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Assessing the influence of artificial intelligence on agri-food supply chain performance: the mediating effect of distribution network efficiency

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ABSTRACT

The urge for greater agri-food supply chain efficiency (AFSCE) has been gaining in prominence increasingly, spurred on by escalating logistics costs and advances in industry 4.0 technologies (e.g artificial intelligence AI). The latter significant contributions in logistics have led academics to point their attention more to AI utility in operations management. Drawing on dynamic capability view (DCV) and organizational information-processing theories, this study aims to examine the effect of AI based technologies on reducing wastes and minimizing afri-food supply chain costs, hence increasing organization profitability. It also analyzes how outbound logistics and distribution network efficiency (DNE) (warehousing, transportation, packaging, etc.) mediates the relationship between AI and AFSCE. This research investigates the moderating impact of AI adoption impediments (AIAI) on the mediating correlation between AI, DNE and AFSCE as well. Using Partial Least Square-Structural Equation Modeling (PLS-SEM) approach, conceptual model and hypothesis were analyzed and tested with 348 responses collected from executives and managers in the Moroccan agri-food industry. As a novel result, distribution network efficiency and by way of mediation AFSCE and organization performance are found to be directly and positively affected by AI integration. The researchers find also that with more AIAI, the relationship between the aforementioned variables weakens.

1. Introduction

One of the major economic drivers of any country and essential to the welfare of its population is the agri-food sector (Lans et al., 2004; Priyadarshini and Abhilash, 2023). In addition, the agri-food sector is becoming increasingly significant to both developing and developed nations due to its role in promoting more environmentally friendly consumption and production patterns, social welfare, business competitiveness and economic progress (Karantininis et al., 2010). Nevertheless, despite its significance, this industry faces a number of difficulties brought on by climate change, tremendous technical advancement, and rising demands for traceability, sustainability, transparency and the pressing need for more effective agri-food supply chains (Ben-Othman et al., 2020). Furthermore, due to energy crisis, the exponential increase of operational costs, and the reduction of most products life cycles, besides the rising demands for food safety and quality, efficient use and resource consumption, and the balanced ecological, economic, and societal performance of agri-food firms, the concept of efficiency is becoming vitally important in the agri-food sector (Kosior, 2018), and when we consider that an additional one-third of the world's population is predicted to rise by 2050 (Turk, 2016), the problem is made worse. As such, businesses in the agri-food industry are in need to improve ecosystem sustainability and get rid of inefficiencies in the supply chain (Esteso et al., 2021). Accordingly, an organization's performance will mostly depend on its ability to reduce operational costs and address every source of waste. To accomplish that, firms must rely on a solid and efficient logistics system helps to address operational bottlenecks, as the latter encompasses one of the major processes that holds the lion's share of costs in the value chain. Therefore, firms' strategies must focus more on managing effectively the downstream supply chain to boost its efficiency and sustainability and withstand the intense competitiveness of the market. Facing all these stumbling blocks, the incorporation of Industry 4.0 technology which is a digital movement that seeks to technologically alter manufacturing processes and finished products, into the agri-food supply chain is suggested as a potential remedy for this tendency by governments, academia and industry (Liu et al., 2021), encouraging a significant digital revolution (Abbasi et al., 2022, p. 0). As a result, it is anticipated that the entire industrial supply chain will

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change and become more independent and intelligent (Sharma et al., 2021a). Similar demands are being put on agri-food supply chains to incorporate technology, including the Internet of Things (IoT), blockchain, big data analytics, artificial intelligence (AI), and robotics (Lezoche et al., 2020).

Nevertheless, AI is one of these crucial cross-industry technology solutions that is less market-ready (Compagnucci et al., 2022) and one strategy to revolutionize the agri-food industry and improve sustainable efficiency. By gathering data and using modern data analytics, algorithms, and AI, it is possible to analyze huge datasets generated from many sources in order to achieve particular goals or outcomes (Monteiro and Barata, 2021). This has already been the case in many other fields, such as medicine, but in order to preserve trust, such actions must be done with caution. The entire supply chain can be informed about how a weather event or other supply chain shock may influence, and whether or when products emergencies are likely to occur through the use of algorithms, advanced data analytics and AI (Morella et al., 2021). As, the AI is the study of programming computers to perform actions required of human behavior, such as reasoning, intelligence and experience, machine learning and Deep learning, and artificial neural networks all provide tremendous possibilities for data-intensive science in agri-food supply chains when combined with high-performance big data and computing technologies (Allam and Dhunny, 2019; Bag et al., 2023). All these potentials have drawn partitioners attentions as it has been applied in a variety of agri-food and supply chain sectors and activities, such as smart soil management, nutrient management and smart irrigation, harvest forecasting, and food and quality safety evaluation (Manning et al., 2022). As regards academic community, AI driven agri-food supply chain management has been the cynosure of numerous in-depth research studies covering a wide range of topics. For instance, (Patrício and Rieder, 2018) explore the use of computer vision and AI algorithms tools in precision agriculture and emphasize a number of advantages of these tools, such as task automation, better profitability, and improved food safety and quality. According to (Hadidi et al., 2021), AI can help greenhouse operators who care about ecological performance forecast the consequences of their production methods on the environment and support claims made about their products. AI encourages smart farming, a sustainable technique that assists in reducing resource waste and promote sustainable development, to replace the conventional agricultural procedures and practices (Javaid et al., 2022). Additionally, AI equips robots to increase productivity (Vadlamudi, 2019), increase job efficiency, and enhance the quality of fresh products (Javaid et al., 2022). As agri-food companies can extract value from data and manage data exchange and access control, this can improve the several agri-food industry methods and operations (Ruiz-Real et al., 2020). Nonetheless, AI has exhibited some contribution levels that go beyond the internal structure of the firms to integrate the logistics processes as well. (Kollia et al., 2021), for instance, examine AI-enabled food chain networks. They discover that AI approaches can automate the examination of retail packaged foods, optimize energy use over a vast network of food cooling system. Similarly, through BD&DM, AI can be used to find potential areas for resource rationalization and resource savings through optimal planning of logistics operations, primarily distribution, transport and inventory, but also ordering and warehousing, hence reducing the consumption of energy and other resources (people, money, time) through better allocation and capacity planning (Krstić et al., 2022). Along these lines fits this research work contribution where the authors try fill the research gap by approaching most specifically the logistics dimension, hence addressing the following issues: RQ1: In what way AI based technologies enhance the overall agri-food supply chain performance? RQ2: To what extend can AI technology deployment support distribution network efficiency of agri-food firms? RQ3: Does distribution logistics efficiency mediate the interplay between AI adoption and the agri-food supply chain performance efficiency? RQ4: How AI adoption impediments moderate such relationships?

To address these questions the current study employs dynamic capability view (DCV) that addresses the firm's ability to deal with environmental changes through optimal resource reconfiguring and organizational information-processing theory (OIPT) that focuses on the alignment of business needs for information processing with company capabilities to carry out those needs. To further examine these questions, a Structural Equation Modeling (SEM) approach is applied using data collected from different companies that function within the agri-food supply chain (manufacturer, wholesalers, distributors, retailers, 3PLs, etc.).

The organization of the paper is as follows: Section 2 presents the agri-food supply chain and AI technologies state-of-the-art; Section 3 is reserved to conceptual model and research hypothesis development. In Section 4, the research methodology and data analysis tools are outlined. Displaying the analysis outcomes are exhibited in Section 5 before discussing the study findings and its contributions in Section 6. Finally, the main conclusions and limitations are presented in Section 7.

2. Agri-food supply chain and AI technologies state-of-the-art

In this section, we discuss the research on the use of AI in agri-food supply chains. With the help of this review, we want to identify potential research gaps. For the sake of simplicity and richness, we have divided the review of the literature into two areas. The first pertains to how AI technology is adopted and decisions are made regarding the qualities of technology, their relative significance, relationships, or usability in supply chain management. The second section discusses how AI technology is changing agri-food supply networks.

2.1. *Artificial intelligence*

Artificial intelligence (AI) is a field of computer science that uses, among other things, deep and machine learning algorithms to learn from and extrapolate data in an attempt to resemble human intellect (Hancock et al., 2020). These networks make predictions by connecting both input and output variables automatically. These forecasts can be used to generate a variety of answers to both simple and complex problems. AI-powered technology is already widely used in daily life. From self-driving cars to mobile face recognition software. Although other industries have benefited greatly from AI technologies and machine learning (ML) capabilities in terms of productivity, it is inconceivable to imagine agriculture undergoing a digital transformation. But AI is taking one of the oldest sectors of the economy into the future. Surprisingly, AI has several uses in agriculture. Artificial intelligence enables precision farming. Using ML data, AI may assist farmers with pest management, harvesting, crop rotation, crop selection, and planting (Smith, 2018).

As support for many agri-food applications, AI techniques offer significant contributions to cognitive model identification, service generation, and decision-making procedures (Ng et al., 2021). AI provides formal overall algorithms for pattern recognition (Boice et al., 2022), accuracy and performance analysis (Lui et al., 2020), prediction. These algorithms may address knowledge concerns in the agriculture field, such as the identification of pests and the proper treatment techniques. Furthermore, AI helps with the development of applications for farming techniques, such as the allocation of land for the targeted activity (Chen et al., 2021), the analysis and control of irrigation processes (Talaviya et al., 2020), the guidance of robots (Winfield and Jirotka, 2018), etc.

The underlying premise of AI is that human intelligence can be characterized in a way that makes it easy for a computer to replicate and do tasks of all sizes. AI aims to accomplish reasoning, learning, and perception. Across the board, AI is having a huge impact. Every industry seeks to automate particular tasks using sophisticated machinery. It happens when a machine's comprehension of human intelligence is specified. Furthermore, farm AI technology has the ability to change the planet. From easy to difficult tasks, this technology can handle all. A machine's aim is to learn, think, and sense. It helps automate work across a range of industries. Many different tasks are made easier by the usage of intelligent gear.

2.2. How the AI technology transforms the Agri-food supply chains

The agri-food supply chains are under intense pressure to control different sources of uncertainty and risk (food safety and quality, resource needs, market prices, demand) since their exact progression through time could imperil their continued viability. Moving away from "business as usual" is vital, as is creating new solutions and implementing innovative technologies (de Janvry and Sadoulet, 2010). In keeping with this, a digitalized supply chain enables businesses to track material movements in real time, making possible risks obvious and creating strategies for dealing with them in the future. According to (Ivanov et al., 2019, p. 0), the main forces behind the automation of supply chain processes typically include a rise in the manufacturing/logistical systems' responsiveness and flexibility, as well as an increase in the resilience and robustness of the supply chains for food and agriculture.

Data become vital in this situation. The agricultural industry is not an exception to this rule but rather a referent because data is the heart of any company. The agri-food industry will undergo a dramatic change as a result of emerging AI-powered technology (Yeo et al., 2022). Farms all over the world can use cognitive technology and AI to decrease uncertainty, enhance decision-making, sort through data, automate time-consuming tasks, and increase sustainability, efficiency, flexibility, resilience and agility along the entire supply chain, from the farm owners to the final consumers (Pramanik et al., 2018). Thanks to significant improvements in technology, including computers and software, and societies' faith in machine learning (ML), huge amounts of information may now be used to boost agriculture productivity and sustainability (Cravero and Sepúlveda, 2021). The agricultural industry's decision to employ AI technology to improve decision-making was affected by a number of factors. Data accessibility has improved, and there is a clear increase in the volume of data that is available. Sector advancements including expanded sensor use, quicker access to satellite imagery, lower data logger costs, expanded drone use, and enhanced access to government data archives make this possible (Javaid et al., 2022).

In fact, by combining numerous models of autonomous data analysis, archives of historical data, and real-time data flows, the integration of earlier technologies enables a more effective and efficient management of the agri-food supply chains (Wolfert et al., 2017). Companies now have additional options to respond to shifting supply chain situations more swiftly thanks to real-time data and information processing. The agri-food supply chain management is able to move from supporting decisions to assigning them and, eventually, predicting which decisions should be made thanks to this integrated intelligence. The way the agricultural sector organizes and makes decisions is changing as a result of all the aforementioned factors. Table 1 integrates and categorizes the main positive impacts of the AI technologies as well as the challenges to be overcome in accordance with recent studies in the field conducted by various authors in order to provide a comprehensive overview about how the AI technology change the agri-food supply chains. Technologically and economically speaking, AI algorithms due to processing and analyzing huge amount of data can optimize logistics and distribution taking into consideration factors as demand, weather, traffic and inventory level which lead to efficient transportation and reduce waste and increase productivity through structured data driven and informed decisions. Moreover, AI empowered robots and machine learning can perform several tasks relying on the expertise of human resources reducing the reliance on manual labor and addressing labor shortage, hence reducing human risks. All these contributions can leak to competitive advantage acquisition and enhance profitability.

However, finding solutions that work for everyone engaged is challenging due to the diversity of stakeholders joining agri-food supply chains, therefore mechanisms for group decision-making should be established (Weerabahu et al., 2021). Due to this, it will be essential to gather and exchange data as well as to illustrate the worth of innovations relative to their organizations.

Table 1
Artificial intelligence: Impact and challenges.

Artificial intelligence		
References	(Dwivedi et al., 2021; Racine et al., 2019; Sun and Medaglia, 2019; Wirtz et al., 2019; Zerfass et al., 2020)	
Impact	Technological Impact:	• Dirty data can be identified and cleaned using AI, or it can be used to provide perspective for clean data. •AI increases data velocity by enabling quick computer decisions that influence other decisions. •AI reduces variety by acquiring, organizing, and comprehending unstructured data and producing structured data. • AI enables data analysis and decision making.
	Social Impact:	• Combine the expertise of several human beings. • Alleviate the prevalence of human mistake. • Examine transactions that humans with expertise would miss. • Minimize human interference so that experts can focus on more creative tasks
	Economic Impact	• Reduce the expense of staff training • Increase efficiency, shorten the time it takes to solve problems, and improve problem-solving techniques. • Expert systems permit real-time, low-cost, expert-level judgments by non-experts and improve the usage of the majority of the data accessible. They also raise the chance, frequency, and consistency of making effective decisions.
	Business Impact:	• Artificial intelligence goes above and beyond by demonstrating certain learning ability rather than just implementing pre-programmed conclusions. •AI and ML may add value by offering businesses sophisticated big data analysis and capturing structured interpretations of the diverse range of unstructured data that is becoming more and more accessible.
	Functional impact:	• Monitoring is performed more quickly and accurately than with conventional monitoring tools. • Fraud prevention system with unprecedented level, efficiency, and rapidity • Environmental Defense • Manufacturing Planning
Challenges	Technological Challenges:	• Emergent subproblem structures that are helpful for parallelization may be present in AI algorithms created for single-machine contexts. • Expert systems won't be able to respond creatively to uncommon situations the way human experts can. • Failing to realize when there is no solution. • The greatest obstacle to using expert system technology in new domains is knowledge acquisition. • For a relatively big rule base, maintenance and expansion can be challenging.
	Social Challenges:	• substitution of human intervention as a threat

3. Theoretical model and research hypothesis

The conceptual research model of this current study as it's been illustrated in Fig. 1 has undertaken its theoretical foundation from the emerging literature on AI based technology as well as from two approaches which have been well-accepted in many researches dealing with disciplines such as supply chain management, sustainability,

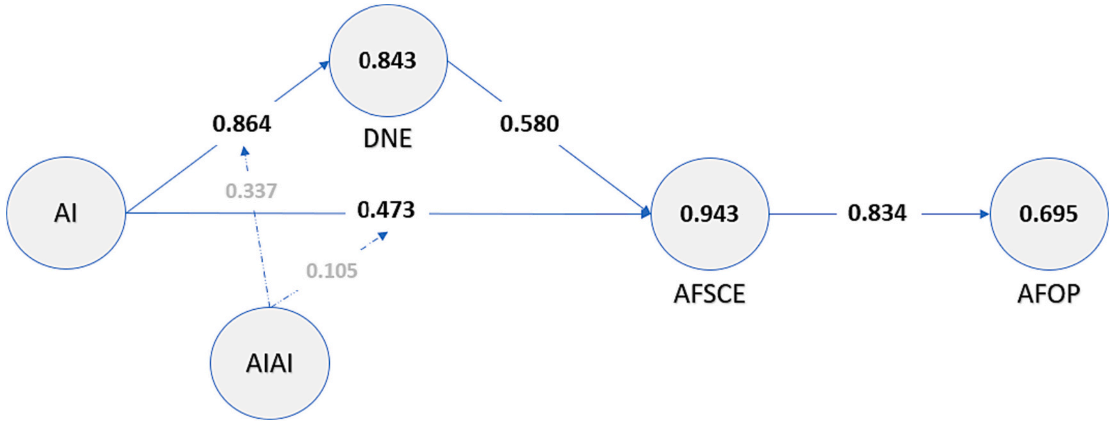

Fig. 1. Structural model.

operations management and digitalization i.e., Dynamic capability view (DCV) and Organizational Information-Processing Theory (OIPT). The model depicts the relational dynamics between the AI based technology and agri-food supply chain performance (AFSCP), and mediated by both distribution network efficiency (DNE) and agri-food supply chain efficiency AFSCE).

3.1. Dynamic capability view and organizational information-processing theories

DCV is considered as one of the well-established perspectives in operations and supply chain management and an enhancement of resource-based theory's basic static vision because it's not confined to the emphasis on resource acquisition but it examines opportunities and threats both within and externally to show how resources contribute to competitive advantages over time (Helfat and Peteraf, 2003). Its main principle is that firms possessing superior dynamic capabilities (DC) would exhibit enhanced performance and other way around (Bag et al., 2021). Accordingly numerous organizational capabilities are categorized in compliance with DCV including ordinary or operational capabilities which implicate the accomplishment and execution of managerial and control related activities even miner day to day tasks of the organization such as distribution logistics and marketing campaigns (Liu et al., 2013). Besides, DCs entail advanced capabilities and strengths that companies can implement on grounds of basic and core competencies to build a long term competitive advantage (Teece, 2014). Meanwhile, the OIPT addresses the fit between the needs regarding information-processing and the firm competencies to fulfill its activities. The main assumption of OIPT is that when information needs and capability are matched, the organization's performance could be enhanced (Premkumar et al., 2005).

On the basis of these two theories, it could be stated that information processing capabilities is of great importance to reduce uncertainties and achieving efficiency and effectiveness not only for the organization itself but for the whole links of the supply chain as well. As such, new technologies such as AI can offer similar capabilities to support real-time data processing for operations management. We therefore base our research model on these theories as they portray the main objective of our study which is to investigate the interrelationship between AI based technology and agri-food supply chain efficiency and consequently its performance. Since the operational efficiency of supply chain depends on how the firm process information resources and needs to minimize logistics costs and improve operational and strategic benefits, AI based technology should in this sense build the conditions and capabilities for the enterprise to deal with high amount of information and data through better decision-making processes (anticipation of demand, weather prediction, route optimization, etc.) (Meindl et al., 2021).

3.2. Distribution network efficiency

Managing outbound logistics has always been the strength of the Supply Chain organization (Chatur, 2006). Therefore, the emphasis on logistics, especially in the industrial world has been on the distribution function. The latter takes place at the downstream supply chain which encompasses all the activities associated to efficient and effective goods movement and transportation from a manufacturer or distributor to customers, retailers or other secondary warehousing/distribution points (Lummus et al., 2001). Therefore, distribution logistics processes are considered the highest in resources and energy consumption. Nevertheless, maintaining the economic efficiency constitute an extremely complex problem, and the turbulence of today's markets may threaten vigorously its achievement (Andrejić et al., 2016). Thus, acquiring a solid and efficient distribution system would support the firm to face operational bottlenecks and challenges.

Efficiency represents a paramount indicator of any organization operations analysis and on which is based and measured its performance. In this regard, monitoring and improving supply chain operational efficiency has been the main priority of 21st century enterprises.

Distribution network efficiency allude to the ability to provide the appropriate product/service at the lowest level of cost that is acceptable to the final customer. It is the ratio of resources employed over the outputs derived (Fugate et al., 2010). Simply put, logistics efficiency can be defined as the ability to manage and use resources expended reasonably.

3.3. Hypothesis development

3.3.1. Interplay between AI technology and distribution network efficiency DNE

As the efficient management of the distribution system calls for coordination between transportation planning and inventory control decision (Stenius et al., 2016), seeking new sources of optimization becomes a top priority. Hence, many organization consider implementing emerging technologies (such as AI) to support their operational efficiency (Wang et al., 2020), especially AFSC because the shelf-life constraints of products. Efficiency centered distribution logistics can more effectively accomplish goals related to cost-effectiveness, inventory management, route optimization, demand forecasting, warehouse automation and customer service with the recourse to AI based technologies.

Using OIPT, we theorize that distribution logistics need to gather, analyze, and interpret data with great efficiencies to withstand uncertainties. Accordingly, the adoption of AI facilitates data processing and enhance analytics capabilities, hence monitor, control and optimize inventory, transportation planning and delivery lead time (Meindl et al., 2021). To this effect, a multitude of prior researches have confirmed the substantial linkage between AI based-technology logistics efficiency. In a study conducted by (Tzachor, 2020), the outbound logistics of agricultural supply chain represents the most SC phase which is receptive to AI adoption and deployment and that includes retail, trade and consumption and waste management.

AI driven distribution logistics represent an efficient and controllable service mode which would by route optimization, time allocation to minimize time processing and response, self-adjustment enhance logistics efficiency (Liu et al., 2022a). Furthermore, intelligent logistics based on AI would assure a real-time monitoring of temperature, air pressure and humidity and prevent products quality from deteriorating (Feng, 2016). For instance the applicability of connected and autonomous vehicles showed a positive potential to incorporate sustainability in food distribution supply chain (Heard et al., 2018).

With the establishment of AI technology, minimizing the risks of unsafe and low quality product, inventory handling and network optimization become possible (Gölge and Türk, 2019). As a result, the application of AIT can enhance the productivity, accuracy and efficiency of the warehouse and the retail process, much less assisting partitioners to solve decision making problems regarding forecasting return of items by tracking expiry dates (Pishvaee et al., 2010). Thus, we hypothesis:

H1. AI based technology has a significant positive effect on DNE.

3.3.2. AI technology and AFSCE

As it's been mentioned earlier in this article, the agri-food supply chain is and has been for so long facing many hurdles and challenges that could threaten and weaken the whole value creation processes. These problems involve lack of storage and warehousing structure, lack of knowledge and digitalization in the agriculture business, inadequate transportation (Arora et al., 2022). These observations have been also the findings of (Gilman, 1917) in his article published over a century ago. And in which the author stated that one of the main problems in agri-food industry is the capability to promptly, efficiently and economically prepare and distribute agri-food products to the customer. Facing all these obstacles, a great attention has been paid to the adoption of AI technology due its positive effect on agri-food supply chain efficiency from the upstream processes of procurement to downstream processes of goods distribution and customer delivery (Morella et al., 2021). According to inherent characteristics, business and supply chain operations, Table 2 illustrates the key aspects of AI applied for a more efficient agri-food supply chain. For instance, AI exhibits a significant ability in reducing costs, diminishing level of inventories, attaining a shorter lead time, minimizing supply interruptions and uncertainties through transportation modes and improving supply chain operational performance (Yang et al., 2019). Similarly, through predictive analytics, AI algorithms can forecast demand fluctuation, market dynamics and potential supply chain disruptions which can help in optimizing inventory levels, productions scheduling, transportation leading to cost saving a better resources allocation (Sharma et al., 2021b). The force of AI reside also within the AI empowered computer vision systems designed for products quality and safety inspection during processing, packaging and delivery reducing the need for manual interference (Vilas-Boas et al., 2022). On the other hand, AFSC can benefit from the AI-enabled traceability systems which improve the traceability and accountability and track the products movements all along the supply chain. That will support managers to quickly identify any disruption that can occur and minimize the impact on the business (Costa et al., 2013; Qian et al., 2022). That is to say, AI enabled technology will not only assure continuous improvement and efficiency, but through precis data and intelligent decision making will help enhance sustainability, flexibility, resilience and agility of the whole supply chain from farmer to the customer (Lezoche et al., 2020). Based on this, the following hypothesis is proposed:

H2. AFSCE is enhanced and supported by the adoption of AI based technology.

3.3.3. Mediating role of DNE on the link between AI and AFSCE

The basis of every AFSC management rely typically on a set of operational processes and activities in a 'farm to fork' perspective. Besides farming, the bulk of these activities take place in the outbound processes which cover storage, packaging, warehousing, transportation, distribution and marketing in order to achieve end customer satisfaction (Tsolakis et al., 2014). As such, AFSC management calls for the coordination of a set of processes notably distribution management and demand management so that the agri-food products can reach the final customer in the most efficient, sustainable and secured manner possible (Routroy and Behera, 2017). Therefore, managing AFSC can be challenging and the role of distribution mechanism gain importance increasingly. The existing literature has been investigating on such AFSCM problems by focusing on a variety of aspect including risk management, food safety and quality and sustainability (Behnke and Janssen, 2020). In addition, another aspect has received more attention and that of the advanced information technologies such as AI (Wolfert et al., 2017). The latter has shown a positive and significant results as far as the AFSC management is concerned. Previous studies recognize that AI holds high capability to address agri-food products safety, security, integrity, reduction of waste, ecological awareness and providing a

Table 2
Aspects of AI use in the agri-food supply chain: innate features and supply chain activities/corporate.

Aspect	Inherent characteristics	Corporate activities / mechanisms	Supply Chain Example	References
Accessibility	Findable, useable, reusable, compatible, private (limited access), public. (Open access)	Standards for information exchange, authorization, privacy, and human (inclusive) availability.	The creation of access rights for robotic milking equipment on farms so that data collected can be properly accessed by farmers, machine makers, veterinarians and dairy consumers	(Bhat et al., 2022; Vern et al., 2022)
Responsibility	Legitimacy, trust.	Societal accountability for businesses. AI creates rules that specify responsibilities and duties.	The use of a management tool for food safety that incorporates an integrated alert system based on the level of accountability in the factory.	(Di Vaio et al., 2020; Liu et al., 2019)
Interpretability	Accountability, clarity, and visibility	assimilating and interpreting information, using tools, analyzing prototypes, and analyzing features	The capacity to interpret technological output in order to use it to guide decision-making, such as the ability to employ scanning equipment and convert the data into knowledge about the severity of disability in a dairy herd.	(Lotfi et al., 2022; Tomasiello and Alijani, 2021)
Accountability	Responsibility, accountability, controllability, and responsiveness	Corporate governance, accountability standards, etc.	The creation of a data governance framework that identifies the uses of data by various stakeholders and specifies who certain data can and cannot be exchanged, such as data related to employees at a food manufacturing facility.	(Tian, 2016; Zhao et al., 2019)
Traceability	Data loss related to identity, mobility, location, and transactions	Tracking, tracing, and keeping records.	The process of tracking an ingredient and products from its source to its destination using a scanning device and barcodes on the package.	(Costa et al., 2013; Qian et al., 2022)

better monitoring and management of the supply chain through enhancing transparency, agility, traceability and efficiency of the AFSC-the most significant risks and challenges that the latter has been facing (Potts, 2019). The deployment of AI in logistics and distribution process will trigger a several changes in the traditional processes in unprecedented way enhancing customization and information and outgoing tasks accuracy (Keding, 2020). Inter alia, the turbulent environment characterizing the business world today highlights the urge for AI technology based on its capability to adjust dynamically delivery schedules to dodge delays and unexpected demand spikes. As far as transportation and delivery are concerned, AI can not only address load balancing issues and vehicles maintenance via sensors and devices to stay alerted about products quality during transit and proceed to quick corrective action in case of damage, but also optimize last-mile delivery by selecting the optimal ways and delivery modes taking into consideration all possible constraints such as traffic conditions and road closures leading consequently to energy, time and costs reduction. That is to say, AI is revolutionizing the agritech sector and that because its fundamental role in improving economic, environmental and energy efficiency. This leads to the following hypothesis:

H3. DNE mediates the relationship between AI technology and AFSCE.

3.3.4. Impact of AFSCE on AFOP

The increasing globalization of food trade has made profonde changes in all processes from sourcing to distribution and marketing which led to the emergence of new risks and more serious consequences of foodborne illness outbreaks (Maan et al., 2021). In this regard agri-food products safety and quality became an integral component of almost every distributer business strategy. This transition has developed the role of every stakeholder and partner. Moreover, the extension of the AFSC has made it very challenging and complex to manage. Some of the main complications which disturbs this system lies in the lack of efficiency, poor traceability, inadequate management and information asymmetry (Stephens et al., 2020). Additionally, with the increase in complex interrelationships the autonomy of the international AFSC has been shifted into an interconnected system. In other words, the agri-food organization performance AFOP depend massively on the effectiveness and potentials of other AFSC links. AFSC lays out a collective system wherein lean practices are necessary for the AFSC performance (Kumari et al., 2022). Therefore, being a part of the whole value chain, the increase in efficiency of the AFSC structure can highly reduce all these complexities and constitute a veritable indicator for sustaining the AFOP. These arguments allow us to define this hypothesis:

H4. Increased AFSCE has a positive relationship with AFOP.

3.3.5. Moderating effect of AI deployment impediments on DNE and AFSCE

Indeed, evidences demonstrate that the contribution of AI based technology in AFSC economic growth and overall performance is undeniable (Zhang et al., 2019). Yet, it's not the case for every region. Despite the significant potentials of AI technology adoption, numerous structural and institutional barriers precluded hinder and preclude its widespread implementation. Most commonly, the challenges are related to a variety of factors such as digital policies, society, digital skills, insufficient finance, lack,of public investments, and so on (Hangl et al., 2022). Foremost, AI based technologies require some specialized skills for it to deploy. As such, lack of technical expertise and AI literacy limits especially in the agribusiness may stand as difficulty for AI tools to be maintained effectively. Thus, the lack of awareness about AI enabled efficient agri-food supply chain results in the non-implementation of such technology. Yet, even if the industry surpasses this hurdle, the infrastructure limitations can paralyze the transition to AI enabled digitalization. Internet and research and development infrastructure lack can impede the AI investment especially in rural regions. This state of affairs makes data fragmented and unavailable which affect data accessibility and quality. Also, the weak investment in AI technology can be generated from financial constraints and lack of funds due to the high implementation costs and sometimes due the inflexible governmental policies and legal regulations (Ada et al., 2021; Horváth and Szabó, 2019). For that reason, identifying and exploring the significant impediments and investigating their moderating effect of AI adoption will provide useful directions for AFSCs. Therefore, it can be hypothesized that:

H5a. AI deployment impediments negatively moderate the link between AI based technology and DNE.

H5b. AI deployment impediments negatively moderate the link between AI based technology and AFSCE.

4. Research methodology

4.1. Research context

The agri-food industry has been the cornerstone of the Moroccan economy for ages. The sector contributes 26 % of the industrial GDP with a turnover of nearly 158 billion DH. Furthermore, in the period between 2000 and 2015, the GDP of Morocco's non agri-food sectors expanded at a low rate over indicating that agri-food industry rose at the fastest rate (Canli, 2017). Supporting development of the agri-food value chains from production, developing storage, processing, distribution, retailing, transport, logistics could promote the industry yet to produce and export to its full capacity which might increase the overall income of the nation (Olivier Treguer, 2019). However, the various disruptions which the agri-food supply chain has witnessed the past three years such as the health and energy crisis in addition to the climate change has made managing the chain flows even more delicate. This period was characterized by a significant increase in raw materials cost and a substantial delay in deliveries. Facing all these hurdles, it's mandatory for Moroccan agri-food organizations to pursue a superior intelligent approach which would provide them with smart cost control, a short- and medium-term visibility and hence more superior resiliency facing risks. Therefore, new technologies such as AI is believed to bring more efficiency to the AFSC through optimization algorithms which can empower the firms with the ability to conduct different simulations for various situation that could weaken the chain beside constructing automated responses regarding distribution planning, inventory handling and final deliveries. The potentials of such technologies in the agri-food value chain reflects the Moroccan government digital transformation orientation (*through the Plan Maroc Numérique 2020 (Digital Morocco Plan) was developed by the Ministry of Industry, Commerce, Investment and the Digital Economy (MICIEN)*) of the industry that is already witnessing a variety of digital enhancements concerning satellite imagery, IoT networks and e-commerce platforms and internet based technologies such as databases like FERTIMAP for production recommendations, Agricultural product price information system (ASAAR) that analyzes products prices according to regions and type of markets and platforms for e-commerce that are beginning to focus on the food industry (Olivier Treguer, 2019). In this context, this study investigates the AI based technology adoption and its potential contribution for the AFSC efficiency in the emergent economy context of Morocco.

4.2. Sampling and data collection

For conducting this research, a quantitative approach was adopted due to the fact that it assures the objectivity of the study. Furthermore, adopting this approach is more efficient regarding cost and time and offer higher response rate as per the qualitative approach. The study was carried out using primary data collected in a survey from experts in both supply chain management and AI fields. The respondents were top managers, directors and specialist from different links of the AFSC (including Agri-food manufacturers, wholesalers, retailers, logistics service providers, head of quality improvements, technology suppliers, etc.) operating in Morocco. In order to pre-test the questionnaire, a preliminary version was sent to a multitude of experts and professors in the SCM field to adjust the items constructed and identifying new ones. After distributing the questionnaire with the assist of the Moroccan Federation of Agri-food Industry (MFAFI) database, the researchers received 349 usable answers out of 1035 sent leading to an acceptable response rate about 34 %.

4.3. Constructs development

To identify our research constructs and items, this study was based on the existing related literature and listed in Appendix A. As such, the questionnaire was divided into six sections. The first one consists on presenting the demographic details such as organization sector for which the authors employed the North American Industry Classification System (NAICS) to establish a well-structured classification of industries. The section emphasizes also specifically on both organizational age and size and respondent experience in the SCM/AI domains as control variables (Table 3). The firms experience can reflect its strategic vision concerning supply chain design and larger organizations would have more resources for investing in IT related activities. Moreover, the expertise of managers in the field represents an appropriate indicator for the expertise of the firms as a whole which may impact the supply chain performance.

The following sections exhibit the constructs of both reflective and formative models forming the theoretical framework which were measured using a five-point Likert scale (1 = strongly disagree/ Extremely worse and 5 = strongly agree/extremely better) respectively. For the construct AI technology, the authors considered 4 items that address the possession of the resources and the applicability of AI results in decision making and developing SCE as items. The third section concern an 8 items scale construct which deal with DNE and that include distribution strategy, flexibility speed of deliveries, warehousing, transportation planning, inventory handling, etc. The last sections were reserved on one hand for AFSCE (6 items) and AFOP (4 items) and indicate the respondent's view on the supply chain and organization performance comparably to other agri-food firms. Finally, the authors allocate the last section to the respondents' insights on the set of AI adoption impediments on DNE and AFSCE.

Table 3
Sample composition.

		Frequency	Percentage
Business activity	Food manufacturing	132	37.9 %
	Distribution	104	29.9 %
	Retail trade	51	14.7 %
	Transportation and warehousing	32	9.2 %
	Computing infrastructure providers	29	8.3 %
Firm age	<10	62	17.8 %
	[11–20]	166	47.7 %
	[21–40]	87	25.0 %
	≥40	33	9.5 %
Years of experience in SC/AI fields	<1	2	0.6 %
	[1–5]	31	8.9 %
	[6–10]	33	9.5 %
	[11–15]	88	25.3 %
	[16–20]	117	33.6 %
	>20	77	22.1 %
Firm size	<10	15	4.3 %
	[10–50]	139	39.9 %
	[51–150]	78	22.4 %
	[151–200]	29	8.3 %
	>200	87	25.0 %

4.4. Common method bias

Due to the fact that our study is based on self-reported data, researchers have considered the chance of common method bias (CMB), as the bias could be a potential issue in survey design, hence for validating the dataset especially since all data came from the same instrument (Podsakoff et al., 2012). As such, an ex-ante approach was adopted to minimize the bias effect, in which the authors have initially collected the data of all constructs from different sources, designing variables of the survey in unsystematic and clear manner, beside ensuring respondent confidentiality to ascertain the objectivity of the feedbacks. With a view to statistical measurement control (ex-post approach), the researchers proceeded in a first place to analyze Common method bias (CMB) based on a single-factor Harman statistical test. The results of the test shows that 44,661 % of total variance is explained by a single factor which is acceptable considering that its value is inferior to the threshold of 50 %. The authors assessed multi-collinearity as well through testing variance inflation factors (VIF) which exhibits acceptable values under 3.3 (Kock, 2015) (Table 3). Accordingly, CMB has no significance on the dataset and subsequently on the validity of the study findings.

4.5. Data analysis

For a roughly complex model such ours, it's often likely to be exposed to biased model fit indices. Therefore, the researches applied Partial Least Square Structural Equation Modeling (PLS-SEM) at the expense of CBSEM, to test and analyze reflective-formative constructs composing our model. Because the latter shows some limitations in similar studies. Incidentally, the adoption of PLS-SEM arises from the fact that our sample size ($n = 348$) is considered as small comparing to the relationship complexity among the model constructs (30 items in our case) (Wright et al., 2012). In order to test the proposed model's fit and the developed hypothesis interrelationship, a two-step procedure was conducted. First, to measure the reliability and validity of the model, a confirmatory factor analysis (CFA) was applied, then structural paths was examined to test the hypothesis.

5. Results

5.1. Measurement model assessment

Prior to establish the structure model, it's necessary to proceed at the outset to assessing the overall model fit based on fit indices. In other words, through CFA, the authors evaluated the measurement scale of the indicators (items) for each latent variables in terms of constructs reliability, convergent and discriminant validity. To accomplish that, the analysis is based on measuring different properties such as: Cronbach's alpha (α), factor loadings (λ), composite reliability (CR), and average variance extracted (AVE). The measurement model outputs satisfy the reliability requirements, as all factor loadings of each item disclose values above 0.6. Moreover, the convergent validity has been confirmed for the composite reliability (CR) surpass the correspondent average variance extracted (AVE) and both criteria exceed 0.7 as shown in Table 4 (Hair, 2009).

Likewise, the measurement model validity calls for discriminant validity testing. For that, this study used square root of AVEs (Fornell-Larcker criterion) and Heterotrait-Monotrait ratio (HTMT) criteria (Henseler et al., 2015). Table 5 exhibits the inter-constructs correlations values and the square root of AVEs represented on the diagonal. The results indicate that the latter values are superior than all construct's correlations which meet the required standards of the Fornell-Larcker criterion.

For further discriminant validity testing, the HTMT display an adequate indicator. The obtained outcomes indicated in Table 6 denote that the most significant value in the matrix is 0.89 respecting therefore the threshold of 0.90. subsequently, the findings of both Fornell-Larcker

Table 4
Reliability and validity test results.

Constructs	Items	Loading/ weights	Cronbach's alpha	CR	AVE	VIF
AI	AI1	0.894	0.922	0.945	0.813	2.368
	AI2	0.969				1.979
	AI3	0.806				1.999
	AI4	0.927				2.844
DNE	DNE1	0.923	0.874	0.904	0.702	2.180
	DNE2	0.923				2.890
	DNE3	0.712				1.726
	DNE4	0.823				2.111
	DNE5	0.945				1.209
	DNE6	0.854				1.802
	DNE7	0.944				1.637
	DNE8	0.887				1.700
AFSCE	AFSCE1	0.851	0.948	0.958	0.766	3.066
	AFSCE2	0.927				2.108
	AFSCE3	0.846				3.205
	AFSCE4	0.829				1.598
	AFSCE5	0.855				2.603
	AFSCE6	0.898				1.557
AFOP	AFOP1	0.963	0.943	0.957	0.79	1.301
	AFOP2	0.955				1.688
	AFOP3	0.973				2.518
	AFOP4	0.938				3.066
AIAI	AIAI1	0.811	0.929	0.944	0.706	3.050
	AIAI2	0.742				1.373
	AIAI3	0.85				1.375
	AIAI4	0.885				1.881
	AIAI5	0.801				2.469

Table 5
Fornell-Larcker test.

	AI	AIAI	DNE	AFOP	AFSCE
AI	0.986				
AIAI	0.446	0.813			
DNE	0.786	0.581	0.952		
AFOP	0.795	0.538	0.854	0.956	
AFSCE	0.782	0.484	0.846	0.737	0.953

Table 6
Heterotrait-monotrait ratio (HTMT) criterion.

	AI	AIAI	DNE	AFOP	AFSCE
AI					
AIAI	0.393				
DNE	0.798	0.592			
AFOP	0.815	0.486	0.879		
AFSCE	0.835	0.483	0.890	0.779	

and HTMT criteria prove the absence of any discriminant validity issues.

5.2. Structural model assessment

The previous section has demonstrated the reliability and the validity of the measurement model, the current step consists in testing developed hypothesis and direct and indirect effects using PLS-SEM and bootstrapping approaches.

As the structural model presented in Fig. 1 shows, the results of path analysis reveal that 69.5 % of the total variance in AFOP is explained by the AFSCE, which in turn 94.3 % of its variance is attributed to AI, DNE and AIAI. In addition, the outcomes show that AI and AIAI explain 84.3 % of the variance in DNE.

The SEM results indicates also that all the direct relationships are positively significant regarding their correspondent outcome constructs. As a consequence, since all R^2 values are above 0.1 (Table 8), all the hypothesis developed in this study H1, H2, H3 and H4 are supported (Falk and Miller, 1992) (See Table 7). Simply put, AI based technology is

Table 7
Hypothesis testing outcomes.

	β	Standard deviation (STDEV)	T statistics	P values	Decision
AI - > DNE H1	0.864	0.042	2.628	0.000	Supported
AI - > AFSCE H2	*0.473*	*0.041*	*2.371*	*0.000*	*Supported*
DNE - > AFSCE H3	0.580	0.035	2.013	0.000	Supported
AFSCE - > AFOP H4	*0.834*	*0.014*	*8.516*	*0.000*	*Supported*

directly and positively related to distribution network efficiency and afri-food supply chain efficiency ($\beta = 0.864$, $P < 0.01/\beta = 0.473$, $P < 0.05$) respectively. Similarly with the mediation constructs which exhibit that DNE is positively associated with AFSCE ($\beta = 0.580$, $P < 0.05$), which in turn directly affect agri-food organizational performance ($\beta = 0.834$, $P < 0.05$).

The model also display that the predictive relevance is established as Q^2 values of all endogenous variable are >0 (Table 8) and a goodness of it with standardized root mean square (SRMR) <0.1 which indicate an acceptable model fit (Esposito Vinzi et al., 2010).

5.3. Moderated mediation test

In order to examen the final hypothesis H5a, H5b which state that AI adoption impediments AIAI moderate the relationship between AI implementation and distribution network efficiency and agri-food supply chain efficiency respectively, a moderation analysis was performed using PROCESS macro (model 58 suggested by Hayes, 2018).

In the context of direct and indirect effects on correspondent outcome construct, the analysis is conducted using 10,000 bootstrap samples at a confidence level of 95 %. In this context, a conditional indirect effects analysis of AI adoption on afri-food organization performance through distribution network as moderated by AI adoption impediments is conducted based on both mediation and moderation effects examination.

Regarding mediation analysis, the outcomes reveal that DNE mediate significantly the relationship between AI adoption and AFSCE ($\beta = 0.367$, $P < 0.05$) and the latter represents a significant mediator of AI and AFOP ($\beta = 0.457$, $P < 0.05$).

According to the PROCESS analysis results, the AI adoption impediments negatively and significantly moderate the effect of AI adoption on both distribution network efficiency (effect $= -0.170$, $P < 0.05$) and AFSCE ($\beta = -0.042$, $P < 0.05$) (Table 9).

Furthermore, the moderating effect of AIAI on the relationship between AI adoption and distribution network and agri-food supply chain efficiencies is shown using Johnson-Neyman plot, which indicate simple slopes comparison between high and low standard deviation (SD) of AIAI. The results exhibit that high AI adoption impediments dampens the positive relationship between AI technology adoption and DNE and AFSCE respectively, hence proving the validation of H5a (simple slope $= -0.034$, $P < 0.05$) and H5b (simple slope $= 0.082$, $P < 0.05$). (See Fig. 2 and Table 10).

Table 8
Predictive capability and relevance.

	R^2	Q^2
DNE	0.843	0.601
AFOP	0.695	0.673
AFSCE	0.943	0.713

Table 9
Moderated mediation analysis.

Total effect	β	SE	T-values	P
AI - > AFOP	0.779	0.017	4.693	0.000
Mediation effects				
AI - > DNE - > AFSCE	0.367	0.019	1.918	0.000
AI - > AFSCE - > AFOP	0.457	0.018	2.473	0.000
AI - > DNE - > AFSCE - > AFOP	0.322	0.019	1.706	0.000
Moderation effect				
AIAI x AI - > DNE - > AFSCE	−0.170	0.169	1.749	0.000
AIAI x AI - > AFSCE - > AFOP	−0.042	0.042	0.073	0.017

6. Discussion

The increasing complexity of today's Moroccan supply chains has made them exposed to numerous sources of disruptions and vulnerability which may impact their functioning and performance. As such, waste eliminating, cost reduction and operations efficiency become a must for ensuring organizations' durability and robustness especially with the challenges of the inclusiveness of agricultural policy and resources scarcity beside manufactured products quality and pace (Lacirignola and Abis, 2016). As such, strengthening the digitalization of Moroccan agri-food supply chain stands as one of the main and appropriate strategies destines to recolonized and innovate agribusinesses to ensure real-time optimization, lead to greater agri-food products security, and improve the efficiency and sustainability of the agri-food industry (Olivier Treguer, 2019). Yet, achieving efficiency hinges on quick and adequate decision making, and operations management and optimization. The existing literature suggests that firms could ensure a digital enabled AFSCE through AI implementation to minimize manufacturing costs and enhance profitability and performance. Current studies remain relatively scarce due to their limitation to the internal processes disregarding the external ecosystem of the chain that is also contextually dependent and little is known about how distribution logistics digitalization can be a critical factor for achieving AFSCE (Helo and Hao, 2021). The main objective of this research is to fill this gap and develop a reliable and valid model that contributes to SCE theoretically and practically through the development of an AFSCE measurement instrument taking into consideration the downstream dimension of the chain.

In that respect, the study has examined the potential impact of AI based technology on enhancing firms' performance in the agri-food industry. Our keys findings based conceptual framework support the current literature as it revealed that the implementation of AI technology significantly influence agri-food supply chain efficiency, hence agri-food firms' performance (Ivanov et al., 2019).

The agri-food supply chain success is highly associated to firms' capability to adapt and innovate their resources to withstand the changing external environment, which indicate the significance effect of processes operational efficiency. Based on dynamic capability view (Teece, 2007, 2014), this study suggests that agri-food firms focus massively on their distribution system and to which the greatest attention should be paid in the future plans and actions to ensure value chains efficiency in the Moroccan territory due to the fact that the distribution logistics account for most of inefficiency sources (inventory, transportation, delivery, etc.) and the energy crisis has increased the network vulnerability. For that, the bulk of the agri-food supply chain partners have shown some proclivity toward digitalization of their logistics operations in order to improve efficiency and take advantage of the productivity gains it generates. Our finding shows that distribution network efficiency plays a crucial role in enhancing the overall AFSCE.

The results indicate that distribution logistics target numerous agri-food areas: first of all, minimizing products waste is the primary concerns for agribusinesses. An efficient distribution system helps in minimizing lead-time for agile reaction to market changes and can provide perishable products movement through the supply chain quickly and safely to the final customer before the expiration date. Furthermore, by developing an efficient distribution network, firms can manage inventory levels more effectively avoiding hence overstocking and understocking which can improve capital utilization. In addition, though efficient routing and transportation mode selection, distribution management can result in cost reduction especially in the agri-food business where transportation expenses can reach a sizeable portion of the overall prices.

Table 10
Moderation effects results.

Levels of moderator	Effect	SE	LLCI	ULCI
Conditional indirect effect of AI on AFSCE via DNE at different levels of AIAI				
Low	−0.253	0.025	0.206	0.304
High	−0.542	0.018	0.504	0.574
Mean	−0.397	0.020	0.357	0.435
Conditional indirect effect of AI on AFOP through AFSCE at different levels of AIAI				
Low	−0.258	0.013	0.206	0.300
High	−0.247	0.024	0.233	0.284
Mean	−0.253	0.017	0.223	0.289

Notes: SE = standard error; LLCI and ULCI = lower and upper levels for the confidence interval.

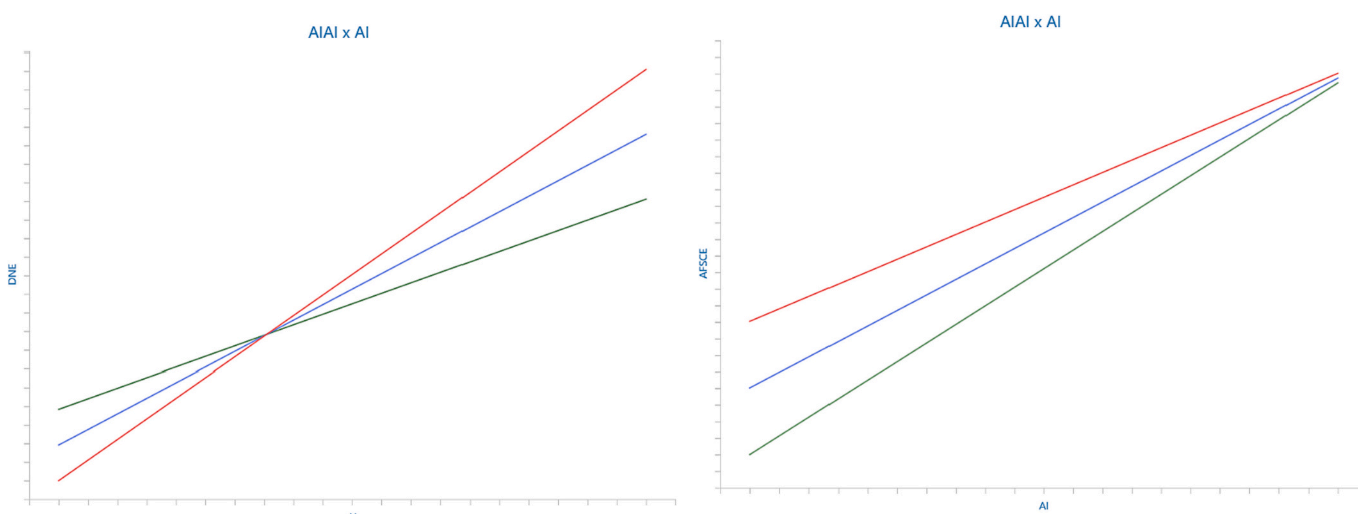

Fig. 2. Moderating effects on the relationship between AI→DNE and AI→AFSCE.

On the other hand, relying on OIPT (Galbraith, 1974), the study exhibits that AI through its capability of assisting firms ability in processing the significance amount of informations, agri-food supply chain stakeholder can identify inefficacies along the chain making by making more informed decision with regards to manufacturing, transportation and distribution. Furthermore, AI based technologies such as sensors and algorithms provide real time data about external environment and market changes which enables firms to enhance their predictive capabilities and forecast demand fluctuations that helps optimize inventory levels and on-time last-mile delivery time through route optimization and dynamic scheduling leading to reducing time, resources consumption and operational costs besides improving resource preservation and customer service. The findings also reveal that AI empowered technologies ensure waste and helps minimizing the risks of unsafe and low quality product by monitoring their state all along the transit (Gölge and Türk, 2019)., energy consumption and earning in sustainability by achieving net-zero supply chains as was conceptualized using OIPT. As a result, the application of AI represents in itself a catalyst of productivity, accuracy and efficiency of the warehouse and the retail process. Not only that, but since the distribution function stands for the almost 90 % of carbon emission among all links, the establishment of AI assists in minimizing wastes and greenhouse emissions and improving service quality enabling therefore agri-food organizations to perform more efficiently not only from sustainability perspective but from an economic point of view as well (Khan et al., 2021, p. 4). Nevertheless, the study has revealed that with smart agri-food industry in Morocco being still in its infancy, numerous challenges such as sector resistance and the absence of vision and digital strategy can preclude the development of this sector in intelligent perspective. Consequently, the digital transition of the agri-food supply chain in Morocco will require a serious effort mobilization from both public and private sectors to build and improve digital infrastructure particularly in rural regions, enhance regulatory framework and boost digital technical knowledge.

6.1. Theoretical implications

Theories can be developed in several ways. Along these words of (Reay and Whetten, 2011) fits our theoretical contributions. Through this research, the authors shed light on new constructs which have not been widely discussed in previous literature such as outbound or distribution logistics and agri-food supply chain efficiencies. This study supports the current knowledge of AI adoption and its impact on firms supply chain efficiency, hence, performance in the afri-food industry, displaying the significance that downstream logistics have in operations management. Instead of relying on a single theory, this study uses both Dynamic capability view (DCV) and Organizational Information-Processing Theory (OIPT). This research suggests an adequate theocratical outline, which was expressed that intelligent transportation, smart warehousing and a sustainable packaging with revers logistics via AI based technology may lead to improvement in agri-food firms whole supply chains. That is to say, AI significance resides in its capability to improve waste management practices and reduce production costs and offer sustainable and economic efficiency.

6.2. Practical implications

Reducing costs and optimizing resources usage has been the paramount issues troubling supply chain managers. Especially in the Moroccan agri-food industry where the cold chain is more concerned with preserving goods quality all along the value chain, but most specifically when handling deliveries to the final customer. As such, driven by the private-public sectors collaboration, the recourse to emerging technologies and digitalization has already entered into execution reflecting the Moroccan vision to ensure the industry efficiency and sustainability. Along these lines fit the study's managerial contributions in providing guidance to managers and policy makers of the agribusiness on the potentials of AI based technologies which integrate the strategy of the decision makers in achieving economic rise. First, it provides a better understanding on how such applications can support data-driven decision making. The real-time information processing provided about firms' both internal and external background enabling the chain stakeholder to apply the appropriate strategies to address production, transportation and distribution. For instance, sensors, drones and other artificial internet of things AIoT based technologies can improve visibility and offer manufacturers clean data about soil and other products conditions in addition the weather patterns. This allows the use of resources with precision minimizing wastage and improving production process. Moreover, the embedding of AI driven machinery reduces the reliance on human capital in processing and harvesting rising as useful strategy facing labor shortage disruptions. Not only that, computer vision systems will facilitate the monitoring of the products state during processing and packaging ensuring that only high-quality products reach the final customer. As far as the distribution system is concern, AI tackles some challenging issues that most executives struggle with. At the outset, implementing AI algorithms helps firms forecast potential disruptions in the market dynamics. This allows them to optimize and synchronize production with inventory levels to circumvent any outstocking hence a lost profit or overstocking culminating in a significance lost saving. Similarly, the outcomes indicate that systems based on AI improve the delivery process as they can optimize resource allocation by adjusting vehicle load balancing and delivery routing minimizing lead time, energy consumption, and the bulk of operational cost ensuring simultaneously the competitiveness of businesses and the sustainable efficiency of the agri-food supply chain. Therefore, the study suggests that the orientation for AI implementation, agri-food organizations supply chains should benefit from both economic and sustainable efficiency. Eventually, for sector experts, exploring the relationship between AI and AFSCE will support the Moroccan ministry campaign to speed the transition toward smart afri-food supply chains.

7. Conclusions and limitations

AI based technologies adoption in supply chains have been the main consideration of numerous researches as of late. Based on DCV and OIPT, the authors explore how agri-food organization can develop their information process capability in achieving efficiency in their operational activities via the implementation of AI technologies. They further examine how logistics notably transportation, warehousing and distribution effectiveness and efficiency mediates the relationship and path of joining AI and agri-food supply chain efficiency as a whole. The contribution to the OIPT lies in providing empirical evidences on how AI driven logistics improve AFCSE by reducing inefficiencies, wastes and costs from economic and environmental perspective. Furthermore, the measured moderating effect of AI adoption barriers on the mediated relationship of AI and AFSCE has shown to be significant.

Nevertheless, the current research is subject to some limitations that can be taken into consideration for future studies. First of all, our theoretical model and hypothesis were developed and tested using a PLS-SEM employing survey-based data. The latter even if constructs' reliability and validity were checked can still be weakened as CMB cannot be eliminated totally. Besides, PLS-SEM does not provide an established goodness of fit measure whish make its utilization in some situations to test theory limited (Hair et al., 2021). the sample used in this study is considered small regarding the complexity of factors which may affect the representativity and data reliability. In addition, the study is limited to the Moroccan agri-food industry which is a limitation itself. All that presents an opportunity for further analysis by considering digital-driven logistics in other industries, regions and countries especially developing ones. Further researches could also develop more valid models and concentrate on scrutinizing profoundly each link of the agri-food supply chain perception of specific AI powered technologies.

CRediT authorship contribution statement

El Mehdi El Bhilat: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft. **Asmae El Jaouhari:** Writing – original draft, Investigation. **L. Saadia Hamidi:** Supervision.

Declaration of competing interest

None.

Data availability

Data will be made available on request.

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Appendix A. Measurement scales

Constructs	Item	Statement	Source
AI	AI1	Our organization has the infrastructure and skilled resources to apply AI to the information processing system	(Frank et al., 2019; Hallikas et al., 2021)
	AI2	Our organization has implemented AI partially or completely in SC supply chains to improve efficiency.	
	AI3	Our organization uses AI results to inform decision making in CS.	
	AI4	Our organization develops statistical, self-learning and predictive tools using AI.	
DNE	DNE1	Our company is able to improve inventory accuracy to track stock levels in real time.	(Heard et al., 2018; Lau, 2013; Liu et al., 2022b; Maqueira et al., 2020)
	DNE2	Our organization can easily modify warehouse space and track load capacity utilization.	
	DNE3	Our organization offers sustainable packaging that is physically designed to optimize materials and energy.	
	DNE4	Deliveries in our organization are able to adjust/modify their routes based on changes in customer demand.	
	DNE5	Our organization can manage outbound transportation and improve freight control by reducing empty miles.	
	DNE6	Our company is able to efficiently manage the return of goods.	
	DNE7	Our organization is able to respond to customer requests without delay	
	DNE8	Our company is able to ship different types of high-quality products in good conditions.	
AFSCE	AFSCE1	Total cost of distribution, including transportation and handling	(Dubois et al., 2019; Tsolakis et al., 2014)
	AFSCE2	Reduction in waste and waste disposal costs	
	AFSCE3	Reduction in energy consumption	
	AFSCE4	Improved efficiency of resource management	
	AFSCE5	Improved compliance with environmental standards	
	AFSCE6	On-time delivery, fast service	
AFOP	AOP1	Ability to reduce manufacturing operating costs	(O'Grady et al., 2019)
	AFOP2	Ability to execute a perfect order (complete, without delay and without damage).	
	AFOP3	Improvement in sales and market share.	
	AFOP4	Improvement of product image.	
AIAI	AIAI1	Lack of digital strategy	(Tzachor, 2021)
	AIAI2	Illiteracy and knowledge lack	
	AIAI3	Lack of clarity on benefits	
	AIAI4	Resistance of agribusiness actors to change	

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