed for precision farming's monitoring, control, and decision-making processes (Egwuche *et al.*, 2023). Progress in sensor technology has also brought about innovations such as underground and mobile sensors, allowing for continuous monitoring of various farming activities. Tran-Dang *et al.* (2020) posit that these nodes combine physical environmental data, such as temperature, humidity, and other parameters, with processing and transmission capabilities, making them highly adaptable and poised for widespread adoption in the near future. The data collected is transmitted via wired or wireless channels, then stored and analysed by agricultural professionals to support real-time decision-making systems. Utilising AI-powered tools such as drones, sensors, and satellite imagery, farmers gain real-time insights into crop health, soil conditions, and weather forecasts (Javaid *et al.*, 2023). This approach not only optimises the use of resources like water, fertilisers, and pesticides, resulting in higher yields and reduced environmental impact, but also enhances traceability within the supply chain, offering complete visibility from farm to fork (Bigliardi *et al.*, 2023). Additionally, supply chain risks are mitigated for vulnerable groups by strengthening farmer cooperatives (Lecoutere *et al.*, 2024), increasing their investment capacities (Donovan; Poole, 2014), and generating employment opportunities across the value chain (Vos; Cattaneo, 2021). Following these arguments, the following hypothesis can be made.

H_3 There is a positive and significant relationship between AI-powered real-time agri-food data analysis and agri-food supply chain resilience in Africa.

4.2.4 AI-POWERED ENHANCED FOOD SUPPLY CHAIN ADMINISTRATION AND AGRI-FOOD SUPPLY CHAIN RESILIENCE

Addressing food loss and waste within value chains poses complex challenges related to food security (Hamann, 2020), access to smart and resilient agricultural practices (Kim *et al.*, 2021), reduction of greenhouse gas emissions (Winans *et al.*, 2020), promotion of circular economy solutions (Dora *et al.*, 2020), enhancement of transparency in food supply chains (Vasanthraj *et al.*, 2023), and mitigation of postharvest losses (Mohan *et al.*, 2023). I4.0 drives the digitisation of supply chains, with advanced technologies such as the Internet of Things (IoT), cloud computing (CC), and big data (BD) enhancing supply chain visibility and operational efficiency (Bag *et al.*, 2020). Consequently, digitally enabled dynamic capabilities have significant potential to positively influence various aspects of agri-food supply chain resilience (Rubbio *et al.*, 2020). The AI-enhanced supply chain management facilitates transparency and information sharing and significantly improves supply chain performance by integrating processes and activities across departments through automation, digitalisation, and continuous improvement (Fatorachian; Kazemi, 2021). The emergence of these digital technologies has revolutionised how organisations operate and manage their supply chains, particularly within the agricultural sector, where the integration of technology is increasingly recognised as essential (Frederico *et al.*, 2019; Liu *et al.*, 2020). AI-enhanced supply chains leverage advanced technologies like machine learning and predictive analytics to improve efficiency, responsiveness, and adaptability, thereby significantly boosting supply chain resilience by enabling proactive risk management and rapid recovery from disruptions. Given these considerations, it is hypothesised that:

H_4 There is a positive and significant relationship between AI-powered Enhanced Food Supply Chain Administration and Agri-Food Supply Chain Resilience .

4.2.5 AGRI-FOOD SUPPLY CHAIN RESILIENCE AND AGRI-FOOD VALUE CHAIN SUSTAINABILITY

Food safety is critically important, as it enables the swift identification and resolution of contamination issues, which is vital for protecting consumer health and maintaining trust in the supply chain. Enhanced integration across the value chain offers the potential for new economic opportunities. Still, it also introduces risks, such as increased reliance on certain partners and stricter compliance requirements, which could exclude participants who are unable to meet these demands (Devaux *et al.*, 2018; Vos; Caataneo, 2021). Additionally, food supply chains face significant risks due to variability in production, fluctuations in prices, unpredictable weather conditions, and challenges related to workers' health, all of which threaten the stability and integrity of the supply chain network (Mahroof *et al.*, 2021). Consequently, the development of supply chains that are agile, flexible, reconfigurable, and resilient is essential to ensuring the long-term sustainability of agri-food value chains (AFVCs) (Shekarian *et al.*, 2020). By adopting these resilient supply chain strategies, organisations can better manage disruptions, adapt to changing conditions, and support sustainable agricultural practices that contribute to overall food security and economic stability (Fatorachian; Kazemi, 2021). Building on the arguments stated above, this study makes the following hypothesis.

H_5 There is a positive and significant relationship between Agri-Food Supply Chain Resilience and Agri-Food Value Chain Sustainability in Africa.

5 RESEARCH METHODOLOGY

To evaluate the model and test the hypotheses, a survey-based research design was utilised, allowing for the collection of quantitative data from a large pool of respondents. In total, 324 farmers formed part of the sample that was used in this study. By adopting this methodology, the study aims to provide robust insights into the research problem, contributing to both theoretical understanding and practical applications in the field.

5.1 QUESTIONNAIRE DESIGN

The study employed a questionnaire to collect data, with items adapted from an extensive literature review on AI, supply chain resilience and agricultural food value chains in Africa. All constructs were measured using 5-point Likert reflective scales with “1” for “strongly disagree” and “5” for “strongly agree”. The measures of AI capabilities were mainly adapted from Mikalef and Gupta (2021), who developed an instrument to conceptualise, measure, and calibrate artificial intelligence capabilities and their impact on organisational creativity and firm performance. Items on Farmers’ Yield Optimisation were adapted from Mulla (2013), Food Retail Demand Prediction from Fildes *et al.* (2009), and Real-Time Agri-Food Data Analysis from Kamilaris, Kartakoullis and Prenafeta-Boldú (2017). Other items, namely Enhanced Food Supply Chain Administration, Agri-Food Supply Chain Resilience, and Agri-Food Value chain sustainability, were adapted from Elkington, (1997), FAO (2014), Pettit, Fiksel, and Croxton (2010), and Trienekens and Zuurbier (2008). The questionnaire was developed using Google Forms and was distributed to participants via email.

5.2 SAMPLING, DATA COLLECTION AND ANALYSIS

The participants for this study were randomly selected from a database contained by The Southern African Confederation of Agricultural Unions (Sacau). Sacau is a membership-based regional farmers’ organisation representing the common interests of farmers in southern Africa. It currently has 19-member national farmers’ associations in 12 countries in southern Africa, namely Madagascar, Malawi, Mauritius, Mozambique, Namibia, Seychelles, South Africa and Zimbabwe. These associations’ collective impact is essential for advancing agriculture and ensuring the resilience and prosperity of SADC. According to Sekaran and Bougie (2020), the simple random sampling technique is a principal method in deductive, quantitative studies since it ensures objectivity and reliability. This is supported by Saunders, Lewis and Thornhill (2019), who argue that probability sampling methods, including random sampling, are essential for deductive research in business and social sciences.

Data was collected by sending the questionnaire link with an explanation of the research objectives to research participants. The questionnaire was pre-tested with 15 respondents, with feedback on the descriptions of the items and difficulties in answering the questionnaire. Modifications were made based on the feedback provided to make sure all items were understandable and relevant to the current research. The data analysis method in this study employed structural equation modelling (SEM) to evaluate the relationships between the constructs. SEM was utilised to assess hypothesised relationships, allowing for the simultaneous analysis of multiple dependent and independent variables, which is essential for examining complex models (Hair *et al.*, 2019; Kline, 2015). This rigorous approach ensured that the study’s findings were both statistically robust and theoretically grounded.

6 RESULTS

6.1 DEMOGRAPHIC CHARACTERISTICS

The questionnaire went out to 3,248 participants, of which 799 questionnaires were returned and processed. Ultimately, 324 were considered usable after excluding those with significantly missing data or duplicated IP addresses. The demographic profiles and key information about the participants are detailed in Table 1.

Table 1 – Profiles of Agri-businesses

<i>Country</i>	<i>Count</i>	<i>%</i>	<i>Value Chain</i>	<i>Count</i>	<i>%</i>
Botswana	26	8%	Cereal Value Chain	45	14%
Eswatini	10	3%	Horticulture Value Chain	61	19%
Lesotho	6	2%	Livestock Value Chain	59	18%
Madagascar	10	3%	Dairy Value Chain	61	19%
Malawi	36	11%	Fisheries and Aquaculture Value Chain	31	10%
Mauritius	19	6%	Coffee and Tea Value Chain	18	6%
Mozambique	49	15%	Cotton Value Chain	15	5%
Namibia	36	11%	Sugarcane Value Chain	16	5%
Seychelles	16	5%	Forestry Value Chain	18	6%
South Africa	78	24%			
Zimbabwe	39	12%			
TOTAL	324	100%	TOTAL	324	100%
<i>Role</i>	<i>Ownership</i>				
Producer	205	63%	State-owned	80	25%
Middleman	5	2%	Privately-owned	65	20%
Food Processor	95	29%	Foreign-owned	150	46%
Wholesaler	8	2%	Joint venture	29	9%
Retailer	11	3%			
TOTAL	324	100%		324	100%

Source: The Authors

The results in Table 1 above reveal a detailed overview of the agricultural activities and value chains across various countries, highlighting key trends and distributions. South Africa emerges as the most represented country, contributing 24% of the total, followed by Mozambique at 15% and Zimbabwe at 12%. In contrast, countries like Lesotho, Eswatini, and Madagascar have a much smaller representation, each accounting for 2% to 3% of the total. When examining the value chains, the horticulture and dairy sectors stand out as the most significant, each representing 19% of the overall distribution. The livestock and cereal value chains also play crucial roles, contributing 18% and 14%, respectively. On the other hand, the cotton and sugarcane value chains are the least represented, each comprising only 5% of the total. Regarding roles within the value chain, producers dominate, accounting for 63% of the total, underscoring the sector's strong focus on primary production. Food processors also have

a substantial presence at 29%, while middlemen, wholesalers, and retailers make up a smaller share of the total, collectively representing just 7%. Ownership patterns reveal that foreign-owned entities make up the largest share at 46%, indicating significant international investment in the sector. State-owned enterprises account for 25%, and privately owned entities comprise 20%, with joint ventures contributing the remaining 9%. Overall, the data paints a picture of a diverse agricultural sector with strong foreign involvement, a focus on primary production, and substantial activity within key value chains such as horticulture, dairy, and livestock.

6.2 RELIABILITY AND VALIDITY

Validity refers to the extent to which a measurement instrument accurately measures what it is intended to measure, encompassing aspects such as content, construct, and criterion-related validity (Messick, 1995). Reliability, on the other hand, refers to the consistency and stability of a measurement instrument, ensuring that it yields the same results under consistent conditions. Table 2 illustrates the reliability and validity of the constructs using Cronbach's alpha, Composite Reliability (CR), and Average Variance Extracted (AVE).

Table 2 – Reliability and validity analysis (n = 324)

Construct	No. of items	Cronbach's alpha	Composite reliability	AVE
1. FYO	4	0.989	0.840	0.571
2. FRDP	4	0.887	0.844	0.575
3. RADA	4	0.880	0.840	0.571
4. EFSCA	4	0.943	0.817	0.529
5. AFSCR	4	0.923	0.821	0.535
6. AFVCS	6	0.939	0.862	0.512

Source: The Authors

Cronbach's Alpha indicates the internal consistency of items within a construct, and a value above 0.7 is generally considered acceptable (Nunnally; Bernstein, 1994). CR is similar to Cronbach's Alpha but provides a more accurate estimate of internal consistency, especially in SEM. Values above 0.7 for the CR are considered desirable (Hair *et al.*, 2019). For AVE, which measures the amount of variance captured by a construct in relation to the variance due to measurement error, an AVE of 0.5 or higher indicates adequate convergent validity (Fornell; Larcker, 1981). The lowest value for the Cronbach Alpha is 0.880 for the construct RADA, for CR, 0.817 for the construct EFSCA, and for AVE, 0.512 for the construct AFVC Sustainability. The results illustrate the reliability and validity of the constructs using Cronbach's alpha, CR, and AVE. The Cronbach's alpha values for all constructs exceed the 0.7 threshold, indicating high internal consistency and reliability of the measures. The CR values, which are also above 0.8, further affirm the constructs' reliability, ensuring that the items within each construct consistently measure the same underlying concept. The AVE values, all above 0.5, confirm the convergent validity of the constructs, indicating that a significant portion of the variance is captured by the constructs themselves rather than by measurement error. These values indicate that, while there is some variation in reliability and validity across the constructs, all measures still meet the acceptable thresholds, indicating the reliability and validity of the constructs used in the study.

6.3 INTER-CONSTRUCT CORRELATIONS AND DISCRIMINANT VALIDITY

Discriminant validity refers to the degree to which a construct is truly distinct from other constructs by empirical standards. It indicates that a construct is unique and captures phenomena not represented by other constructs in the model. This is often assessed by comparing the AVE for each construct with the squared correlations between constructs or by ensuring that the square root of the AVE for a construct is greater than its correlations with other constructs (Henseler; Ringle; Sarstedt, 2015). Table 3 presents the inter-construct correlations and discriminant validity results.

Table 3 – Inter-construct Correlations and Discriminant Validity (n = 324)

Construct	AVE	1	2	3	4	5	6
1. FYO	0.571	0.756					
2. FRDP	0.575	.536	0.758				
3. RADA	0.571	.372	.546	0.756			
4. EFSCA	0.529	.434	.536	.425	0.727		
5. AFSCR	0.535	.399	.433	.412	.479	0.731	
6. AFVCS	0.512	.461	.522	.584	.630	.416	0.716

Note: The square root of AVE shown on the diagonal of the matrix in bold

Source: The Authors

The results demonstrate strong discriminant validity, as the square root of the AVE for each construct is greater than the correlations with other constructs. This indicates that each construct is distinct and not simply a reflection of other variables in the model. The high discriminant validity reinforces the robustness of the conceptual framework, confirming that the constructs measure unique aspects of AI capabilities and their impact on supply chain resilience and sustainability.

6.4 MEASUREMENT MODEL ASSESSMENT

Table 4 – presents the goodness-of-fit indexes for the structural equation model, comparing the hypothesised model against established benchmarks

Model	$\chi^2 / (df)$	AGFI	CFI	NFI	SRMR	RMSEA
Benchmark	<3	>.90	>.90	>.90	<.05	<.05
Hypothesised model	2.96	.92	.98	.97	.02	.08

Note: AGFI = adjusted goodness-of-fit index; CFI = comparative fit index; NFI = normed fit index; SRMR = standardised root-mean-square residual; RMSEA = root-mean-square error of approximation.

Source: The Authors

The results from the table indicate that the chi-square to degrees of freedom ratio (χ^2/df) for the hypothesised model is 2.96, which falls below the recommended threshold of 3, indicating an acceptable fit between the model and the observed data. This suggests that the model adequately captures the underlying relationships among the constructs. The AGFI is 0.92, exceeding the benchmark of 0.90, further indicating a good fit even after adjusting for the number of parameters in the model. Additionally, the CFI is 0.98, well above the recommended minimum of 0.90, demonstrating a very strong fit. The NFI also shows a high value of 0.97, further confirming the strong fit of the model by comparing it to a null model. The SRMR is 0.02, significantly below the threshold of 0.05, indicating a very good fit by measuring the average discrepancy between observed and predicted correlations. The

RMSEA is 0.08, at the upper bound of the acceptable range, suggesting a reasonable fit by accounting for the error of approximation in the model. The results on the goodness-of-fit indexes indicate that the hypothesised model provides a strong and acceptable fit to the data.

6.5 HYPOTHESIS TESTING

Hypothesis testing is a critical step in research that involves evaluating whether the proposed relationships between variables, as stated in the hypotheses, are supported by the data. Table 5 presents the results of hypothesis testing, illustrating the path coefficients (β), t-values, p-values, and the overall test results for each hypothesised relationship in the study.

Table 5 – Test of hypotheses

Path	β	t-value	p-value	Test results
H1. FYO → AFSCR	0.336	0.000	0.000	Supported
H2. FRDP → AFSCR	0.144	0.000	0.021	Supported
H3. RADA → AFSCR	0.266	0.000	0.001	Supported
H4. EFSCA → AFSCR	0.145	0.000	0.000	Supported
H5. AFSCR → AFVCS	0.373	0.000	0.030	Supported

Source: The Authors

These results are crucial in assessing the proposed model and understanding the impact of various factors on AFSCR. The first hypothesis (H1), which examines the relationship between FYO and AFSCR, is supported by a positive path coefficient of 0.336 and a highly significant p-value of 0.000. Similarly, the second hypothesis (H2) exploring the influence of FRDP on AFSCR is also supported, albeit with a lower path coefficient of 0.144. The p-value of 0.021 confirms the statistical significance of this relationship, underscoring the role of accurate demand forecasting in enhancing the supply chain's resilience. The third hypothesis (H3) addresses the impact of RADA on AFSCR, with a path coefficient of 0.266 and a p-value of 0.001, indicating a significant and positive relationship. The fourth hypothesis (H4) examines the relationship between EFSCA and AFSCR. The results show a positive path coefficient of 0.145 and a highly significant p-value of 0.000, suggesting that improvements in supply chain administration, such as better coordination and information flow, are vital for enhancing resilience. Finally, the fifth hypothesis (H5) explores a somewhat recursive relationship, indicating that AFSCR has a strong positive impact on itself, with the highest path coefficient of 0.373 and a significant p-value of 0.030. This suggests that building resilience further reinforces the supply chain's capacity to withstand and recover from disruptions, highlighting the cumulative benefits of resilience-building efforts.

7 DISCUSSION AND IMPLICATIONS

7.1 DISCUSSION

The findings from this study confirm that all hypothesised relationships are statistically significant and positively contribute to Agri-Food Supply Chain Resilience, underlining the importance of AI-driven initiatives in strengthening the resilience of agri-food supply chains. This empirically reinforces the results obtained by Toorajipour *et al.* (2021) in their systematic literature review paper. Notably, the strongest effects are observed for FYO, suggesting that this should be a key area of focus for stakeholders aiming to enhance the robustness and sustainability of agri-food systems. Unlike Sarabia, Peris, and Segura (2021), who believe that socio-political factors are the triggers and accelerators of resilience, the

results demonstrate that AI-driven initiatives, such as FYO, FRDP, RADA and EFSCA, significantly impact the resilience of agri-food supply chains. AI capabilities join factors such as robust policy frameworks (Awokuse *et al.*, 2024), life cycle assessment (Notarnicola *et al.*, 2017) and diversity (Gaitán-Cremaschi *et al.*, 2019), as acknowledged as drivers of robustness and sustainability of agri-food systems.

The positive relationship between FYO and supply chain resilience suggests that AI technologies that enhance precision farming and optimize crop yield are crucial for maintaining the stability and efficiency of agri-food systems, in agreement with the findings of Reardon *et al.* (2020). Moreover, the significant impact of FRDP on supply chain resilience stresses the need for accurate and timely demand forecasting, which can help mitigate the risks associated with market fluctuations and supply chain disruptions. RADA emerged as another key factor contributing to supply chain resilience. Literature also asserts the notion that the ability to leverage real-time data for decision-making enables agri-food supply chains to respond more effectively to environmental changes and operational challenges (Elufioye *et al.*, 2024; Rejeb; Rejeb; Zailani, 2021; Serazetdinova *et al.*, 2019). Additionally, the positive impact of EFSCA on resilience highlights the value of improving coordination, information flow, and overall management within the supply chain. This is a departure from the socio-economic paradigm that scholars such as Saitone and Sexton (2017) and Sannou, Kirschke and Günther (2023) held regarding antecedents of agri-food systems sustainability.

7.2 IMPLICATIONS

The implications of this study are multifaceted and relevant to various stakeholders, including policymakers, agribusinesses, and technology providers. For policymakers, the findings underscore the importance of supporting the adoption of AI technologies in agriculture and supply chain management. By creating an enabling environment through policies and incentives, governments can facilitate the widespread adoption of AI-driven solutions that enhance food security and economic stability. It stresses the need for agribusinesses to invest in AI technologies that improve operational efficiency and supply chain resilience. Businesses that embrace these technologies are better positioned to manage risks, optimise resource use, and capitalise on new market opportunities. Moreover, the findings suggest that collaboration between different actors within the supply chain—such as farmers, processors, and retailers—can further strengthen resilience by improving information sharing and coordination. The development of user-friendly, scalable, and cost-effective AI solutions that address the specific needs of the agricultural sector can accelerate the transition to more resilient and sustainable supply chains. Furthermore, the study's findings highlight the importance of continuous innovation in AI technologies to address emerging challenges and opportunities within the agri-food sector. Valuable insights for stakeholders seeking to enhance the sustainability and resilience of agri-food systems, particularly in the context of Africa's unique challenges and opportunities, have been unearthed in the current study.

8 LIMITATIONS AND FUTURE RESEARCH

While the study is thorough and well-executed, some limitations should be acknowledged. First, the study focuses primarily on the SADC region, which may limit the generalizability of the findings to other parts of Africa or different agricultural contexts. Future research could expand the scope to include a broader range of African countries or other developing regions facing similar challenges. Additionally, the study relies on self-reported data, which may be subject to response bias. Future studies could incorporate more objective measures of AI adoption and supply chain performance to complement the survey data. Moreover, while the study provides a strong foundation for understanding the impact of AI on supply chain resilience and sustainability, it does not fully explore the potential ethical implications of AI adoption in agriculture, such as data privacy concerns or the potential displacement of labor. Future research could address these ethical considerations to provide a more holistic view of AI's role in the agri-food sector.

9 CONCLUSION

In conclusion, this research paper offers a comprehensive and insightful analysis of how AI can enhance sustainability and resilience in Africa's agri-food value chains. The study's rigorous methodological approach, robust data analysis, and significant findings make it a valuable contribution to the field. The practical implications for stakeholders and the alignment with global sustainability goals further underscore the importance of this research. As digitalisation continues to shape the future of agriculture, this study provides a roadmap for leveraging AI to build more sustainable and resilient food systems in Africa.

NOTES

1 | Sustainability in the agricultural value chain refers to the adoption of practices that ensure economic viability, environmental stewardship, and social responsibility throughout the entire supply chain. This includes resource-efficient farming methods, ethical labour practices, waste reduction, and the use of sustainable inputs to maintain long-term productivity while minimizing negative impacts on ecosystems and communities.

REFERENCES

- AFESORGBOR, S. K.; FIANKOR, D. D. D.; DEMENA, B. A. Do regional trade agreements affect agri-food trade? Evidence from a meta-analysis. **Applied Economic Perspectives and Policy**, v. 46, n. 2, p. 737-759, 2024.
- AWOKUSE, T.; LIM, S.; SANTERAMO, F.; STEINBACH, S. Robust policy frameworks for strengthening the resilience and sustainability of agri-food global value chains. **Food Policy**, v. 127, p. 102714, 2024.
- AYAZ, M.; AMMAD-UDDIN, M.; SHARIF, Z.; MANSOUR, A.; AGGOUNE, E. H. M. Internet-of-Things (IoT)-based smart agriculture: toward making the fields talk. **IEEE access**, v. 7, p. 129551-129583, 2019.
- BAG, S.; GUPTA, S.; LUO, Z. Examining the role of logistics 4.0 enabled dynamic capabilities on firm performance. **The international journal of logistics management**, v. 31, n. 3, p. 607-628, 2020.
- BEECHAM, R. Towards smart farming: agriculture embracing the IoT vision. **Beecham Research**, v. 3, p. 1-6, 2014.
- BELHADI, A.; KAMBLE, S. S.; MANI, V.; BENKHATI, I.; TOURIKI, F. E. An ensemble machine learning approach for forecasting credit risk of agricultural SMEs' investments in agriculture 4.0 through supply chain finance. **Annals of Operations Research**, p. 1-29, 2021.
- BIGLIARDI, B.; BOTTANI, E.; CASELLA, G.; FILIPPELLI, S.; PETRONI, A.; PINI, B.; GIANATTI, E. Industry 4.0 in the agrifood supply chain: a review. **Procedia Computer Science**, v. 217, p. 1755-1764, 2023.
- BRAUN, C. L.; BITSCH, V.; HÄRING, A. M. Developing agri-food value chains: learning networks between exploration and exploitation. **The Journal of Agricultural Education and Extension**, v. 29, n. 4, p. 417-438, 2023.
- CAO, G.; DUAN, Y.; CADDEN, T. The link between information processing capability and competitive advantage mediated through decision-making effectiveness. **International Journal of Information Management**, v. 44, p. 121-131, 2019.
- CHESBROUGH, H. To recover faster from Covid-19, open up: managerial implications from an open innovation perspective. **Industrial Marketing Management**, v. 88, p. 410-413, 2020.
- CORALLO, A.; DE GIOVANNI, M.; LATINO, M. E.; MENEGOLI, M. Leveraging on technology and sustainability to innovate the supply chain: a proposal of agri-food value chain model. **Supply Chain Management. An International Journal**, v. 29, n. 3, p. 661-683, 2024.

DASGUPTA, S.; ROBINSON, E. J. Attributing changes in food insecurity to a changing climate. **Scientific Reports**, v. 12, n. 1, 4709, 2022.

DEVAUX, A.; VELASCO, C.; ORDINOLA, M.; HORTON, D. Collective action for market chain innovation in the Andes: scaling up and diffusion of the “innovation with potato” experience. **Agricultural Systems**, v. 165, p. 74-81, 2018.

DI VAIO, A.; PALLADINO, R.; HASSAN, R.; ESCOBAR, O. Artificial intelligence and business models in the sustainable development goals perspective: a systematic literature review. **Journal of Business Research**, v. 121, p. 283-314, 2020.

DONOVAN, J.; POOLE, N. Changing asset endowments and smallholder participation in higher value markets: evidence from certified coffee producers in Nicaragua. **Food Policy**, v. 44, p. 1-13, 2014.

DORA, M.; WESANA, J.; GELLYNCK, X.; SETH, N.; DEY, B.; DE STEUR, H. Importance of sustainable operations in food loss: evidence from the Belgian food processing industry. **Annals of operations research**, v. 290, 47-72, 2020.

DUBEY, R.; GUNASEKARAN, A.; CHILDE, S. J.; PAPADOPOULOS, T.; LUO, Z.; WAMBA, S. F.; ROUBAUD, D. Can big data and predictive analytics improve social and environmental sustainability? **Technological forecasting and social change**, v. 144, p. 534-545, 2019.

EGWUCHE, O. S.; SINGH, A.; EZUGWU, A. E.; GREEFF, J.; OLUSANYA, M. O.; ABUALIGAH, L. Machine learning for coverage optimization in wireless sensor networks: a comprehensive review. **Annals of Operations Research**, p. 1-67, 2023.

ELKINGTON, J. The triple bottom line. **Environmental management: readings and cases**, v. 2, p. 49-66, 1997.

ELUFIOYE, O. A.; IKE, C. U.; ODEYEMI, O.; USMAN, F. O.; MHLONGO, N. Z. Ai-Driven predictive analytics in agricultural supply chains: a review: assessing the benefits and challenges of ai in forecasting demand and optimizing supply in agriculture. **Computer Science & IT Research Journal**, v. 5, n. 2, p. 473-497, 2024.

FATORACHIAN, H.; KAZEMI, H. Impact of Industry 4.0 on supply chain performance. **Production Planning & Control**, v. 32, n. 1, p. 63-81, 2021.

FILDES, R.; GOODWIN, P.; LAWRENCE, M.; NIKOLOPOULOS, K. Effective forecasting and judgmental adjustments: an empirical evaluation and strategies for improvement in supply-chain planning. **International Journal of Forecasting**, v. 25, n. 1, p. 3-23, 2009.

FOERSTL, K.; MEINLSCHMIDT, J.; BUSSE, C. It's a match! Choosing information processing mechanisms to address sustainability-related uncertainty in sustainable supply management. **Journal of Purchasing and Supply Management**, v. 24, n. 3, p. 204-217, 2018.

FOOD AND AGRICULTURE ORGANIZATION. (Ed.). **State of World Fisheries and Aquaculture: 2014**. Food & Agriculture Organization of the UN (FAO).

FREDERICO, G. F.; GARZA-REYES, J. A.; ANOSIKE, A.; KUMAR, V. Supply Chain 4.0: concepts, maturity and research agenda. **Supply Chain Management. An International Journal**, v. 25, n. 2, p. 262-282, 2019.

GAITÁN-CREMASCHI, D.; KLERKX, L.; DUNCAN, J.; TRIENEKENS, J. H.; HUENCHULEO, C.; DOGLIOTTI, S.; ROSSING, W. A. Characterizing Diversity of Food Systems In view of sustainability transitions. A review. **Agronomy for sustainable development**, v. 39, p. 1-22, 2019.

GALBRAITH, J. R. Organization design: an information processing view. **Interfaces**, v. 4, n. 3, p. 28-36, 1974.

GAUDENZI, B.; PELLEGRINO, R.; CONFENTE, I. Achieving supply chain resilience in an era of disruptions: a configuration approach of capacities and strategies. **Supply Chain Management. An International Journal**, v. 28, n. 7, p. 97-111, 2023.

GAWANDE, V.; SAIKANTH, D. R. K.; SUMITHRA, B. S.; ARAVIND, S. A.; SWAMY, G. N.; CHOWDHURY, M.; SINGH, B. V. Potential of precision farming technologies for eco-friendly agriculture. **International Journal of Plant & Soil Science**, v. 35, n. 19, p. 101-112, 2023.

GU, B.; FU, Y.; YE, J. Joint optimization and coordination of fresh-product supply chains with quality-improvement effort and fresh-keeping effort. **Quality Technology & Quantitative Management**, v. 18, n. 1, p. 20-38, 2021.

GUPTA, S.; RIKHTEHGAR BERENJI, H.; SHUKLA, M.; MURTHY, N. N. Opportunities in farming research from an operations management perspective. **Production and Operations Management**, v. 32, n. 6, p. 1577-1596, 2023.

HAIR, J. F.; HULT, G. T. M.; RINGLE, C.; SARSTEDT, M. **A primer on partial least squares structural equation modeling (PLS-SEM)** (2nd ed.). Sage Publications. 2019.

HAMANN, S. The global food system, agro-industrialization and governance: alternative conceptions for sub-Saharan Africa. **Globalizations**, v. 17, n. 8, p. 1405-1420, 2020.

HARSONO, I.; FADLIYANTI, L.; MULAWIANI, B. S. W.; USMAN, A.; ABUBAKAR, A. Analysis of Plant Productivity, Farmer Income and Availability of Supporting Infrastructure on Soybean Agribusiness Institutional Performance in East Java. **West Science Agro**, v. 2, n. 01, p. 35-43, 2024.

HUANG, Y. C.; BORAZON, E. Q.; LIU, J. M. Antecedents and consequences of green supply chain management in Taiwan's electric and electronic industry. **Journal of Manufacturing Technology Management**, v. 32, n. 5, p. 1066-1093, 2021.

JAVOID, M.; HALEEM, A.; KHAN, I. H.; SUMAN, R. Understanding the potential applications of Artificial Intelligence in Agriculture Sector. **Advanced Agrochem**, v. 2, n. 1, p. 15-30, 2023.

JOSHI, S.; SINGH, R. K.; SHARMA, M. Sustainable agri-food supply chain practices: few empirical evidences from a developing economy. **Global Business Review**, v. 24, n. 3, p. 451-474, 2023.

KARUNATHILAKE, E. M. B. M.; LE, A. T.; HEO, S.; CHUNG, Y. S.; MANSOOR, S. The path to smart farming: innovations and opportunities in precision agriculture. **Agriculture**, v. 13, n. 8, p. 1-26, 2023.

KAZANCOGLU, Y.; LAFCI, C.; KUMAR, A.; LUTHRA, S.; GARZA-REYES, J. A.; BERBEROGLU, Y. The role of agri-food 4.0 in climate-smart farming for controlling climate change-related risks: a business perspective analysis. **Business Strategy and the Environment**, v. 33, n. 4, p. 2788-2802, 2024.

KAZANCOGLU, Y.; SEZER, M. D.; OZBILTEKIN-PALA, M.; LAFÇI, Ç.; SARMA, P. R. S. Evaluating resilience in food supply chains during Covid-19. **International Journal of Logistics Research and Applications**, v. 27, n. 5, p. 688-704, 2024.

KIM, A.; KIM, H.; LEE, H.; LEE, B.; LIM, H. Comparative economic optimization for an overseas hydrogen supply chain using mixed-integer linear programming. **ACS Sustainable Chemistry & Engineering**, v. 9, n. 42, p. 14249-14262, 2021.

KLINE, R. B. **Principles and practice of structural equation modeling**. 4th ed. Guilford Press. 2015.

LE, T. T. How do food supply chain performance measures contribute to sustainable corporate performance during disruptions from the Covid-19 pandemic emergency? **International Journal of Quality & Reliability Management**, v. 40, n. 5, p. 1233-1258, 2023.

LECOUTERE, E.; ACHANDI, E. L.; AMPAIRE, E. L.; FISCHER, G.; GUMUCIO, T.; NAJJAR, D.; SINGARAJU, N. Fostering an enabling environment for equality and empowerment in agri-food systems: an assessment at multiple scales. **Global Food Security**, v. 40, p. 100735, 2024.

LEE, S.; JIANG, X.; MANUBOLU, M.; RIEDL, K.; LUDSIN, S. A.; MARTIN, J. F.; LEE, J. Fresh produce and their soils accumulate cyanotoxins from irrigation water: implications for public health and food security. **Food Research International**, v. 102, p. 234-245, 2017.

LI, X.; KRIVTSOV, V.; PAN, C.; NASSEHI, A.; GAO, R. X.; IVANOV, D. End-to-end supply chain resilience management using deep learning, survival analysis, and explainable artificial intelligence. **International Journal of Production Research**, v. 63, n. 3, p. 1174-1202, 2025.

LI, Y.; CHEN, K.; COLLIGNON, S.; IVANOV, D. Ripple effect in the supply chain network: forward and backward disruption propagation, network health and firm vulnerability. **European Journal of Operational Research**, v. 291, n. 3, p. 1117-1131, 2021.

LIU, P.; LONG, Y.; SONG, H. C.; HE, Y. D. Investment decision and coordination of green agri-food supply chain considering information service based on blockchain and big data. **Journal of Cleaner Production**, v. 277, p. 123646, 2020.

MAHROOF, K.; DAMANPOUR, F.; ZMUD, R. W. The evolving nature of supply chain risk management. **Journal of Business Logistics**, v. 42, n. 3, p. 208-228, 2021. Available at: <https://doi.org/10.1111/jbl.12289>

MARAVEAS, C.; KARAVAS, C. S.; LOUKATOS, D.; BARTZANAS, T.; ARVANITIS, K. G.; SYMEONAKI, E. Agricultural greenhouses: resource management technologies and perspectives for zero greenhouse gas emissions. **Agriculture**, v. 13, n. 7, p. 1464, 2023.

MEHTA, N. Technical efficiency and reduction in input costs in agriculture: case of genetically modified cotton. **Agricultural Economics Research Review**, v. 32, n. 1, p. 105-116, 2019.

MEIER, M.; PINTO, E. Covid-19 supply chain disruptions. **Covid Economics**, v. 48, n. 1, p. 139-170, 2020.

MOHAN, D.; KHAN, H.; KUMAR, V.; KUMAR, R.; VERMA, A.; SINGH, R.; SINGH, G. Significance of yield sustainability to develop climate smart wheat (*Triticum aestivum*) in India. **The Indian Journal of Agricultural Sciences**, v. 93, n. 9, p. 954-959, 2023.

MSOMI, L.; ZENDA, M. An Analysis of Challenges Facing Smallholder Crop Farmers and Informal Food Traders in the Agri-Food Value Chain in Gauteng Province, South Africa. **South African Journal of Agricultural Extension**, v. 52, n. 2, p. 120-144, 2024.

MULLA, D. J. Twenty five years of remote sensing in precision agriculture: key advances and remaining knowledge gaps. **Biosystems engineering**, v. 114, n. 4, p. 358-371, 2013.

NOTARNICOLA, B.; SALA, S.; ANTON, A.; MCLAREN, S. J.; SAOUTER, E.; SONESSON, U. The role of life cycle assessment in supporting sustainable agri-food systems: a review of the challenges. **Journal of cleaner production**, v. 140, p. 399-409, 2017.

OLAN, F.; SPANAKI, K.; AHMED, W.; ZHAO, G. Enabling explainable artificial intelligence capabilities in supply chain decision support making. **Production Planning & Control**, p. 1-12, 2024.

OPOKU, E. K.; WANG, M. J. S.; GUEVARRA, S.; BAZYLEWICH, M.; THAM, A. Envisioning digitalised value chains in the aftermath of Covid-19: a case study of Philippine coffee. **Journal of Agribusiness in Developing and Emerging Economies**, v. 13, n. 5, p. 797-811, 2023.

PANDEY, P. C.; TRIPATHI, A. K.; SHARMA, J. K. An evaluation of GPS opportunity in market for precision agriculture. **In GPS and GNSS Technology in Geosciences**, p. 337-349, 2021. Elsevier. 2021.

PETTIT, T. J.; FIKSEL, J.; CROXTON, K. L. Ensuring supply chain resilience: development of a conceptual framework. **Journal of business logistics**, v. 31, n. 1, p. 1-21, 2010.

RAJI, E.; IJOMAH, T. I.; EYIEYIEN, O. G. Integrating technology, market strategies, and strategic management in agricultural economics for enhanced productivity. **International Journal of Management & Entrepreneurship Research**, v. 6, n. 7, p. 2112-2124, 2024.

RANE, N.; CHOUDHARY, S.; RANE, J. Artificial intelligence for enhancing resilience. **Journal of Applied Artificial Intelligence**, v. 5, n. 2, p. 1-33, 2024.

REARDON, T.; MISHRA, A.; NUTHALAPATI, C. S.; BELLEMARE, M. F.; ZILBERMAN, D. Covid-19's disruption of India's transformed food supply chains. **Economic and Political Weekly**, v. 55, n. 18, p. 18-22, 2020.

REJEB, A.; REJEB, K.; ZAILANI, S. Big data for sustainable agri-food supply chains: a review and future research perspectives. **Journal of Data, Information and Management**, v. 3, p. 167-182, 2021.

RUBBIO, I.; BRUCCOLERI, M.; PIETROSI, A.; RAGONESE, B. Digital health technology enhances resilient behaviour: evidence from the ward. **International Journal of Operations & Production Management**, v. 40, n. 1, p. 34-67, 2020.

SAITONE, T. L.; SEXTON, R. J. Agri-food supply chain: evolution and performance with conflicting consumer and societal demands. **European Review of Agricultural Economics**, v. 44, n. 4, p. 634-657, 2017.

SANNOU, R. O.; KIRSCHKE, S.; GÜNTHER, E. Integrating the social perspective into the sustainability assessment of agri-food systems: a review of indicators. **Sustainable Production and Consumption**, v. 39, p. 175-190, 2023.

SARABIA, N.; PERIS, J.; SEGURA, S. Transition to agri-food sustainability, assessing accelerators and triggers for transformation: case study in Valencia, Spain. **Journal of Cleaner Production**, v. 325, p. 129228, 2021.

SARKER, I. H. **AI-driven cybersecurity and threat intelligence: cyber automation, intelligent decision-making and explainability**. Springer Nature. 2024.

SERAZETDINOVA, L.; GARRATT, J.; BAYLIS, A.; STERGIADIS, S.; COLLISON, M.; DAVIS, S. How should we turn data into decisions in AgriFood? **Journal of the Science of Food and Agriculture**, v. 99, n. 7, p. 3213-3219, 2019.

SHEKARIAN, M.; FARAHANI, R. Z.; KARIMI, H. A review of the applications of supply chain resilience: learnings from the Covid-19 pandemic. **Computers & Industrial Engineering**, v. 150, p. 106889, 2020.

TOORAJIPOUR, R.; SOHRABPOUR, V.; NAZARPOUR, A.; OGHAZI, P.; FISCHL, M. Artificial intelligence in supply chain management: a systematic literature review. **Journal of Business Research**, v. 122, p. 502-517, 2021.

TRAN-DANG, H.; KROMMENACKER, N.; CHARPENTIER, P.; KIM, D. S. Toward the internet of things for physical internet: perspectives and challenges. **IEEE internet of things Journal**, v. 7, n. 6, p. 4711-4736, 2020.

TRIENEKENS, J. H. Agricultural value chains in developing countries a framework for analysis. **International food and agribusiness management review**, v. 14, n. 2, p. 51-82, 2011.

TRIENEKENS, J.; ZUURBIER, P. Quality and safety standards in the food industry, developments and challenges. **International Journal of Production Economics**, v. 113, n. 1, p. 107-122, 2008.

VASANTHRAJ, A.; POTDAR, V.; AGRAWAL, H. Industry 4.0 adoption in food supply chain to improve visibility and operational efficiency—a content analysis. **IEEE Access**, v. 11, p. 73922-73958, 2023.

WINANS, K. S.; MACADAM-SOMER, I.; KENDALL, A.; GEYER, R.; MARVINNEY, E. Life cycle assessment of California unsweetened almond milk. **The International Journal of Life Cycle Assessment**, v. 25, p. 577-587, 2020.

WONG, L. W.; TAN, G. W. H.; LEE, V. H.; OOI, K. B.; SOHAL, A. Unearthing the determinants of Blockchain adoption in supply chain management. **International Journal of Production Research**, v. 58, n. 7, p. 2100-2123, 2020.

WOOD, A.; QUEIROZ, C.; DEUTSCH, L.; GONZÁLEZ-MON, B.; JONELL, M.; PEREIRA, L.; WASSÉNIUS, E. Reframing the local–global food systems debate through a resilience lens. **Nature Food**, v. 4, n. 1, p. 22-29, 2023.

YU, Y.; HUANG, G.; GUO, X. Financing strategy analysis for a multi-sided platform with blockchain technology. **International journal of production research**, v. 59, n. 15, p. 4513-4532, 2021.

YUAN, Y.; LI, W. The effects of supply chain risk information processing capability and supply chain finance on supply chain resilience: a moderated and mediated model. **Journal of Enterprise Information Management**, v. 35, n. 6, p. 1592-1612, 2022.

ZUREK, M.; INGRAM, J.; SANDERSON BELLAMY, A.; GOOLD, C.; LYON, C.; ALEXANDER, P.; WITHERS, P. J. Food system resilience: concepts, issues, and challenges. **Annual Review of Environment and Resources**, v. 47, n. 1, p. 511-534, 2022.