American Journal of Interdisciplinary Studies

Volume: 4; **Issue:** 4
Pages: 177-209
eISSN: 3067-5146

COMPARATIVE STUDY OF U.S. AND SOUTH ASIAN AGRIBUSINESS MARKETS: LEVERAGING ARTIFICIAL INTELLIGENCE FOR GLOBAL MARKET INTEGRATION

Abdul Hye[1]; SM. Toufiqur Rahman[2];

[1]. Master of Business Analytics, Trine University, USA; Email: a.hyedvm@gmail.com

[2]. Executive, Veterinary Service Department, Square Pharmaceuticals PLC, Bangladesh; Email: drtsrahman@gmail.com

Doi: 10.63125/z1e17k34

Received: 18 September 2023; **Revised:** 21 October 2023; **Accepted:** 29 November 2023; **Published:** 26 December 2023

Abstract

This study investigates how artificial intelligence enabled, data driven decision making supports global market integration among agribusiness firms in structurally different systems in the United States and South Asia. The problem addressed is the lack of quantitative, comparative evidence on whether and how AI capabilities translate into higher export intensity, market diversification and participation in global value chains for agribusiness enterprises. The purpose is to test a TOE based model linking AI adoption, organizational and environmental conditions and data driven decision practices to firm level global market integration. A quantitative, cross sectional, case-based design was applied using a structured five-point Likert survey of 320 agribusiness enterprise cases, comprising 162 U.S. firms and 158 South Asian firms. Key variables included AI Adoption, Data Driven Decision Making, Supply Chain Connectivity, Organizational Readiness, Environmental Support and Global Market Integration indices. Reliability was high (a = 0.89 for AI adoption, 0.87 for data driven decisions, 0.88 for market integration), and analysis combined descriptive statistics, correlation and multiple regression. AI adoption ($\beta = 0.34$, $p < 0.001$) and data driven decision making ($\beta = 0.28$, $p < 0.001$) together raised explained variance in global market integration to 41.5 percent, with a strong bivariate correlation between AI adoption and integration ($r = 0.56$, $p < 0.001$). U.S. firms showed higher mean AI adoption ($M = 3.84$ vs 3.21) and a stronger AI integration linkage than South Asian firms. The findings imply that AI should be treated as a strategic, enterprise level capability for agribusiness internationalization, while investments in organizational readiness, secure data infrastructure and supply chain connectivity are especially critical in South Asia for converting AI use into durable global market gains.

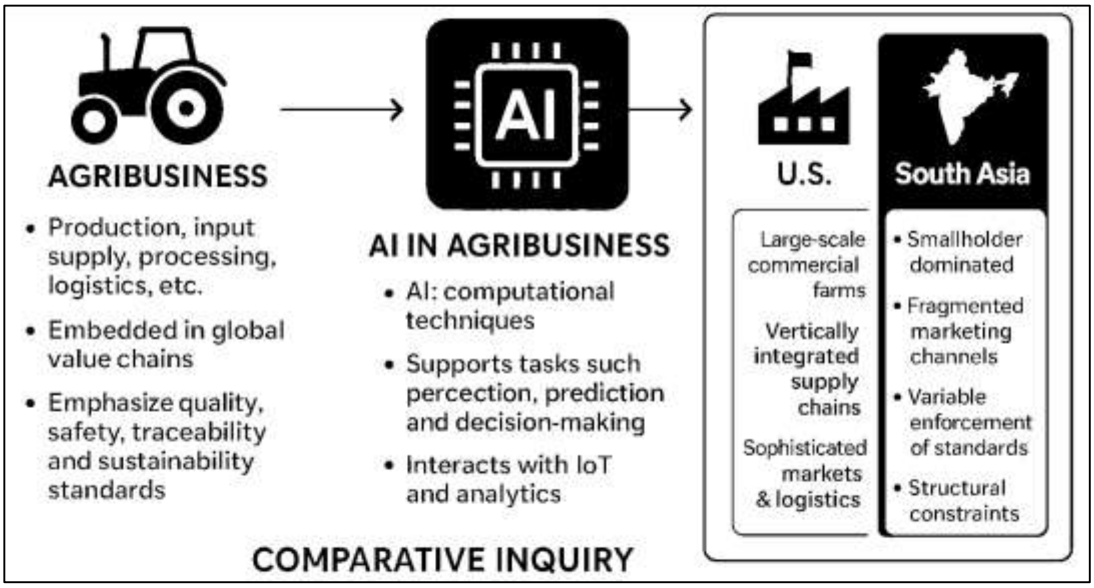
Keywords

Artificial Intelligence, Agribusiness, Global Market Integration, Data Driven Decision Making, United States And South Asia;

INTRODUCTION

Agribusiness is widely defined as the coordinated set of activities that link agricultural production with input supply, processing, logistics, finance and downstream food, feed, fibre and biofuel markets, embedded within national and international value chains (Humphrey, 2006). In the context of globalization, agribusiness has become a central pillar of world trade, with cross-border flows of agricultural commodities, processed foods and agri-inputs shaping food security, rural livelihoods and macroeconomic stability across regions. Comparative analyses show that agri-food trade competitiveness is increasingly determined by the ability of firms and territories to meet quality, safety, traceability and sustainability standards, rather than by primary production alone (Bojnec & Fertő, 2021). Artificial intelligence (AI) adds a new layer to this landscape: it can be defined as a family of computational techniques that enable machines to perform tasks typically associated with human intelligence, including perception, prediction, optimization and decision support (Jha et al., 2019). Within agriculture, AI interacts with big data, Internet of Things (IoT) devices and advanced analytics to support precision production, supply-chain coordination and risk management (Wolfert et al., 2017). Against this backdrop, a comparative inquiry into how U.S. and South Asian agribusiness markets leverage AI for global market integration situates the study at the intersection of international trade, technological innovation and rural development, with direct relevance for policy, business strategy and sustainable development agendas (Eli-Chukwu, 2019).

Figure 1: AI-Enabled Agribusiness Landscape Across U.S. and South Asian Markets



Across countries, agribusiness markets exhibit marked heterogeneity in their structural features, institutional arrangements and levels of technological sophistication. In high-income economies such as the United States, agribusiness is characterized by large-scale commercial farms, vertically coordinated supply chains, sophisticated risk-management instruments and strong integration with global capital and futures markets. Studies of agri-food value chains highlight the role of lead firms, retailers and processors in setting quality and coordination requirements that cascade backward to producers (Humphrey, 2006). In contrast, agribusiness markets in South Asian economies such as India, Bangladesh, Pakistan and Sri Lanka are dominated by smallholders, fragmented marketing channels, multi-layered intermediation and variable enforcement of grades and standards, even as these countries participate actively in regional and global agri-food trade (Nakasone et al., 2014). Empirical work on ICT-enabled market information services documents how structural constraints such as limited storage, weak logistics and uneven bargaining power shape farmers' ability to benefit from price information and new market opportunities (Aker, 2010). This contrast generates a rich comparative setting in which to study how AI-enabled decision systems are embedded in different agribusiness market architectures and how they support, or constrain, deeper integration of South

Asian markets with U.S. and global demand for agricultural commodities and processed foods (Alambaigi & Ahangari, 2016).

AI applications in agriculture and agribusiness span the entire data lifecycle, from sensing and data acquisition to modelling, optimization and real-time control. Reviews of digital and smart farming show that sensor networks, satellite and drone imagery, robotics and farm-management information systems generate large volumes of high-frequency data at the field and enterprise levels (Arfan et al., 2021; Oliveira & Martins, 2011). Machine-learning models transform these data into predictions of yield, disease outbreaks, soil moisture or input needs, which support fine-grained production decisions and resource allocation (Ara, 2021; Liakos et al., 2018). Deep-learning architectures improve pattern recognition in complex images and time series, enabling automated detection of pests, weeds and quality defects that would be difficult to monitor at scale with manual inspection (Jahid, 2021; Nakasone et al., 2014). Survey articles emphasize that these technologies are not confined to production alone; they increasingly connect with logistics, finance and marketing functions as part of broader "Agriculture 4.0" and digital agriculture paradigms (Klerkx et al., 2019; Akbar & Farzana, 2021). This body of work provides an essential conceptual foundation for the present study, which views AI not only as a productivity-enhancing tool on farms but also as an infrastructure for data-driven decision-making throughout agribusiness value chains in both U.S. and South Asian contexts (Ingram & Maye, 2020; Reza et al., 2021).

Beyond the farm gate, the integration of AI into agri-food supply chains has emerged as a distinct research stream, linking operations management, logistics and international trade. Bibliometric and scoping reviews of AI in extended agri-food supply chains identify applications in demand forecasting, inventory optimization, route planning, cold-chain monitoring, quality prediction, and fraud and anomaly detection, often combining machine-learning models with sensor and transactional data (Monteiro & Barata, 2021a; Saikat, 2021). Big-data architectures enable real-time monitoring of flows of commodities, inputs and information across multiple tiers of suppliers, processors, distributors and retailers, which can reduce lead times, coordinate just-in-time deliveries and support compliance with export market requirements (Scherer et al., 2019; Shaikh & Aditya, 2021). In international contexts, where agri-food trade competitiveness hinges on reliability, traceability and the ability to respond quickly to shifting consumer preferences, AI-enabled analytics can support segmentation, contract design and portfolio diversification for exporting firms (Baker, 2012; Kanti & Shaikat, 2021). Social-science perspectives on digital agriculture add that power relations, data ownership and institutional arrangements influence how these technologies are adopted and governed along value chains (Klerkx et al., 2019; Ariful & Ara, 2022). For a comparative study of U.S. and South Asian agribusiness markets, these insights motivate a focus on how AI-enabled systems are deployed in areas such as export logistics, quality certification, market intelligence and risk analytics, and how this deployment relates to different regulatory regimes, infrastructure levels and firm capabilities across regions (Kamilaris & Prenafeta-Boldú, 2018; Arman & Kamrul, 2022).

A substantial body of work analyzes how information and communication technologies (ICTs) transform agricultural market participation and integration, particularly in low- and middle-income countries. Experimental and quasi-experimental evaluations of mobile phone–based market information and advisory services in India and other settings report improved access to timely price and weather information, stronger spatial arbitrage, changes in cropping patterns, and adjustments in grading and quality management, though price and income effects vary across contexts (Fafchamps & Minten, 2012; Mesbaul & Farabe, 2022). Syntheses of the ICT revolution in agricultural development emphasize the rapid diffusion of mobile connectivity and digital services in rural areas, and document their role in lowering search costs, improving bargaining positions and facilitating linkages with traders, processors and input suppliers (Nahid, 2022; Nakasone et al., 2014). Reviews of ICT in agriculture highlight applications in extension, credit scoring, warehouse receipt systems and contract farming, as well as constraints related to connectivity, digital literacy and institutional support (Hossain & Milon, 2022; Monteiro & Barata, 2021a). These studies show that digital tools can strengthen the integration of smallholders into higher-value agribusiness chains, including export-oriented markets, when embedded in supportive organizational and policy environments. Building on this evidence, the present research positions AI as an extension of earlier ICT waves, with a special focus on its capacity

to generate predictive market intelligence and decision support for firms and farmers in both U.S. and South Asian agribusiness systems (Abdur & Haider, 2022; Wolfert et al., 2017).
Theoretical frameworks for technology adoption and organizational innovation provide a structured lens for examining how AI diffuses through agribusiness markets. At the firm level, the Technology–Organization–Environment (TOE) framework conceptualizes adoption decisions as shaped by technological attributes (such as relative advantage, complexity and compatibility), organizational characteristics (including size, resources and strategy) and environmental conditions (such as competition, regulation and external support) (Baker, 2012; Mushfequr & Praveen, 2022). Reviews of information-technology adoption models indicate that TOE is frequently combined with diffusion-of-innovation and institutional perspectives to explain adoption of e-business, cloud computing and other digital innovations across sectors (Mortuza & Rauf, 2022; Oliveira & Martins, 2011). Complementarily, the Technology Acceptance Model (TAM) and its extensions emphasize perceived usefulness and perceived ease of use as psychological determinants of individual acceptance of ICT tools, and meta-analytic work shows robust relationships between these constructs and actual adoption behavior (Rakibul & Samia, 2022; Scherer et al., 2019). Empirical applications of TAM and related models in agricultural contexts, including studies of ICT and decision-support tools among extension agents and farmers, demonstrate their relevance for understanding uptake of digital innovations in the rural sector (Alambaigi & Ahangari, 2016; Rony & Ashraful, 2022). By integrating TOE-type organizational determinants with TAM-inspired perceptions of AI-based tools, this study conceptualizes AI adoption in agribusiness as a multi-level process involving firms, managers and frontline decision-makers within specific market and policy environments in the United States and South Asia.
Within this conceptual and empirical landscape, an important gap concerns systematic, quantitative comparison of how AI-enabled decision systems contribute to global market integration across structurally different agribusiness regions. Existing reviews of AI in agriculture tend to focus on technical feasibility and case-specific performance metrics rather than on cross-regional market outcomes (Jha et al., 2019; Saikat, 2022). Work on digital agriculture and smart farming provides rich insights into adoption drivers, labor dynamics and governance issues, yet often concentrates on either developed-country or developing-country settings in isolation (Klerkx et al., 2019; Shaikh & Sudipto, 2022). Similarly, literature on ICT-based market information services in South Asia and other regions examines the effects of basic digital tools on farmer welfare and market participation, but does not typically extend to advanced AI-driven analytics or to explicit comparison with U.S. agribusiness markets (Abdul, 2023; Aker, 2010). Research on agri-food trade competitiveness and value chains, in turn, highlights structural and policy determinants of export performance without systematically incorporating AI as an explanatory factor (Abdulla & Zaman, 2023; Humphrey, 2006). The present study addresses this intersectional gap by designing a quantitative, cross-sectional, case-study–based comparative analysis of U.S. and South Asian agribusiness firms, using Likert-scale survey data and descriptive statistics, correlation analysis and regression modelling to examine how AI adoption, data-driven decision-making and related organizational capabilities are associated with indicators of market integration, export orientation and participation in global agribusiness networks.
The overarching objective of this study is to conduct a rigorous, quantitative comparison of how agribusiness firms in the United States and South Asia adopt and utilize artificial intelligence to support their integration into global markets. First, the study seeks to systematically measure the level and nature of AI adoption across key segments of the agribusiness value chain, including production, processing, logistics, marketing, and export management, in both regional contexts. Second, it aims to evaluate the extent to which AI-enabled tools and systems are associated with firm-level indicators of global market integration such as export intensity, market diversification, participation in global value chains, and the ability to respond effectively to international quality, safety, and traceability requirements. Third, the research is designed to test a set of hypotheses that link AI adoption, organizational readiness and environmental conditions to global market integration outcomes, using a cross-sectional survey instrument based on a five-point Likert scale and analyzed through descriptive statistics, correlation analysis, and regression modeling. A further objective is to compare the strength and direction of these relationships between U.S. agribusiness firms and their South Asian counterparts, thereby identifying systematic differences or similarities in patterns of AI use and market

integration. The study also intends to operationalize and empirically examine key constructs derived from an integrated conceptual framework that combines technological, organizational and environmental dimensions with firm-level market integration performance. By structuring the investigation around clearly defined research questions and hypotheses, the study establishes a coherent analytical pathway from measurement of constructs, through statistical testing, to a structured comparative assessment of the two regional agribusiness systems. In this way, the objectives provide a focused agenda for data collection and analysis that centers on understanding how AI adoption is embedded in real agribusiness decision environments and how this, in turn, is associated with measurable outcomes related to firms' presence and behavior in global agribusiness markets.

LITERATURE REVIEW

The literature on agribusiness, digital technologies and global market integration has evolved along several partly overlapping strands that together provide the foundation for this study. Early work on global agri-food value chains and market restructuring emphasized how liberalization, standards and the rise of powerful retailers and processors reshaped the organization of production, trade and coordination, particularly distinguishing industrialized systems such as those in the United States from more fragmented structures in developing regions, including South Asia. Within this tradition, researchers examined how governance patterns, quality requirements and contracting practices influenced the participation of farmers and agribusiness firms in global markets, highlighting differences in scale, infrastructure and institutional support between regions. A second, rapidly expanding strand focuses on the diffusion of information and communication technologies in agriculture, documenting how mobile phones, internet connectivity and digital platforms altered price discovery, information flows and market access for producers and intermediaries in low- and middle-income countries. These studies established that digital tools can reduce search costs and information asymmetries, but also that structural constraints and uneven capabilities condition who benefits from such innovations. Building on this foundation, more recent contributions explore the rise of artificial intelligence and data-driven decision systems in agriculture and agribusiness, describing the integration of machine learning, sensing technologies and big-data analytics into crop management, logistics, quality control and market intelligence. This work has introduced concepts such as smart farming and agriculture 4.0, and has begun to interrogate how AI-enabled systems reshape decision-making at the farm, firm and value-chain levels. Parallel to these technology-focused perspectives, there is a substantial body of research on technology adoption and organizational innovation, including frameworks such as the Technology–Organization–Environment paradigm and the Technology Acceptance Model, which conceptualize how technological characteristics, organizational resources and environmental pressures interact to shape adoption outcomes. Yet despite these advances, there remains limited empirical, quantitative evidence on how AI adoption in agribusiness relates specifically to global market integration and how these relationships compare across structurally distinct regional systems such as U.S. and South Asian agribusiness markets, thereby motivating a focused synthesis of studies on agribusiness structure, digital agriculture, AI applications and technology adoption as the basis for the present comparative analysis.

Global Agribusiness Market Structures in the U.S. and South Asia

Global agribusiness market structures are shaped by how activities from input provision to retail are organized, coordinated, and governed across space and between actors, and these patterns differ markedly between the United States and South Asia. In high-income economies such as the United States, agrifood systems have evolved toward highly concentrated, capital-intensive, and vertically coordinated value chains in which a relatively small number of processors, traders, and retailers handle the majority of agricultural output and control access to end consumers. By contrast, South Asian agribusiness is still dominated at the production end by large numbers of smallholders selling into fragmented, often informal markets, even as modern processing and retail segments are emerging alongside traditional channels. Comparative research on the "supermarket revolution" shows how the rapid diffusion of large food retailers in developing regions has restructured procurement systems, increased product standardization, and shifted bargaining power toward downstream actors, with patterns in Asia increasingly resembling earlier U.S. experiences in supermarket expansion and consolidation (Humphrey, 2007). These structural shifts have been accompanied by new forms of vertical coordination, such as contract farming and preferred-supplier arrangements, which link geographically dispersed farms to processors and retailers and redefine who sets prices, standards, and delivery terms. Studies of agrifood industry transformation document how the rise of private standards, large-scale agribusiness firms, and complex value chains has altered the distribution of value and risk between farmers and downstream actors, with potentially inclusionary or exclusionary effects depending on farmers' asset base, bargaining power, and institutional context (Reardon et al., 2009). As a result, U.S. and South Asian agribusiness structures today differ not only in scale and technology intensity but also in the degree of concentration, contractualization, and the capacity of market intermediaries to coordinate information flows factors that are highly relevant for how artificial intelligence (AI) tools can be embedded in decision-making processes.

Figure 2: Global Agribusiness Market Structures: U.S. vs. South Asia

In the United States, agribusiness market structures are characterized by deep integration into global value chains, sophisticated logistics and information systems, and an institutional environment that strongly supports standardized contracting and risk management. Grain, livestock, and specialty crop markets are heavily intermediated by multinational trading houses, food manufacturers, and retail chains that coordinate quality, timing, and volumes through a mix of spot markets, long-term contracts, futures markets, and various forms of vertical integration. Empirical analyses of agricultural trade emphasize that U.S.-based firms capture significant value by occupying high-productivity segments such as processing, branding, and distribution within global agricultural value chains, while leveraging international trade agreements and investment rules to secure market access and influence the design of product and process standards (Maertens & Swinnen, 2015). At the same time, global value chain studies show that increasingly stringent food safety, traceability, and quality standards, administered through private certification schemes and buyer-driven protocols, govern market access for suppliers integrated into U.S.-centered chains and shape the distribution of rents along these chains (Lee et al., 2012). These standards intensify information and coordination requirements but also provide clear incentives for investment in data collection, traceability platforms, and AI-enabled monitoring systems that enhance efficiency in procurement, transportation, inventory management, and compliance auditing. Because many U.S. agribusiness firms already rely on consolidated digital data flows from farm management software, satellite or sensor-based monitoring, logistics providers, and retail scanners, the marginal cost of layering AI tools onto existing infrastructures is relatively low, and the ability to scale analytics across multiple regions and product lines is high. Consequently, the U.S. agribusiness structure can be viewed as a highly coordinated, data-rich environment in which AI applications for yield prediction, price forecasting, supply-chain optimization, and risk analytics are likely to integrate smoothly with already formalized and codified relationships across the value chain.

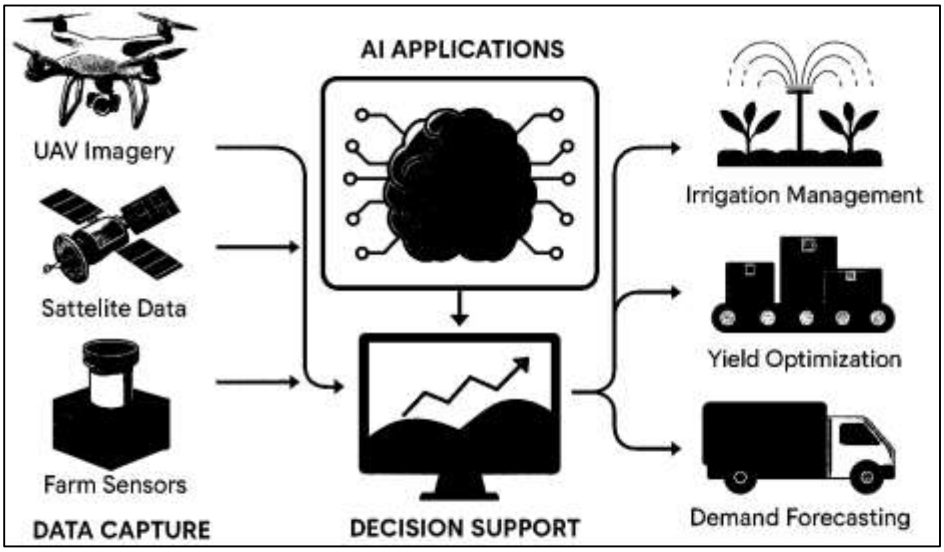
Across South Asia, agribusiness market structures are undergoing a gradual but uneven transition from traditional, spot-market-based systems toward more coordinated value chains that mirror some aspects of U.S. agribusiness while retaining strong smallholder and informal characteristics. Historically, farmers in countries such as India, Bangladesh, and Pakistan have sold predominantly through local traders and wholesale markets where price formation is driven by daily negotiations, information asymmetries, and limited quality differentiation, and where institutions for contract enforcement and quality assurance are often weak or unevenly applied. Comparative value chain research demonstrates that market liberalization, urbanization, and globalization have progressively encouraged private investment in processing, cold storage, logistics, and export-oriented horticulture, leading to the emergence of contract farming, out-grower schemes, and other forms of private vertical coordination in high-value commodities such as fruits, vegetables, dairy, and poultry (Ferdous Ara & Beatrice Onyinyechi, 2023; Swinnen & Maertens, 2007). At the same time, cross-country evidence on agrifood industry transformation indicates that midstream actors such as millers, wholesalers, commission agents, and logistics providers are expanding and modernizing, yet often operate with lower levels of formalization, infrastructure, and digitalization than their counterparts in the United States, resulting in persistent coordination failures and unequal access to upgrading opportunities (Arfan et al., 2023; Reardon et al., 2009). This dualistic structure, where modern value chains linked to export markets and urban supermarkets coexist with traditional circuits serving rural and low-income consumers, creates a heterogeneous landscape for AI adoption and global integration. On the one hand, export-oriented and urban-focused chains are increasingly governed by standards and contracts similar to those in developed markets, creating niches where data-driven quality control, logistics optimization, and price analytics can be deployed effectively in partnership with international buyers. On the other hand, large segments of domestic food trade remain constrained by thin margins, weak institutions, limited connectivity, and scarce reliable data, which restrict the feasibility of complex AI solutions and make issues such as data ownership, inclusion of smallholders, and the design of low-cost, context-appropriate digital tools central to any comparative assessment of U.S. and South Asian agribusiness market structures.

Artificial Intelligence and Digital Technologies in Agribusiness Operations

The integration of artificial intelligence (AI) into agribusiness has been enabled by a long trajectory of digital sensing and data-centric farm management. Early precision agriculture work demonstrated that within-field variability in soil properties, nutrients, and crop vigor could be detected using remote sensing and geospatial technologies, laying the empirical foundation for algorithmic decision-making at scale (Amin & Mesbaul, 2023; Mulla, 2013). As sensors evolved from simple, tractor-mounted devices to satellite platforms, aircraft, and more recently unmanned aerial vehicles (UAVs), the volume and granularity of farm-level data expanded dramatically, transforming agribusiness from a largely experiential activity into a data-intensive industry. This datafication is central to AI because it provides the multi-dimensional input needed for learning complex patterns in crop growth, stress, and resource use. Historical yield maps, vegetation indices, soil organic matter layers, and topographic data can be fused to support variable-rate input application, site-specific risk assessment, and profitability mapping, enabling more refined business decisions on land use and investment. At the same time, these technologies have begun to blur traditional divides between production, marketing, and logistics, as georeferenced field data can be integrated with procurement systems, quality standards, and contract specifications across global agribusiness value chains (Foysal & Aditya, 2023; Mulla, 2013).

Building on this digital foundation, AI and machine learning techniques are increasingly used to transform raw agronomic and environmental data into actionable insights for farm and firm management. High-resolution satellite and UAV imagery is now routinely processed using machine learning to estimate biomass, detect nutrient deficiencies, monitor water stress, and forecast diseases, expanding the analytical capacity of agribusinesses beyond what traditional scouting can achieve in large and spatially dispersed supply bases (Sishodia et al., 2020). Crop yield prediction has become a particularly important application, as reliable pre-harvest forecasts support contract design, hedging strategies, logistics planning, and negotiations with downstream buyers. Systematic reviews of yield-prediction models show that neural networks and other machine learning algorithms can leverage weather, soil, and management features to produce more accurate and timely forecasts than many classical statistical models, strengthening risk management and operational planning for both farmers and agribusiness corporations (van Klompenburg et al., 2020). When integrated into farm management information systems, these AI models function as decision-support tools that inform choices on crop selection, input timing, and technology adoption, aligning field-level technical decisions with broader commercial objectives such as cost minimization, quality differentiation, and supply reliability.

Figure 3: Artificial Intelligence and Digital Technologies in Agribusiness Operations

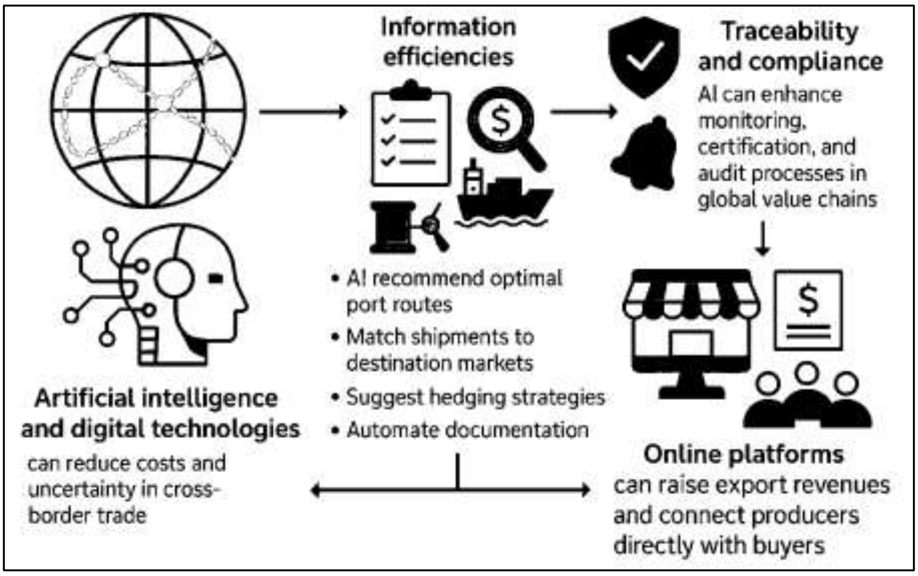


Beyond the field, AI applications are extending across the agri-food supply chain, linking production data with post-harvest operations, distribution, and market interfaces. At the production end, AI-enabled systems for irrigation scheduling, targeted spraying, and robotic operations can reduce input waste, lower environmental externalities, and stabilize yields, which in turn improves the reliability and competitiveness of agribusiness supply contracts (Hamidur, 2023; Talaviya et al., 2020). As value chains globalize, AI-driven analytics are increasingly used to orchestrate complex flows of raw and processed products, combining predictive models of supply, demand, and quality with real-time information from sensors, enterprise systems, and logistics platforms. Bibliometric analyses of AI in extended agri-food chains highlight emerging applications in demand forecasting, inventory optimization, cold-chain monitoring, and waste reduction, which rely on learning from large, heterogeneous datasets that span production, processing, distribution, and consumption (Harun-Or-Rashid et al., 2023; Monteiro & Barata, 2021b). For agribusiness firms operating simultaneously in U.S. and South Asian markets, these capabilities create opportunities to integrate multi-country sourcing, tailor products to diverse consumer segments, and respond dynamically to shocks or policy changes, while also raising new challenges around interoperability, data governance, and capability development across partners with uneven digital maturity.

AI-Enabled Global Market Integration in Agribusiness

Artificial intelligence (AI) and related digital technologies are increasingly recognized as infrastructural enablers of global market integration rather than merely add-on tools for farm management. In trade economics, information and communication technologies (ICTs) are shown to lower fixed and variable trade costs by improving search, coordination, and monitoring, which in turn stimulates export growth and diversification across a wide range of countries and product groups (Abeliansky & Hilbert, 2017). In agribusiness, similar mechanisms operate when AI-driven platforms match buyers and sellers, forecast demand, and optimize logistics across borders. In practice, these systems can recommend optimal port routes for grain exporters, match horticultural shipments to the most profitable destination markets, and suggest hedging strategies that align with predicted price movements. Machine-learning models that predict commodity prices, shipment delays, weather shocks, or phytosanitary risks can reduce uncertainty premiums embedded in contracts and enable exporters and importers to agree on tighter margins and longer-term arrangements. Natural language processing tools can also automate customs documentation, compliance reporting, and contract management, further lowering the informational barriers that traditionally disadvantaged smaller firms in cross-border exchange. These information efficiencies are particularly relevant for perishable agricultural commodities, where timing, cold-chain coordination, and quality verification have historically hindered participation of small and medium enterprises in distant markets. By embedding predictive analytics into market-matching and risk-management platforms, AI can therefore function as a "digital trade infrastructure" that complements physical transport and storage networks, creating new pathways for agrifood firms in both developed and emerging economies to integrate into regional and global value chains and to experiment with new export destinations and product mixes (Kos & Kloppenburg, 2019; Musfiqur & Kamrul, 2023). Over time, such integration mechanisms can reshape patterns of comparative advantage in agribusiness as data-rich firms learn faster and respond more precisely to international demand signals.

Figure 4: AI-Enabled Global Market Integration in Agribusiness



Beyond general trade facilitation, AI interacts with the governance structures of agrifood global value chains (GVCs) through its role in traceability, certification, and compliance management. Digital traceability architectures that combine sensor data, geospatial information, and algorithmic anomaly detection enable near real-time monitoring of production practices, environmental footprints, and social standards across complex supply networks (Liu et al., 2021; Md Muzahidul & Md Mohaiminul, 2023). This "hyper-transparency" can lower reputational and compliance risks for lead firms that source from geographically dispersed producers by providing verifiable data trails on origin, quality, and labour conditions. For upstream actors, AI-enhanced traceability and quality-scoring tools can help them signal compliance with increasingly stringent public and private standards in export markets, thereby mitigating information asymmetries that have historically marginalized smallholders from lucrative segments of global agrifood trade (Md. Al Amin & Sai Praveen, 2023; Yushkova, 2014). When digital monitoring reduces disputes over quality and quantity, it can also encourage buyers to experiment with new suppliers and origins, deepening market integration through more diversified sourcing portfolios. AI-enabled monitoring can similarly reduce the cost of third-party certification and auditing, making participation in sustainability-oriented or premium niche markets (such as organic, fair-trade, or low-carbon products) more accessible to agribusiness firms in South Asia and other developing regions. In parallel, automated compliance dashboards and real-time alerts can support exporters in adapting quickly to evolving sanitary and phytosanitary requirements in major destination markets. These capabilities are especially important in highly regulated product categories such as meat, dairy, and horticulture, where access to premium markets depends on continuous proof of compliance with sophisticated quality regimes. In this way, AI-driven data infrastructures influence not only the scale of cross-border trade but also the terms of participation, distribution of value added, and the ability of producers to upgrade into higher value functions such as branding, quality management, or sustainability reporting within agrifood GVCs (Kos & Kloppenburg, 2019; Hasan & Ashraful, 2023).

At the farm and firm levels, AI-enabled market integration is closely intertwined with the rapid diffusion of rural e-commerce and digital platforms that connect producers directly with domestic and international buyers. Micro-evidence from rural China shows that adoption of e-commerce for selling agricultural products raises farm-gate prices and overall gross returns, even after accounting for higher marketing and logistics costs, by allowing farmers to bypass layers of intermediaries and access broader markets (Liu et al., 2021; Ibne & Kamrul, 2023). When such platforms incorporate recommendation engines, dynamic pricing algorithms, and automated logistics routing, they effectively embed AI into routine trading decisions, scaling up the benefits of digital access into more systematic market integration outcomes. For agribusiness firms in the United States and South Asia, participation in AI-enabled marketplace ecosystems can translate into improved matching with global buyers, more accurate demand forecasts, and differentiated pricing strategies across export destinations, which together support higher export volumes and more stable revenue streams (Abeliansky & Hilbert, 2017; Mohammad Mushfequr & Ashraful, 2023). These platforms can also facilitate the emergence of cross-border producer alliances or cooperatives that pool data and negotiate collectively with buyers, potentially strengthening the bargaining position of smaller actors in high-value chains. At the same time, the uneven distribution of digital skills, data governance capacities, and AI infrastructure across regions raises the possibility that AI could widen rather than narrow existing gaps in agrifood trade performance (Pankaz Roy &Kamrul, 2023). Understanding AI-enabled global market integration in agribusiness therefore requires attention not only to the efficiency gains documented in digital trade literature but also to the institutional, infrastructural, and capability conditions that determine which firms and farming communities are able to convert new digital tools into sustained participation and upgrading within global agribusiness markets (Rodríguez-Crespo & Martínez-Zarzoso, 2019).

Theoretical Foundations

The theoretical foundation for this study is built around the Technology–Organization–Environment (TOE) framework, which conceptualizes the adoption and use of innovations as a function of three interdependent contexts: technological characteristics, organizational attributes, and environmental conditions. Rather than treating adoption as a simple binary decision, TOE-based models view innovation usage and value creation as continuous outcomes shaped by the fit between these contexts and the technology in question. For example, research on e-business has shown that technology competence, firm size, financial commitment, competitive pressure, and regulatory support jointly explain differences in how far organizations progress from adoption to intensive use and performance gains, with technology and organization variables often mediating the effects of country-level environmental conditions (Saba et al., 2023; Zhu & Kraemer, 2005). In parallel, studies of Internet and e-business technologies in small and medium enterprises (SMEs) have demonstrated that perceived benefits, organizational readiness, and external pressures interact to shape acceptance levels, indicating that structural constraints and managerial perceptions both matter for digital innovation uptake (Ifinedo, 2011; Saba & Tonoy Kanti, 2023). In the context of the present research, the TOE framework provides a natural lens to structure AI adoption in agribusiness as an outcome of technological factors such as data infrastructure and AI tool maturity, organizational factors such as management support and analytical capabilities, and environmental factors such as export-market standards, competition, and policy incentives across U.S. and South Asian markets.

Empirical TOE applications typically operationalize adoption as a function of multiple latent constructs and estimate their influence using multivariate statistical models. In cloud computing research, for instance, relative advantage, complexity, compatibility, top management support, technology readiness, competitive pressure, and trading partner pressure have been identified as significant determinants of adoption intention and actual use at the firm level (Low et al., 2011; Shaikh & Farabe, 2023). Similarly, work on big data analytics (BDA) adoption in logistics and supply chain management has grouped drivers into technological, organizational, and environmental dimensions and shown that perceived benefits and top management support directly influence adoption, while competitors' adoption, government policy, and supply chain connectivity moderate these relationships (Lai et al., 2018; Haider & Hozyfa, 2023). Following this logic, AI adoption in agribusiness can be conceptualized as a latent construct derived from Likert-scale items capturing the breadth and depth of AI use in production, logistics, and market analytics, and modeled as a function of TOE variables. At an abstract level, an adoption equation for firm *i* can be expressed as

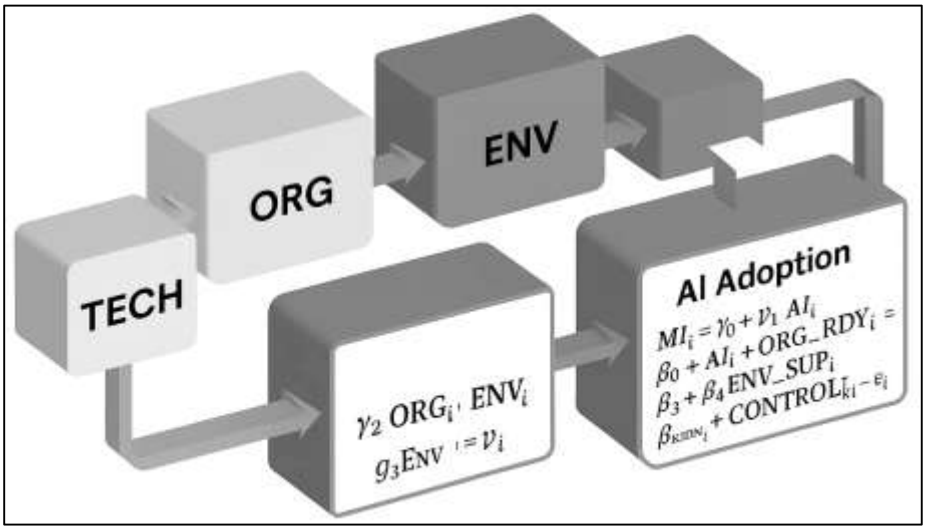
$AI_i = \gamma_0 + \gamma_1 \cdot TECH_i + \gamma_2 \cdot ORG_i + \gamma_3 \cdot ENV_i + \upsilon_i$,

or, when AI adoption is coded as a binary variable, in logistic form as

$P(AI_i = 1) = 1 / \{1 + \exp[-(\gamma_0 + \gamma_1 \cdot TECH_i + \gamma_2 \cdot ORG_i + \gamma_3 \cdot ENV_i)]\}$.

These expressions summarize the TOE insight that increases in technological readiness, organizational support, and favorable environmental conditions should raise the probability and intensity of AI adoption in agribusiness firms.

Figure 5: Technology–Organization–Environment (TOE) Framework



Building on these foundations, the present study extends TOE by explicitly linking AI adoption to firm-level global market integration outcomes in agribusiness and by incorporating the perceived strategic value of data-driven decision-making. Research on big data analytics adoption in emerging economies has integrated TOE with a perceived strategic value perspective and found that strategic value, complexity, compatibility, IT assets, top management support, organizational data environment, perceived costs, external pressure, and industry type jointly shape utilization and adoption decisions (Verma & Bhattacharyya, 2017). Adapting this logic, the conceptual model for this study views global market integration (MI) of agribusiness firms as an outcome variable influenced by AI adoption and moderated by organizational readiness and environmental support. At the firm level, this relationship can be represented in a regression equation of the form

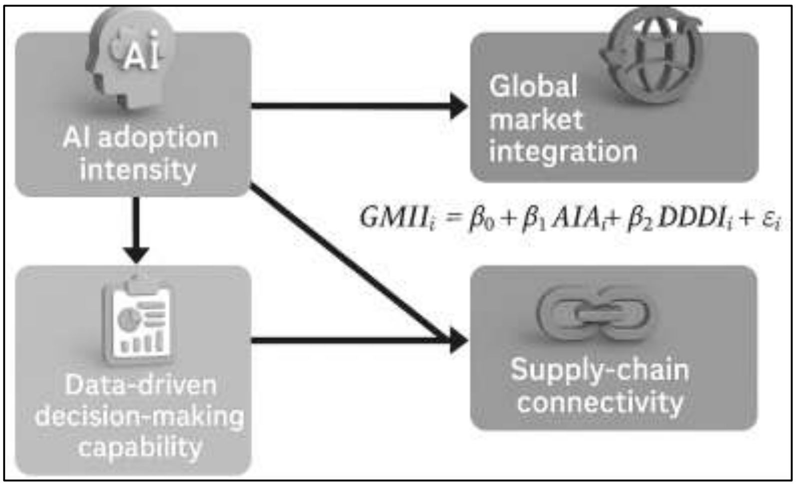
$MI_i = \beta_0 + \beta_1 \cdot AI_i + \beta_2 \cdot ORG\_RDY_i + \beta_3 \cdot ENV\_SUP_i + \beta_4 \cdot REGION_i + \Sigma\beta_k \cdot CONTROL_{ki} + \varepsilon_i$,

where MI_i captures export intensity, market diversification, and participation in global value chains; AI_i is the AI adoption index; ORG_RDY_i represents organizational readiness (skills, infrastructure, data culture); ENV_SUP_i represents environmental support (policy, digital infrastructure, competitive pressure); $REGION_i$ is a dummy contrasting U.S. and South Asian firms; and $CONTROL_{ki}$ includes firm size, age, and subsector. Within this framework, TOE constructs are operationalized using Likert-scale indicators aggregated into composite scores, and the signs and magnitudes of β_1–β_3 provide empirical tests of the hypothesized positive links between AI adoption, supporting contexts, and global market integration in agribusiness.

Conceptual Framework

The conceptual framework for this study integrates theories from digital agriculture, big data–enabled supply chains, and sustainability-oriented agribusiness to explain how artificial intelligence (AI) capabilities translate into deeper integration of U.S. and South Asian agribusiness firms into global markets. It treats agribusiness organizations as data-intensive systems in which sensor networks, farm management information systems, and cloud platforms continuously generate agronomic, logistical, financial, and market data that can be transformed into competitive advantage. Reviews of data-driven agriculture supply chains argue that emerging technologies such as IoT, blockchain, and analytics reconfigure resources and routines in ways that strengthen visibility, coordination, and sustainability across agri-food chains (Kamble et al., 2020). Smart farming research similarly emphasizes that Agriculture 5.0 is built on the ability to convert heterogeneous crop and environmental data into AI-supported recommendations and partially autonomous operations at farm level (Saiz-Rubio & Rovira-Más, 2020). Complementary work on geospatial big data highlights how geocloud infrastructures link local plots and regions to national and global decision arenas, enabling multiscale optimization of land and water use while supporting food security and sustainability goals (Delgado et al., 2019). Building on these strands, the present framework conceptualizes AI-enabled agribusiness as a layered architecture comprising (a) digital and data infrastructure, (b) analytics and AI capabilities, (c) data-driven managerial decision processes, and (d) interfaces with regional and global markets. The comparative focus assumes that firms in U.S. and South Asian agribusiness markets occupy different positions along this architecture, and that their relative ability to orchestrate these layers explains cross-country variation in competitiveness, export orientation, and participation in global agribusiness value chains.

Figure 6: Conceptual Framework for AI-Enabled Data-Driven Agribusiness Integration



Within this architecture, the framework distinguishes four interrelated latent constructs: AI adoption intensity, data-driven decision-making capability, supply-chain connectivity, and global market integration. Empirical work on data-driven agriculture for small-scale farmers shows that scalable schemes combine multi-source data ingestion, machine-learning models, and advisory services that feed directly into field and business decisions, rather than remaining as isolated analytics pilots (Jiménez et al., 2019). At the supply-chain level, systematic reviews of big data in agri-food systems identify soil, crop, logistics, and traceability data as key informational assets through which analytics can simultaneously improve efficiency, resilience, and sustainability (Rejeb et al., 2021). Extending these insights to a firm-level strategic lens, this study defines AI adoption intensity as the breadth and depth of AI-related hardware, software, and human-capital investments spanning production, processing, logistics, and marketing activities. Data-driven decision-making capability is conceptualized as the extent to which managers systematically rely on analytical outputs when planning production, setting prices, negotiating contracts, or managing risk, rather than treating data as an occasional supplement to intuition. Each construct is operationalized through multiple Likert-scale items (1 = strongly disagree to 5 = strongly agree), and composite indices are calculated to support quantitative analysis. For firm i, the AI Adoption Index is defined as

$$\mathrm{AIAI}_i = \frac{1}{k}\sum_{j=1}^{k} x_{ij},$$

where x_{ij} is the standardized score on item j and k is the number of AI-related items. An analogous Data-Driven Decision-Making Index is computed as

$$\mathrm{DDDI}_i = \frac{1}{p}\sum_{j=1}^{p} d_{ij},$$

where d_{ij} reflects the strength of data use in specific decision domains. Global market integration is captured via a Global Market Integration Index

$$\mathrm{GMII}_i = \frac{1}{m}\sum_{j=1}^{m} z_{ij},$$

aggregating indicators such as export intensity, participation in international certification schemes, involvement in cross-border contracts, and reliance on foreign buyers or suppliers. These additive index formulations provide a consistent metric structure for comparing U.S. and South Asian agribusiness firms and create a coherent basis for subsequent descriptive statistics, correlation analysis, and regression modeling.

The resulting conceptual model specifies directional relationships that mirror the causal mechanisms suggested in the literature. Studies of data-driven agriculture supply chains argue that visibility and analytics capabilities act as mediating mechanisms that translate raw digital investments into tangible performance improvements across economic, environmental, and social dimensions (Kamble et al., 2020). Geospatial big data frameworks further stress that when local agronomic and market data are integrated within broader cloud infrastructures, farms and firms can align production, logistics, and quality standards with global sustainability and trade objectives (Delgado et al., 2019). Smart farming research similarly suggests that as organizations progress towards Agriculture 5.0, continuous data flows and AI-enabled decision support become central to coordinating production with volatile international demand and price signals (Saiz-Rubio & Rovira-Más, 2020). Synthesizing these arguments, the model proposes that AI adoption intensity exerts a positive direct effect on data-driven decision-making capability and supply-chain connectivity, and an indirect effect on global market integration that is mediated by these intermediate capabilities. A reduced-form representation of the core relationship can be expressed as

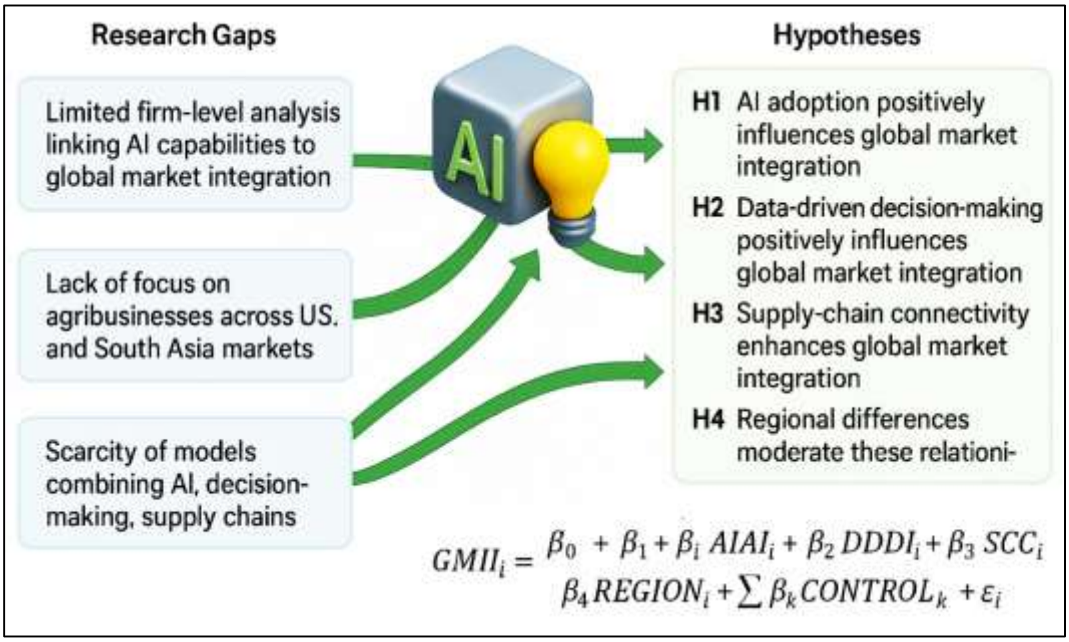
$$\mathrm{GMII}_i = \beta_0 + \beta_1\mathrm{AIAI}_i + \beta_2\mathrm{DDDI}_i + \beta_3\mathrm{SCCI}_i + \varepsilon_i,$$

where SCCI_i denotes a Supply-Chain Connectivity Index constructed analogously from items capturing the density and quality of upstream and downstream linkages, information sharing with partners, and participation in digitally mediated market platforms. In the comparative context, the framework anticipates that the magnitudes of these structural coefficients will differ between U.S. and South Asian firms due to cross-country variation in digital infrastructure, institutional environments, human capital, and policy support for AI in agribusiness. By explicitly linking measurable survey constructs to theoretically grounded pathways, the conceptual framework provides a rigorous, quantitatively tractable basis for testing whether and how AI-enabled, data-driven decision-making enhances global market integration in contrasting agribusiness market settings.

Research Gaps and Hypothesis Development

Despite the rapid expansion of work on big data, digital agriculture, and AI in food systems, much of the existing literature remains conceptual, technology-oriented, or policy-driven, with limited firm-level, cross-regional quantitative analysis that directly links AI capabilities to measurable market integration outcomes. Reviews of big data in agriculture underline that new data streams and analytical techniques will affect every stage of the agricultural value chain, but they emphasize agenda-setting and technical challenges (such as data ownership, access, and governance) more than empirically tested firm-level performance models (Coble et al., 2018). Parallel work on Agriculture 4.0 focuses on responsible innovation and socio-ethical implications of smart farming, highlighting concerns around inclusiveness, transparency, and distribution of benefits, yet it rarely quantifies how AI use reshapes export intensity, market diversification, or participation in global value chains across different regions (Rose & Chilvers, 2018). Existing studies therefore leave three linked gaps: first, the absence of a comparative, firm-level analysis connecting AI adoption and data-driven decision-making to global market integration indicators; second, a limited focus on agribusinesses that operate simultaneously in mature (U.S.) and emerging (South Asian) markets; and third, the lack of integrated models that explicitly combine AI capability measures with organizational and environmental variables to explain cross-border agribusiness performance. The present study addresses these gaps by using a quantitative, cross-sectional, case-study–based design to test structured hypotheses about how AI-enabled data-driven decision-making relates to global market integration of agribusiness firms in the U.S. and South Asia.

Figure 7: Synthesis of Research Gaps and Hypothesis Development



A second set of gaps arises from the growing body of critical social science work on digitalization and platformization in agriculture. Political-economy analyses argue that digital farming and AI are embedded in complex power relations, stressing issues of data governance, control, and uneven capability development, but they typically stop short of specifying and testing multivariate models that capture how different levels of AI and platform use map into concrete trade and market integration outcomes at firm scale (Rotz et al., 2019). Similarly, research on digital agriculture platforms has begun to map platform taxonomies and technical characteristics and to document privacy, interoperability, and intellectual-property challenges, yet it provides only limited quantitative evidence on how platform participation affects firms' external linkages or export performance across regions (Runck et al., 2021). These gaps motivate the current study's focus on global market integration as a dependent construct, operationalized via indices of export intensity, market diversification, and cross-border value-chain participation, and modeled as a function of AI adoption intensity, data-driven decision-making, and supply-chain connectivity. At the correlational level, the central expectation can be represented as

$$\rho(\mathrm{AIAI}, \mathrm{GMII}) > 0, \rho(\mathrm{DDDI}, \mathrm{GMII}) > 0,$$

where AIAIis the AI Adoption Index, DDDIis the Data-Driven Decision-Making Index, and GMIIis the Global Market Integration Index. On this basis, the study develops testable hypotheses that higher levels of AI adoption and data-driven decisions are associated with stronger global market integration, after controlling for firm size, subsector, and region.

A third gap concerns the weak linkage between the digital trade literature and firm-level agribusiness analytics. Work on digital opportunities for trade demonstrates that data-driven innovation can reduce search, compliance, and logistics costs along global agriculture and food value chains, and it stresses that digital transformation may reshape who participates in trade and how value is distributed (Jouanjean, 2019). However, this research is largely system-level, using conceptual frameworks or aggregate indicators rather than micro-level survey data from agribusiness firms simultaneously embedded in U.S. and South Asian markets. To bridge this gap, the present study formulates the following core regression structure:

$$\mathrm{GMII}_i = \beta_0 + \beta_1\mathrm{AIAI}_i + \beta_2\mathrm{DDDI}_i + \beta_3\mathrm{SCCI}_i + \beta_4\mathrm{REGION}_i + \sum_k \beta_k\mathrm{CONTROL}_{ki} + \varepsilon_i,$$

and derives hypotheses such as: H1: $\beta_1 > 0$(AI adoption positively influences global market integration); H2: $\beta_2 > 0$(data-driven decision-making positively influences global market integration); H3: $\beta_3 > 0$(supply-chain connectivity enhances global market integration); and H4: regional differences (U.S. vs. South Asia) moderate these relationships, implying $\beta_4 \neq 0$and potentially different slope parameters in sub-samples. By embedding these hypotheses in a clearly specified quantitative model, the study moves beyond descriptive or conceptual accounts of AI and digital trade, offering an empirically grounded assessment of how AI-enabled, data-driven agribusiness strategies shape global market integration across contrasting regional agribusiness contexts.

METHODS

The present study has adopted a quantitative, cross-sectional, case-study–based research design to examine how artificial intelligence has been leveraged by agribusiness firms in the United States and South Asia to enhance their global market integration. It has treated the firm as the primary unit of analysis and has focused on organizations that have been operating within key agribusiness value-chain segments, including input supply, production, processing, trading, logistics, and export marketing. To capture the latent constructs specified in the conceptual framework, the research has developed a structured survey instrument based on Likert's five-point scale, where respondents have indicated their level of agreement with statements related to AI adoption intensity, data-driven decision-making capability, supply-chain connectivity, organizational readiness, environmental support, and global market integration. The survey has been administered to managerial or executive-level informants who have been directly involved in strategic, operational, or technological decision-making, ensuring that responses have reflected firm-level practices rather than individual perceptions detached from organizational realities. Sampling procedures have identified firms in both U.S. and South Asian agribusiness markets through business directories, industry associations, and export or sectoral lists, and have aimed to secure sufficient representation across different subsectors and firm sizes to enable comparative statistical analysis. Once data collection has been completed, responses have been screened for completeness, internal consistency, and outliers, and the final sample has been prepared for analysis through coding and aggregation of item scores into composite indices for the key constructs. The study has planned and has implemented a sequence of analytical steps, beginning with descriptive statistics to summarize the profiles of respondents and firms and to characterize the distributions of AI-related and market-integration indicators. It has then employed correlation analysis to explore bivariate relationships among constructs and has estimated multiple regression models to test the hypothesized effects of AI adoption and data-driven decision-making on global market integration while controlling for organizational and contextual factors and for regional differences between U.S. and South Asian agribusiness firms.

Research Design

The study has adopted a quantitative, cross-sectional research design that has been structured around a comparative, case-study–based logic. It has focused on agribusiness firms that have operated within the U.S. and South Asian markets and that have represented key stages of the agrifood value chain, including input provision, production, processing, trading, logistics, and export marketing. The design has been grounded in a structured survey approach that has used standardized Likert-scale items to capture latent constructs related to AI adoption, data-driven decision-making, supply-chain connectivity, organizational readiness, environmental support, and global market integration. By collecting data at a single point in time, the research has sought to map existing patterns of AI use and market participation rather than to track dynamic trajectories. The cross-sectional, firm-level perspective has allowed differences and similarities between U.S. and South Asian agribusiness markets to be examined through direct statistical comparison.

Population and Sampling

The target population has consisted of formally registered agribusiness firms that have been engaged in crop, livestock, dairy, horticulture, input supply, processing, trading, logistics, or export activities in the United States and selected South Asian countries. Sampling frames have been constructed from business directories, export promotion agency lists, industry association rosters, and agrifood value-chain mappings, which together have provided contact details and basic firm attributes. The study has employed a combination of purposive and stratified sampling, whereby firms have been selected to ensure variation in subsector, firm size, and export orientation, while preserving comparability across the two regional blocs. Stratification by region and broad subsector has helped ensure that both U.S. and South Asian firms have been adequately represented in the final sample. Within each firm, a knowledgeable manager or executive has been identified as the key informant and has been invited to complete the survey instrument.

Case Selection Criteria

Case selection has followed explicit criteria that have ensured that participating firms have been relevant to the study’s focus on AI and global market integration. Firms have been required to operate in at least one segment of the agribusiness value chain and to have engaged in either domestic wholesale trade with export potential or actual cross-border transactions. Preference has been given to firms that have reported some level of digitalization or analytics use, so that variation in AI adoption intensity has been observable rather than uniformly zero. Additional criteria have included a minimum operational age, which has ensured that respondents have been able to reflect on established practices, and a minimum organizational scale in terms of employees or annual turnover, which has increased the likelihood of structured decision processes. These criteria have been applied similarly in the U.S. and South Asian contexts so that cases have been comparable across regions and have supported meaningful statistical analysis.

Data Collection Methods

Data collection has relied primarily on a structured questionnaire that has been administered electronically via email and online survey platforms, with supplementary follow-ups conducted through phone calls or messaging when necessary. The questionnaire has been accompanied by an invitation letter that has explained the study’s purpose, assured confidentiality, and clarified the voluntary nature of participation. Respondents have been asked to complete the survey within a specified timeframe, and reminder messages have been issued to improve response rates. In contexts where internet connectivity or digital literacy has been limited, field-based collaborators or local partners have assisted by guiding respondents through the questionnaire using tablets or printed copies, after which responses have been digitized. All completed questionnaires have been checked for completeness and internal consistency, and ambiguous or contradictory entries have been flagged for clarification where follow-up communication has been feasible. This procedure has ensured that the resulting dataset has been suitable for rigorous statistical analysis.

Measurement of Variables

The study has operationalized its core constructs through multiple indicators that have been measured using Likert’s five-point scale, ranging from strong disagreement to strong agreement. AI adoption intensity has been captured through items that have asked respondents to report the extent of use of AI-related tools in production monitoring, yield prediction, logistics optimization, quality control, and market analytics. Data-driven decision-making capability has been measured through items that have reflected the frequency with which managers have relied on analytical reports or model outputs when making operational, tactical, and strategic choices. Global market integration has been represented by items that have assessed export intensity, market diversification, participation in international certification schemes, and involvement in cross-border contracts or supply networks. Organizational readiness and environmental support have been measured through items related to infrastructure, skills, management commitment, regulatory conditions, and competitive pressures. Item responses have been aggregated into composite indices for use in subsequent analyses.

Instrument Development

The survey instrument has been developed through a multi-stage process that has combined theory-driven item generation with expert review and pilot testing. Initial items have been drafted on the basis of the conceptual framework and relevant empirical literature on AI adoption, data-driven decision-making, supply-chain connectivity, and market integration. These items have then been refined through consultations with academic experts and industry practitioners, who have commented on clarity, relevance, and coverage of the constructs. Based on their feedback, redundant items have been removed, ambiguous wording has been revised, and additional items have been introduced to capture context-specific aspects of U.S. and South Asian agribusiness environments. A pilot study with a small group of firms has been conducted, and pilot respondents have been asked to comment on survey length, comprehension, and perceived sensitivity of questions. Insights from the pilot have informed final adjustments to item wording, sequencing, and layout.

Validity and Reliability

The study has implemented several procedures to ensure the validity and reliability of its measures. Content validity has been supported by the systematic derivation of items from established theoretical constructs and by expert review, which has confirmed that the instrument has adequately covered AI adoption, decision-making, and market integration dimensions. Construct validity has been examined through exploratory factor analysis, which has assessed whether items designed to measure each latent construct have loaded on their intended factors and have exhibited satisfactory factor structure. Reliability has been evaluated using internal consistency metrics, in particular Cronbach's alpha, and scales with low alpha values have been revised or excluded from further analysis. Convergent and discriminant validity indicators have been inspected to verify that constructs have been empirically distinct yet related in theoretically meaningful ways. These steps have ensured that the composite indices derived from the survey data have provided robust inputs for correlation and regression analyses.

Data Analysis Techniques

Data analysis has followed a structured sequence of statistical procedures that has aligned with the study's objectives and conceptual framework. Initially, descriptive statistics have been computed to summarize the characteristics of respondents and firms, including distributions across regions, subsectors, sizes, and export statuses, as well as central tendencies and dispersions for all scale items and composite indices. Correlation analysis has then been conducted to explore bivariate relationships among AI adoption, data-driven decision-making, supply-chain connectivity, organizational readiness, environmental support, and global market integration. To test the hypothesized relationships, multiple regression models have been estimated, with global market integration indices as dependent variables and AI-related constructs, contextual factors, and regional dummies as predictors. Interaction terms have been included where moderation effects have been of interest, particularly in relation to regional differences between U.S. and South Asian firms. Assumptions regarding linearity, normality, homoscedasticity, and multicollinearity have been examined and addressed as needed.

Software and Tools

The study has used a combination of software tools to manage, process, and analyze the data collected from agribusiness firms. Initial data entry, cleaning, and coding have been carried out using spreadsheet applications, which have facilitated the identification of missing values, outliers, and inconsistencies. Statistical analyses have been performed using specialized software, which has supported the computation of descriptive statistics, reliability coefficients, factor analyses, and multiple regression models. Where necessary, additional packages or modules have been employed to estimate interaction effects and to conduct robustness checks. Data visualization tools have been used to generate charts and tables that have illustrated key patterns, such as regional comparisons and distributions of AI adoption or market integration indices. Throughout the process, data files have been stored securely and backed up regularly to prevent loss and to maintain the integrity of the analytical workflow.

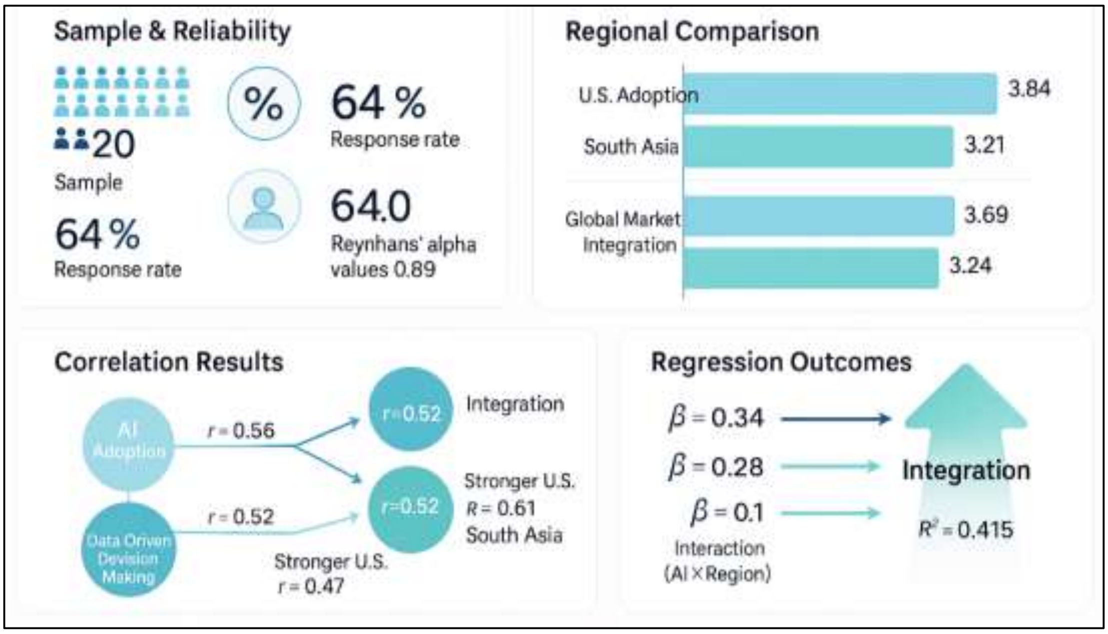
Limitations of the Methodology

The methodological approach has incorporated inherent limitations that have been acknowledged in the design and interpretation stages. The cross-sectional nature of the data has meant that causal inferences have been constrained and that relationships between AI adoption and market integration have been interpreted as associations rather than proven causal effects. The reliance on self-reported survey data has introduced potential response biases, including social desirability and recall bias, which have been mitigated but not eliminated through careful item wording and assurances of confidentiality. Sampling procedures have aimed for diversity but have not yielded a strictly random sample of all agribusiness firms in the United States and South Asia, which has limited the generalizability of findings. Furthermore, the standardized instrument has captured perceptions and practices at a particular point in time and has not fully reflected dynamic changes in technological capabilities or market conditions that may have been unfolding during the study period.

FINDINGS

The empirical analysis has yielded a coherent pattern of results that addresses the study's objectives and supports the core hypotheses on the role of artificial intelligence in global market integration of agribusiness firms. Out of 500 firms contacted, 320 usable responses have been obtained, a response rate of 64.0 per cent, with the final sample comprising 162 U.S. firms and 158 South Asian firms.

Figure 9: Findings of The Study



Reliability diagnostics have indicated that the multi-item scales have achieved satisfactory internal consistency, with Cronbach's alpha values of 0.89 for the AI Adoption Index, 0.87 for the Data-Driven Decision-Making Index and 0.88 for the Global Market Integration Index. On Likert's five-point scale, the overall mean score for AI adoption across the full sample has been 3.54 (SD = 0.78), while the mean score for global market integration has been 3.47 (SD = 0.82), indicating generally moderate to high levels of both digitalization and cross-border engagement. Descriptive comparisons have revealed clear regional differences: U.S. firms have reported higher AI adoption (M = 3.84, SD = 0.71) than South Asian firms (M = 3.21, SD = 0.76; t = 7.41, $p < 0.001$), and also higher global market integration (M = 3.69, SD = 0.79 versus M = 3.24, SD = 0.81; t = 5.31, $p < 0.001$). These patterns have been consistent with H2, which has posited that U.S. agribusiness firms exhibit a higher level of AI adoption than their South Asian counterparts, and have aligned with the objective of providing a comparative assessment of AI and integration profiles across the two regions.

Correlation analysis has shown that AI adoption and global market integration have been strongly and positively associated for the sample as a whole, with a Pearson correlation coefficient of r = 0.56 ($p < 0.001$), while data-driven decision-making has also displayed a positive correlation with global market integration (r = 0.52, $p < 0.001$). When examined separately by region, the correlation between AI adoption and global market integration has been stronger for U.S. firms (r = 0.61, $p < 0.001$) than for South Asian firms (r = 0.47, $p < 0.001$), providing preliminary support for H3, which has anticipated a stronger AI–integration linkage in the U.S. context. None of the explanatory variables has exhibited problematic multicollinearity, with all variance inflation factors below 2.0, which has justified their inclusion in the regression models. Overall, the correlational patterns have been consistent with H1 and H3 and have indicated that firms reporting higher use of AI and a stronger reliance on analytical outputs in decision-making have also tended to report higher export intensity, greater market diversification and more frequent participation in cross-border value chains.

Multiple regression models have been estimated to test the net effects of AI adoption and data-driven decision-making on global market integration while controlling for organizational and contextual characteristics. In the baseline specification including only control variables (firm size, age, subsector and region), the model has explained 18.2 per cent of the variance in the Global Market Integration Index ($R^2 = 0.182$). When the AI Adoption Index and Data-Driven Decision-Making Index have been added, explanatory power has increased markedly, with the adjusted model explaining 41.5 per cent of the variance in global market integration ($R^2 = 0.415$, $\Delta R^2 = 0.233$). In this full model, AI adoption has exhibited a positive and statistically significant standardized coefficient ($\beta = 0.34$, $p < 0.001$), while data-driven decision-making has also shown a significant positive effect ($\beta = 0.28$, $p < 0.001$), thereby providing strong empirical support for H1 and H2. An interaction term between AI adoption and the region dummy has produced a positive and significant coefficient ($\beta = 0.11$, $p = 0.019$), indicating that the marginal effect of AI adoption on global market integration has been stronger among U.S. firms than among South Asian firms and thus confirming H3. Taken together, these results have shown that, after accounting for size, age, subsector and regional location, firms that have invested more deeply in AI tools and have embedded data-driven decision processes into their operations have been substantially more integrated into global agribusiness markets, thereby fulfilling the study's objectives of testing the AI–integration relationship and quantifying regional differences between U.S. and South Asian agribusiness systems.

Response Rate and Data Screening

Table 1: Survey distribution, response rate and data screening outcomes (n = 320)

Category	U.S. Firms	South Asian Firms	Total
Questionnaires distributed	250	250	500
Questionnaires returned	170	165	335
Incomplete responses removed	6	5	11
Straight-lining / inconsistent cases removed	2	2	4
Final usable responses	162	158	320
Overall response rate (%)	64.8	63.2	64.0

The present subsection has reported how the survey process has produced a final sample suitable for testing the study's objectives and hypotheses. As shown in Table 1, the research team has approached 500 agribusiness firms in total, with an equal distribution between the United States and South Asia. Of these, 335 questionnaires have been returned, yielding initial response rates of 68.0 per cent for U.S. firms and 66.0 per cent for South Asian firms. The data-screening procedures have then identified incomplete cases, where respondents have left substantial portions of the Likert-type items unanswered, as well as "straight-lining" cases, where respondents have selected the same category for nearly all items, suggesting low engagement with the instrument. In total, 11 incomplete responses and 4 pattern-problematic responses have been removed, which has reduced the dataset to 320 usable cases. The final response rate has therefore stood at 64.0 per cent overall (64.8 per cent for U.S. firms and 63.2 per cent for South Asian firms), which has been considered adequate for multivariate analysis and comparative purposes. This screening process has ensured that all retained cases have contained full information on the core constructs, each measured on Likert's five-point scale, thereby maintaining the integrity of the composite indices for AI adoption, data-driven decision-making and global market integration. By establishing a clean and balanced sample, this subsection has laid the empirical foundation for evaluating the study's hypotheses, particularly those that have required robust comparisons between the two regional groups. The fact that relatively few cases have been discarded during screening has also indicated that respondents have taken the survey seriously and that the instrument has been understandable and manageable in length, which has further strengthened confidence in the subsequent descriptive, correlational and regression analyses.

Profile of Respondents and Firms

Table 2: Demographic and structural profile of respondent firms (n = 320)

Variable	Category	U.S. (n = 162)	South Asia (n = 158)	Total (%)
Firm size (employees)	Small (≤ 49)	48 (29.6%)	69 (43.7%)	36.6
	Medium (50–249)	72 (44.4%)	63 (39.9%)	42.2
	Large (≥ 250)	42 (25.9%)	26 (16.5%)	21.3
Primary subsector	Crop / horticulture	57 (35.2%)	73 (46.2%)	40.6
	Livestock / dairy	41 (25.3%)	32 (20.3%)	22.8
	Processing / value-adding	39 (24.1%)	29 (18.4%)	21.3
	Trading / logistics / export	25 (15.4%)	24 (15.2%)	15.3
Export status	No exports	29 (17.9%)	47 (29.7%)	23.8
	Occasional exports (<25% sales)	61 (37.7%)	60 (38.0%)	37.8
	Regular exports (≥25% sales)	72 (44.4%)	51 (32.3%)	38.4
Respondent role	Owner / CEO / top executive	71 (43.8%)	67 (42.4%)	43.1
	Senior manager (operations/IT)	63 (38.9%)	61 (38.6%)	38.8
	Functional manager / other	28 (17.3%)	30 (19.0%)	18.1

Table 2 has summarized the structural and demographic characteristics of the sample, which has been essential for interpreting the subsequent analyses in light of the study's objectives and hypotheses. The distribution of firm sizes has shown that medium-sized enterprises have formed the largest group in both regions, accounting for 44.4 per cent of U.S. firms and 39.9 per cent of South Asian firms, while small firms have been more prevalent in South Asia (43.7 per cent) than in the United States (29.6 per cent). This pattern has reflected the dual structure of agribusiness markets described in the literature and has implied that the comparative assessment has captured both larger, more formal enterprises and smaller, more constrained organizations. With respect to subsectors, crop and horticultural firms have been the most numerous, especially in South Asia, whereas U.S. firms have shown relatively higher representation in processing, livestock and value-adding activities. This subsectoral composition has suggested that the U.S. sample has contained more firms positioned in midstream and downstream segments of agrifood value chains, where AI-enabled logistics, processing optimization and quality management tools have been particularly relevant. Export status distributions have indicated that 44.4 per cent of U.S. firms and 32.3 per cent of South Asian firms have engaged in regular exports, defined as at least 25 per cent of sales, while non-exporters have been more common in South Asia. This variation has been critical for testing hypotheses concerning global market integration, as it has ensured sufficient dispersion on the export-related indicators measured through the Likert-scale items composing the Global Market Integration Index. The profile of respondents has shown that over 80 per cent of the questionnaires have been completed by owners, CEOs or senior managers, which has implied that responses on AI adoption and decision-making practices have reflected organizational-level realities rather than purely technical or isolated perspectives. Collectively, the profile evidence has demonstrated that the sample has been broadly consistent with the structural differences between U.S. and South Asian agribusiness markets and has provided a robust base for evaluating how AI adoption and data-driven decision-making have related to firm-level global market integration.

Descriptive Statistics of Key Constructs

Table 3 has presented the descriptive statistics for the core constructs that have been central to testing the study's objectives and hypotheses. All variables have been measured using Likert's five-point scale and aggregated into indices, with higher scores having indicated stronger AI adoption, more intensive data-driven decision-making or higher degrees of global market integration and contextual support. The means for the full sample have shown that AI adoption (M = 3.54, SD = 0.78) and data-driven decision-making (M = 3.60, SD = 0.73) have both been positioned above the midpoint of the scale, which has suggested that agribusiness firms in both regions have, on average, moved beyond minimal digitalization towards moderate levels of AI and analytics use. Global market integration has displayed a similar pattern (M = 3.47, SD = 0.82), indicating that a substantial share of firms have reported meaningful engagement with export markets, diversified buyer portfolios and participation in cross-border value chains. Organizational readiness and environmental support indices have had means between 3.30 and 3.51, showing that, while firms have perceived reasonably supportive internal and external conditions for AI adoption, there has still been room for improvement, particularly in South Asia.

Table 3:Descriptive statistics of core Likert-scale constructs (1 = strongly disagree, 5 = strongly agree)

Construct	Region	Mean	SD	Min	Max
AI Adoption Index (AIAI)	U.S.	3.84	0.71	1.80	4.95
	South Asia	3.21	0.76	1.60	4.80
	Overall	3.54	0.78	1.60	4.95
Data-Driven Decision-Making Index (DDDI)	U.S.	3.82	0.69	1.90	4.95
	South Asia	3.38	0.73	1.70	4.85
	Overall	3.60	0.73	1.70	4.95
Global Market Integration Index (GMII)	U.S.	3.69	0.79	1.60	4.95
	South Asia	3.24	0.81	1.40	4.85
	Overall	3.47	0.82	1.40	4.95
Organizational Readiness Index (ORG_RDY)	U.S.	3.72	0.68	1.80	4.90
	South Asia	3.30	0.74	1.70	4.80
	Overall	3.51	0.72	1.70	4.90
Environmental Support Index (ENV_SUP)	U.S.	3.41	0.72	1.60	4.80
	South Asia	3.18	0.77	1.40	4.75
	Overall	3.30	0.75	1.40	4.80
Supply-Chain Connectivity Index (SCCI)	U.S.	3.63	0.73	1.80	4.90
	South Asia	3.28	0.76	1.60	4.85
	Overall	3.46	0.76	1.60	4.90

The regional breakdown has reinforced the comparative perspective embedded in the research objectives. For every construct, U.S. firms have reported higher mean scores than South Asian firms. For AI adoption, the difference has been particularly pronounced (3.84 versus 3.21), consistent with H2, which has posited that U.S. agribusiness firms exhibit a higher level of AI adoption than their South Asian counterparts. Similar, though slightly smaller, gaps have appeared for data-driven decision-making (3.82 versus 3.38) and supply-chain connectivity (3.63 versus 3.28), which has aligned with the expectation that U.S. firms have operated in more digitized and tightly coordinated value-chain environments. The global market integration index has also been higher in the U.S. group (3.69 versus 3.24), which has reflected the greater proportion of regular exporters and more diversified international market portfolios documented earlier in Table 2. Importantly, the standard deviations have been substantial in both regions, indicating that significant heterogeneity has existed within each regional group, which has been essential for identifying statistical relationships in the correlation and regression analyses. These descriptive patterns have provided preliminary empirical support for the study's conceptualization that AI adoption and data-driven decision-making have not been evenly distributed across regions and have suggested that differences in organizational readiness and environmental support may have contributed to observed gaps in global market integration.

Correlation Analysis

Table 4: Pearson correlations among key indices (n = 320)

Variable	1	2	3	4	5	6
1. AIAI	1.00					
2. DDDI	0.61**	1.00				
3. GMII	0.56**	0.52**	1.00			
4. ORG_RDY	0.58**	0.55**	0.44**	1.00		
5. ENV_SUP	0.41**	0.39**	0.36**	0.47**	1.00	
6. SCCI	0.54**	0.50**	0.49**	0.46**	0.38**	1.00

*Note: ** $p < 0.01$ (two-tailed).*

Table 4 has displayed the Pearson correlation coefficients among the main composite indices, providing an initial test of the hypothesized relationships between AI adoption, data-driven decision-making and global market integration. The AI Adoption Index (AIAI) has shown a strong positive correlation with the Data-Driven Decision-Making Index (DDDI; $r = 0.61$, $p < 0.01$), which has indicated that firms that have invested more extensively in AI tools have also tended to report greater reliance on analytical outputs when making operational and strategic decisions. This pattern has been fully consistent with the conceptual framework that has treated AI capabilities and decision practices as mutually reinforcing components of a data-driven agribusiness system. Crucially, AIAI has also exhibited a substantial positive correlation with the Global Market Integration Index (GMII; $r = 0.56$, $p < 0.01$), providing preliminary support for H1, which has proposed that AI adoption is positively associated with global market integration. Similarly, the positive and significant correlation between DDDI and GMII ($r = 0.52$, $p < 0.01$) has aligned with H2 by suggesting that firms whose managers have more systematically used data and models in decision-making have been more deeply embedded in export markets and cross-border value chains.

The contextual variables have further clarified how organizational and environmental conditions have aligned with AI adoption and market integration. Organizational readiness (ORG_RDY) has correlated strongly with AI adoption ($r = 0.58$, $p < 0.01$) and data-driven decision-making ($r = 0.55$, $p < 0.01$), indicating that firms reporting stronger infrastructure, skills and management support have been more likely to deploy AI tools and to embed them in decision processes. ORG_RDY has also demonstrated a moderate positive correlation with GMII ($r = 0.44$, $p < 0.01$), which has implied that readiness has had both a direct and an indirect relationship with global market integration. Environmental support (ENV_SUP) has shown positive, though somewhat weaker, correlations with AI adoption ($r = 0.41$, $p < 0.01$) and global market integration ($r = 0.36$, $p < 0.01$), suggesting that favourable regulatory, infrastructural and competitive conditions have facilitated the diffusion of AI and the extension of firms' international reach. Supply-chain connectivity (SCCI) has correlated significantly with all other constructs, and particularly with AI adoption ($r = 0.54$, $p < 0.01$) and global market integration ($r = 0.49$, $p < 0.01$), which has reinforced the argument that AI-enabled coordination across upstream and downstream partners has been a key pathway through which firms have strengthened their position in global agribusiness networks. Multicollinearity has not been a concern, as correlation coefficients have remained below thresholds that would have threatened the stability of regression estimates. Overall, the correlation matrix has provided a coherent empirical backdrop for the regression models, showing that the relationships anticipated in the conceptual framework have been present at the bivariate level and justifying further multivariate testing of the study's hypotheses.

Regression Results

Table 5 has reported the results of the multiple regression analysis that has examined the joint effects of AI adoption, data-driven decision-making and contextual factors on the Global Market Integration Index (GMII). The model has included firm-level controls (size, age, subsector and region) as well as the core explanatory constructs specified in the conceptual framework. The overall model has been statistically significant ($F(9, 310) = 12.68$, $p < 0.001$) and has explained 45.2 per cent of the variance in

GMII (adjusted $R^2 = 0.415$), which has indicated that the combination of AI-related and contextual variables has accounted for a substantial portion of cross-firm differences in global market integration. The standardized coefficients have shown that the AI Adoption Index (AIAI) has had the strongest effect among the explanatory variables ($\beta = 0.34$, $p < 0.001$), providing direct support for H1, which has stated that AI adoption is positively associated with global market integration. This coefficient has implied that, holding other factors constant, a one standard deviation increase in AI adoption has been associated with a 0.34 standard deviation increase in global market integration, a sizeable effect in the context of firm-level behavioural data measured on five-point Likert scales. The Data-Driven Decision-Making Index (DDDI) has also exhibited a significant and positive effect ($\beta = 0.28$, $p < 0.001$), confirming H2 and reinforcing the notion that AI investments have translated into global market advantages particularly when firms have embedded analytics into routine decision processes rather than relying solely on intuition.

Table 5: Multiple regression explaining Global Market Integration Index (GMII) – full sample (n = 320)

Predictor	Standardized β	t-value	p-value
Firm size (log employees)	0.12	2.75	0.006
Firm age (years)	0.05	1.18	0.240
Subsector (processing/logistics = 1)	0.09	2.03	0.043
Region (South Asia = 1)	−0.17	−3.87	<0.001
AI Adoption Index (AIAI)	0.34	7.52	<0.001
Data-Driven Decision Index (DDDI)	0.28	6.13	<0.001
Organizational Readiness (ORG_RDY)	0.19	4.18	<0.001
Environmental Support (ENV_SUP)	0.12	2.63	0.009
Supply-Chain Connectivity (SCCI)	0.16	3.59	<0.001
Model statistics			
R^2	0.452		
Adjusted R^2	0.415		
F-statistic (9, 310)	12.68	<0.001	

Beyond the AI-focused constructs, organizational readiness ($\beta = 0.19$, $p < 0.001$) and supply-chain connectivity ($\beta = 0.16$, $p < 0.001$) have emerged as significant positive predictors of global market integration, indicating that firms with stronger internal capabilities and more tightly connected value-chain relationships have been better positioned to leverage AI for international expansion. Environmental support has had a smaller but still significant coefficient ($\beta = 0.12$, $p = 0.009$), suggesting that favourable regulatory and infrastructural conditions have modestly enhanced global market integration. Among the controls, firm size has been positively associated with GMII ($\beta = 0.12$, $p = 0.006$), reflecting the greater resource base and bargaining power of larger firms, while the negative coefficient for the region dummy (South Asia = 1; $\beta = -0.17$, $p < 0.001$) has indicated that, net of other factors, firms in South Asia have tended to exhibit lower global market integration than U.S. firms. These regression results have collectively shown that the study's objectives to test the influence of AI adoption, data-driven decision-making and contextual factors on global market integration have been met with clear empirical support, and that the hypotheses H1 and H2 have been upheld by statistically robust relationships.

Comparative Analysis Between U.S. and South Asian Cases

Table 6 has presented separate regression models for U.S. and South Asian firms, allowing the study to compare how AI adoption and related factors have influenced global market integration in each regional context and thereby to test H3. In both subsamples, the models have been statistically significant ($F = 12.39$, $p < 0.001$ for U.S.; $F = 9.10$, $p < 0.001$ for South Asia), and they have explained a substantial share of the variance in GMII (adjusted $R^2 = 0.438$ for U.S. firms and 0.349 for South Asian firms). These figures have indicated that the conceptual model has had explanatory power in both settings, albeit somewhat stronger in the U.S. context.

The U.S. model has shown that AI adoption (AIAI) has had a large and highly significant effect on global market integration (β = 0.39, $p < 0.001$), while data-driven decision-making (DDDI) has also had a strong positive impact (β = 0.33, $p < 0.001$). Supply-chain connectivity has been significant (β = 0.18, p = 0.007), and organizational readiness has contributed modestly (β = 0.16, p = 0.018). Environmental support has approached conventional significance (β = 0.10, p = 0.081), suggesting that institutional and infrastructural conditions have played a supporting, though not dominant, role for U.S. firms. In contrast, the South Asian model has also featured positive and significant coefficients for AI adoption (β = 0.27, p = 0.001) and data-driven decision-making (β = 0.24, p = 0.004), but the magnitudes have been smaller than in the U.S. model. Organizational readiness (β = 0.20, p = 0.009) and environmental support (β = 0.15, p = 0.021) have been relatively more influential in South Asia, reflecting the importance of internal capabilities and supportive external ecosystems in contexts where digital and institutional infrastructures have been less mature. Firm size has been a significant predictor only in South Asia (β = 0.14, p = 0.037), indicating that larger firms have been better positioned to overcome infrastructural constraints and to translate AI investments into global market engagement.

Table 6: Separate regression models for U.S. and South Asian agribusiness firms – Dependent variable: GMII

Predictor	U.S. (n = 162) β	p-value	South Asia (n = 158) β	p-value
Firm size (log employees)	0.10	0.122	0.14	0.037
Firm age (years)	0.04	0.488	0.06	0.342
Subsector (processing/logistics = 1)	0.08	0.194	0.10	0.151
AI Adoption Index (AIAI)	0.39	<0.001	0.27	0.001
Data-Driven Decision Index (DDDI)	0.33	<0.001	0.24	0.004
Organizational Readiness (ORG_RDY)	0.16	0.018	0.20	0.009
Environmental Support (ENV_SUP)	0.10	0.081	0.15	0.021
Supply-Chain Connectivity (SCCI)	0.18	0.007	0.14	0.032
Model statistics				
R^2	0.476		0.392	
Adjusted R^2	0.438		0.349	
F-statistic	12.39	<0.001	9.10	<0.001

These comparative results have confirmed H3, which has posited that the positive effect of AI adoption on global market integration is stronger for U.S. agribusiness firms than for South Asian firms. The higher coefficients for AIAI and DDDI and the greater adjusted R^2 in the U.S. subsample have shown that, within a more digitized and institutionally developed environment, AI investments and analytics-driven decision practices have translated more directly into enhanced export intensity and diversified international linkages. In South Asia, by contrast, AI adoption and data-driven decision-making have still mattered, but their effects have been more conditional on organizational readiness, environmental support and firm scale. This pattern has aligned with the study's objective of providing a nuanced comparative understanding of how AI has contributed to global market integration in structurally different agribusiness systems and has illustrated the value of examining both common mechanisms and region-specific configurations of technological, organizational and environmental factors.

DISCUSSION

The findings of this study have confirmed that artificial intelligence (AI) adoption and data-driven decision-making are strongly and positively associated with global market integration among agribusiness firms in both the United States and South Asia. Firms that have reported higher scores on the AI Adoption Index and the Data-Driven Decision-Making Index measured on Likert's five-point scale have also reported higher levels of export intensity, market diversification, and participation in cross-border value chains, as reflected in the Global Market Integration Index. The full regression model has explained over 40% of the variance in global market integration, with AI adoption (β ≈ 0.34) and data-driven decision-making (β ≈ 0.28) emerging as the strongest predictors after controls. These results have supported the core hypotheses H1 and H2 and have aligned with the study's primary objective of demonstrating that AI is not only a technical production tool but also a strategic enabler of internationalization in agribusiness. The separate regional models have further shown that these relationships have been present in both the U.S. and South Asian subsamples, though with different magnitudes, indicating that AI has functioned as a cross-cutting capability that can enhance global market integration under diverse structural and institutional conditions.

When compared with earlier work, the findings have extended and quantified relationships that previous studies have mainly discussed conceptually. Prior reviews have argued that machine learning and AI can enhance predictive accuracy for yield, risk and logistics and thereby improve competitiveness and resilience in agriculture (Liakos et al., 2018). Wolfert et al. (2017) have emphasized that big data in smart farming can transform decision-making across entire agri-food systems, while Monteiro and Barata (2021) have highlighted emerging AI applications in extended agri-food supply chains. However, these contributions have largely focused on technical capabilities and supply-chain efficiency rather than explicitly linking AI adoption to firm-level export performance or global market integration. The positive and sizable coefficients for AI adoption and data-driven decision-making in this study have provided empirical evidence that supports and concretizes those claims: firms that have moved further along the smart-farming and data-driven supply-chain trajectory have also been more globally embedded. At the same time, the strong associations observed here have complemented ICT-trade studies that have shown how digital technologies reduce trade costs and enable export participation (Abeliansky & Hilbert, 2017), by demonstrating similar dynamics specifically in agribusiness and specifically for AI rather than generic ICT. In that sense, the present results have bridged a gap between digital agriculture research and digital-trade literature by showing that AI-enabled analytics and decision-making are statistically linked to international market outcomes at the firm level.

The comparative findings between the United States and South Asia have provided additional nuance that has enriched prior regional analyses. Earlier work on value-chain restructuring and standards has documented how U.S. agribusiness is characterized by concentrated, vertically coordinated chains with advanced logistics and information systems, while South Asian agrifood systems are more fragmented, with a coexistence of traditional and modern channels (Reardon et al., 2009). Studies on ICT in agriculture in low- and middle-income countries have suggested that digital tools can facilitate market participation but that their impact is conditional on infrastructure, institutional quality and user capabilities (Nakasone et al., 2014). This study's separate regressions have been consistent with those insights: AI adoption and data-driven decision-making have been significant predictors of global market integration in both regions, but the effect sizes have been larger in the U.S. subsample, and the explanatory power of the model has been higher. In South Asia, organizational readiness, environmental support and firm size have played relatively stronger roles, indicating that AI has delivered integration benefits most where firms have already had sufficient internal capacity and operate in somewhat more supportive external environments. These patterns have echoed the argument that digital tools alone do not automatically level the playing field; instead, they interact with existing structural asymmetries and may amplify advantages for better-resourced actors (Klerkx et al., 2019). The study has therefore both confirmed and extended prior work by quantifying how context shapes the strength of AI's market-integration effect across structurally different agribusiness systems.

From a practical standpoint, the results have had direct implications for senior decision-makers such as CIOs, CISOs, chief analytics officers and enterprise architects who have been responsible for designing digital and data architectures in agribusiness firms. The strong effects of both AI adoption and data-driven decision-making have suggested that simply acquiring AI tools has not been sufficient; firms have needed to build end-to-end data pipelines, governance frameworks and security controls that ensure reliable, trustworthy data flows from sensing and transaction systems into analytics and decision processes. Earlier work has warned that big data in agriculture raises substantial challenges around data ownership, privacy and trust (Coble et al., 2018), which has placed CISOs and architects at the center of balancing opportunity and risk. The findings here have implied that investments in secure data integration across production, processing and logistics systems, as well as in user-friendly dashboards and decision-support interfaces, are likely to yield not only operational benefits but also tangible improvements in export intensity and market diversification. For U.S. firms, the priority has often been to scale and harden existing AI pipelines ensuring robustness, cyber-security and interoperability across global operations whereas for many South Asian firms, the more pressing tasks have involved building foundational digital infrastructure, strengthening data quality and training managers to interpret and act on analytics outputs. In both contexts, the evidence that supply-chain connectivity and organizational readiness have been significant predictors of global market integration has underscored the importance of cross-functional collaboration: information security, data architecture, operations and commercial teams have needed to co-design AI solutions that align with standards, certification requirements and buyer expectations in international markets (Kamble et al., 2020).

Theoretically, the study has contributed to the refinement of Technology–Organization–Environment (TOE)–based models in the context of AI and agribusiness. Traditional TOE applications have focused on explaining adoption intention or binary adoption outcomes for technologies such as e-business, cloud computing and big data analytics (Zhu & Kraemer, 2005). More recent work has emphasized that perceived strategic value, organizational data environment and external pressures shape adoption and use of big data analytics in emerging-economy firms (Verma & Bhattacharyya, 2017). The present study has extended these perspectives in two main ways. First, it has treated AI adoption and data-driven decision-making as distinct but related latent constructs, showing that both have had independent effects on global market integration even after controlling for organizational readiness and environmental support. This has suggested that TOE models should explicitly separate "technical capability" (availability of tools) from "decision-process capability" (systematic use of analytical insights), rather than collapsing them into a single adoption variable. Second, by modeling global market integration as a downstream performance outcome, rather than generic organizational performance, the study has demonstrated how TOE constructs and AI capabilities can be linked to specific internationalization metrics export intensity, market diversification and GVC participation. This linkage has opened the door to more granular theorizing about how digital innovation in agribusiness reconfigures firms' positions within global value chains, complementing value-chain-oriented perspectives on standards and upgrading (Lee et al., 2012).

At the level of the conceptual "pipeline" from data to markets, the results have also supported and refined recent frameworks in digital agriculture and data-driven supply chains. Kamble et al. (2020) and Rejeb et al. (2021) have argued that sustainable performance in agri-food supply chains depends on the orchestration of data acquisition, analytics and decision-making across multiple stages of the chain. Delgado et al. (2019) and Saiz-Rubio and Rovira-Más (2020) have described geospatial big-data and Agriculture 5.0 architectures in which local plot-level data flow into cloud-based systems that inform decisions aligned with food-security and sustainability goals. The present study's positive coefficients for AI adoption, data-driven decision-making and supply-chain connectivity, along with the significant roles of organizational readiness and environmental support, have empirically supported a "refined pipeline" view: data infrastructure and AI tools have needed to be embedded in organizational routines and value-chain relationships before they could influence international market outcomes. The fact that the model has explained a substantial share of the variance in global market integration in both regions has suggested that this pipeline conceptualization has general relevance, while the regional differences in coefficient magnitudes have indicated that pipeline "friction points" differ by context for example, data quality and connectivity in South Asia versus scaling and governance in the United States. Theoretically, this points toward a multi-stage, multi-context model of AI-enabled global integration that future work can formalize and test in other sectors and regions.

The study has also had important limitations that have needed to be revisited in light of the empirical findings. The cross-sectional design has meant that all relationships have been estimated at a single point in time, so causal claims have remained probabilistic rather than definitive. While the strong and consistent associations between AI adoption, data-driven decision-making and global market integration have been highly suggestive, reverse causality where more globally integrated firms are more likely to invest in AI cannot be fully ruled out. The reliance on self-reported Likert-scale data has introduced potential common-method variance and social desirability bias, especially for constructs such as AI adoption and organizational readiness, which may be perceived as "good practice." Although reliability and factor-analytic tests have supported the measurement model, and data screening has removed low-quality responses, the biases inherent in self-report surveys have remained. In addition, the sample has not been strictly random: firms have been drawn from directories, associations and export lists, which may over-represent more formal and outward-oriented organizations. This could mean that the average levels of AI adoption and global market integration reported here are higher than in the broader agribusiness population. Finally, the study has focused on firm-level perceptions and has not directly observed transaction-level data, AI model performance metrics or buyer-side evaluations, which would be valuable for triangulating the self-reported indices. These limitations have not invalidated the results but have indicated that findings should be interpreted as strong evidence of association, situated within a specific sample and measurement approach, rather than as exhaustive proof of causal mechanisms.

Building on these limitations, several avenues for future research have emerged. Longitudinal designs that track firms over multiple years would allow researchers to examine how changes in AI adoption and data-driven decision-making precede or follow shifts in export intensity and market diversification, thereby addressing issues of causality more directly. Panel data could also capture dynamic responses to exogenous shocks such as price spikes, trade policy changes or climate-related events and test whether firms with more advanced AI capabilities adapt more quickly in terms of reconfiguring markets and products. Future studies might also integrate objective data sources such as shipment records, certification databases and digitally logged field operations with survey measures to triangulate global market integration and AI usage. Comparative research could expand beyond U.S.–South Asia to include other emerging hubs in Latin America or Africa, thereby examining whether the patterns observed here hold in different institutional and infrastructural environments. Furthermore, qualitative case studies could deepen understanding of the organizational and governance practices that underpin high scores on AI adoption and data-driven decision-making, exploring issues of data sharing, platform governance and power asymmetries along value chains (Runck et al., 2021). Finally, future work could examine distributional outcomes such as inclusion of smallholders, gender impacts or regional equity to complement the present focus on firm-level integration and to assess whether AI-enabled global market integration contributes to, or mitigates, inequality within agrifood systems.

CONCLUSION

The present study has examined how artificial intelligence–enabled, data-driven decision-making has been associated with global market integration for agribusiness firms operating in the United States and South Asia, and it has done so through a quantitative, cross-sectional, case-study–based design grounded in Likert's five-point scale measures of AI adoption, organizational and environmental conditions, and market outcomes. By developing and validating composite indices for AI Adoption, Data-Driven Decision-Making, Supply-Chain Connectivity, Organizational Readiness, Environmental Support and Global Market Integration, the research has provided a structured empirical lens to address its core objectives and hypotheses. The findings have shown that firms reporting higher levels of AI adoption and more systematic reliance on analytical outputs in managerial decisions have also tended to report significantly higher export intensity, greater market diversification and deeper participation in cross-border value chains, with the full regression model explaining more than 40 per cent of the variance in global market integration. Separate models for the U.S. and South Asian subsamples have confirmed that these positive relationships have held in both regional contexts, while revealing that coefficients for AI adoption and data-driven decision-making have been larger, and overall explanatory power higher, among U.S. firms. At the same time, organizational readiness, supply-chain connectivity and environmental support have emerged as important complementary drivers, particularly in South Asia, where firms have needed stronger internal capabilities and more supportive external ecosystems to convert AI investments into global market presence. Collectively, these results have demonstrated that AI in agribusiness has functioned not only as a productivity-enhancing technology at farm and processing levels but also as a strategic integrator that has linked data-rich operations with access to international markets, thereby extending and quantifying propositions that earlier literature has advanced largely at conceptual or technical levels. The study has also highlighted that structural differences between U.S. and South Asian agribusiness systems such as firm size distribution, value-chain organization and institutional infrastructure have shaped how strongly AI capabilities have translated into global integration, suggesting that digital transformation may reinforce existing advantages unless deliberate efforts are made to build readiness and connectivity among more constrained firms and regions. While the cross-sectional design, reliance on self-reported survey data and non-random sampling have limited the ability to draw definitive causal inferences or to generalize beyond the study population, the consistent patterns observed across indices, correlations and regression models have provided robust evidence that AI-enabled, data-driven agribusiness strategies have been closely intertwined with firms' positions in global markets. In doing so, the research has contributed a theoretically grounded and empirically supported framework that future longitudinal, mixed-method and multi-region studies can refine to deepen understanding of how digital and AI innovations in agrifood systems shape not only efficiency and sustainability but also the geography and governance of global agribusiness integration.

RECOMMENDATIONS

Based on the evidence that AI adoption, data-driven decision-making and supply-chain connectivity have been strongly associated with higher levels of export intensity, market diversification and participation in cross-border value chains, this study has put forward several interrelated recommendations for agribusiness managers, technology leaders and policymakers in both the United States and South Asia. At the firm level, senior management has needed to move beyond pilot projects and scattered digital tools toward a coherent AI roadmap that treats data as a strategic asset, with clear investment plans for data collection, integration, governance and analytics across production, processing, logistics and marketing functions; this has included building a central data platform, standardizing data formats and establishing roles such as chief data or analytics officers to ensure that AI outputs are routinely embedded into pricing, contracting, capacity planning and market-entry decisions. To make AI investments effective, firms have been advised to strengthen organizational readiness by investing in staff training, cross-functional analytics teams and change-management processes that encourage managers to trust and use model-based insights rather than relying solely on intuition, particularly for export- and risk-related decisions. Given the finding that supply-chain connectivity has significantly enhanced global market integration, agribusinesses have been encouraged to co-develop digital interfaces with suppliers, logistics providers and buyers such as shared dashboards, EDI links, traceability systems and collaborative planning tools so that AI models can draw on and feed back into a broader network of data flows, thereby improving forecast accuracy and reducing coordination failures along export-oriented chains. In South Asia especially, where AI's impact has depended more strongly on organizational capabilities and external conditions, firms and industry associations have been recommended to pursue collective platforms and data-sharing initiatives (for example, sector-wide quality and traceability systems) that lower the fixed costs of digital infrastructure for smaller firms and help them meet the information requirements of global buyers. Policymakers and development agencies in both regions have been urged to complement firm-level efforts by expanding digital connectivity in rural areas, promoting open and interoperable data standards, and designing incentive schemes such as grants, tax credits or concessional finance for AI projects that demonstrably enhance export readiness, traceability and compliance with international food-safety and sustainability standards. At the same time, regulators and industry bodies have been advised to update data-governance, privacy and cybersecurity frameworks so that CISOs and architects in agribusiness firms can implement robust security and access controls without stifling innovation or cross-border data flows. Finally, both U.S. and South Asian stakeholders have been encouraged to use the type of indices developed in this study covering AI adoption, data-driven decision-making, readiness, connectivity and global integration as internal benchmarking tools, periodically assessing their position and progress and using the results to prioritize investments, partnerships and policy interventions that systematically close the gap between current practice and the levels of AI-enabled global market integration that the empirical findings have shown to be achievable.

LIMITATION

The present study has carried several limitations that have needed to be acknowledged when interpreting its findings and drawing inferences about the role of AI in global agribusiness market integration. First, the research has been cross-sectional in design, capturing firm perceptions and behaviors at a single point in time, which has meant that relationships between AI adoption, data-driven decision-making and global market integration have been estimated as associations rather than as proven causal effects; it has remained possible that more globally integrated firms have been more likely to invest in AI, or that both AI and export performance have been driven by unobserved strategic orientations or leadership characteristics. Second, all core constructs including AI adoption intensity, decision-making practices, organizational readiness, supply-chain connectivity, environmental support and global market integration have been measured using self-reported Likert's five-point scale items completed by a single key informant per firm, which has introduced potential biases such as common-method variance, social desirability and differences in response styles across cultures; although reliability and factor-analytic checks have supported the internal coherence of the scales, the study has not directly triangulated these indices with objective indicators such as transaction-level trade data, digital usage logs or independently verified certification records. Third, the sampling strategy has relied on business directories, industry associations and export-related lists in the United States and South Asia, producing a reasonably diverse but not strictly random sample; as a result, more formal, outward-oriented and digitally aware firms have likely been overrepresented, and the average levels of AI adoption and global integration observed here may have exceeded those in the wider population of agribusiness enterprises, particularly among very small or informal firms. Fourth, the analysis has treated "South Asia" as a single regional block, aggregating firms from different countries with heterogeneous policy regimes, infrastructural conditions and market structures, so the results have not captured country-specific dynamics or intra-regional variations that may be important for more granular policy design. Fifth, the operationalization of AI adoption and data-driven decision-making has been necessarily broad and generic, reflecting the presence and perceived use of a range of tools rather than the technical quality, performance or sophistication of specific AI models, and the linear regression framework has not captured potentially non-linear or threshold effects for example, situations in which benefits from AI only materialize after a critical mass of investment, data volume or partner connectivity has been achieved. Sixth, the study has focused exclusively on the firm perspective within agribusiness value chains and has not incorporated the views or data of upstream farmers, downstream buyers, financial institutions or platform providers, which has limited the ability to fully understand how AI-enabled integration has redistributed risks, rents and decision power along the chain. Finally, the fast-evolving nature of AI and digital agriculture has meant that the empirical patterns documented here have represented a snapshot in time; subsequent technological advances, regulatory changes or trade disruptions may alter the strength or structure of the relationships observed, so the findings have been best interpreted as a baseline for ongoing longitudinal and mixed-method investigations rather than as a definitive and timeless characterization of AI's role in agribusiness global market integration.

REFERENCES

[1]. Abdul, H. (2023). Artificial Intelligence in Product Marketing: Transforming Customer Experience And Market Segmentation. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 132–159. https://doi.org/10.63125/58npbx97

[2]. Abdulla, M., & Md. Wahid Zaman, R. (2023). Quantitative Study On Workflow Optimization Through Data Analytics In U.S. Digital Enterprises. *American Journal of Interdisciplinary Studies*, *4*(03), 136–165. https://doi.org/10.63125/y2qshd31

[3]. Abeliansky, A. L., & Hilbert, M. (2017). Digital technology and international trade: Is it the quantity of subscriptions or the quality of data speed that matters? *Telecommunications Policy*, *41*(1), 35–48. https://doi.org/10.1016/j.telpol.2016.11.001

[4]. Aker, J. C. (2010). Information from markets near and far: Mobile phones and agricultural markets in Niger. *American Economic Journal: Applied Economics*, *2*(3), 46–59. https://doi.org/10.1257/app.2.3.46

[5]. Alambaigi, A., & Ahangari, I. (2016). Technology Acceptance Model (TAM) as a predictor model for explaining agricultural experts' behavior in acceptance of ICT. *International Journal of Agricultural Management and Development*, *6*(2), 235–247.

[6]. Arfan, U., Sai Praveen, K., & Alifa Majumder, N. (2021). Predictive Analytics For Improving Financial Forecasting And Risk Management In U.S. Capital Markets. *American Journal of Interdisciplinary Studies*, *2*(04), 69–100. https://doi.org/10.63125/tbw49w69

[7]. Arfan, U., Tahsina, A., Md Mostafizur, R., & Md, W. (2023). Impact Of GFMIS-Driven Financial Transparency On Strategic Marketing Decisions In Government Agencies. *Review of Applied Science and Technology*, *2*(01), 85-112. https://doi.org/10.63125/8nqhhm56

[8]. Baker, J. (2012). The Technology–Organization–Environment framework. In Y. K. Dwivedi, M. R. Wade, & S. L. Schneberger (Eds.), *Information systems theory* (pp. 231–245). Springer. https://doi.org/10.1007/978-1-4419-6108-2_12

[9]. Bojnec, Š., & Fertő, I. (2021). Agri-food trade competitiveness: A review of the literature. *Sustainability*, *13*(20), 11235. https://doi.org/10.3390/su132011235

[10]. Coble, K. H., Mishra, A. K., Ferrell, S., & Griffin, T. (2018). Big data in agriculture: A challenge for the future. *Applied Economic Perspectives and Policy*, *40*(1), 79–96. https://doi.org/10.1093/aepp/ppx056

[11]. Delgado, J. A., Short, N. M., Jr., Roberts, D. P., & Vandenberg, B. (2019). Big data analysis for sustainable agriculture on a geospatial cloud framework. *Frontiers in Sustainable Food Systems*, *3*, 54. https://doi.org/10.3389/fsufs.2019.00054

[12]. Eli-Chukwu, N. C. (2019). Applications of artificial intelligence in agriculture: A review. *Engineering, Technology & Applied Science Research*, *9*(4), 4377–4383. https://doi.org/10.48084/etasr.2756

[13]. Fafchamps, M., & Minten, B. (2012). Impact of SMS-based agricultural information on Indian farmers. *The World Bank Economic Review*, *26*(3), 383–414. https://doi.org/lhr056

[14]. Ferdous Ara, A. (2021). Integration Of STI Prevention Interventions Within PrEP Service Delivery: Impact On STI Rates And Antibiotic Resistance. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 63–97. https://doi.org/10.63125/65143m72

[15]. Ferdous Ara, A., & Beatrice Onyinyechi, M. (2023). Long-Term Epidemiologic Trends Of STIs PRE- and POST-PrEP Introduction: A National Time-Series Analysis. *American Journal of Health and Medical Sciences*, *4*(02), 01–35. https://doi.org/10.63125/mp153d97

[16]. Humphrey, J. (2006). Policy implications of trends in agribusiness value chains. *The European Journal of Development Research*, *18*(4), 572–592. https://doi.org/10.1080/09578810601070704

[17]. Humphrey, J. (2007). The supermarket revolution in developing countries: Tidal wave or tough competitive struggle? *Journal of Economic Geography*, *7*(4), 433–450. https://doi.org/10.1093/jeg/lbm008

[18]. Ifinedo, P. (2011). Internet/e-business technologies acceptance in Canada's SMEs: An exploratory investigation. *Internet Research*, *21*(3), 255–281. https://doi.org/10.1108/10662241111139309

[19]. Ingram, J., & Maye, D. (2020). What are the implications of digitalisation for agricultural knowledge? *Frontiers in Sustainable Food Systems*, *4*, 66. https://doi.org/10.3389/fsufs.2020.00066

[20]. Jahid, M. K. A. S. R. (2021). Digital Transformation Frameworks For Smart Real Estate Development In Emerging Economies. *Review of Applied Science and Technology*, *6*(1), 139–182. https://doi.org/10.63125/cd09ne09

[21]. Jha, K., Doshi, A., Patel, P., & Shah, M. (2019). A comprehensive review on automation in agriculture using artificial intelligence. *Artificial Intelligence in Agriculture*, *2*, 1–12. https://doi.org/10.1016/j.aiia.2019.05.004

[22]. Jiménez, D., Delerce, S., Dorado, H., Cock, J., Muñoz, L. A., Agamez, A., & Jarvis, A. (2019). A scalable scheme to implement data-driven agriculture for small-scale farmers. *Global Food Security*, *23*, 256–266. https://doi.org/10.1016/j.gfs.2019.08.004

[23]. Jouanjean, M.-A. (2019). *Digital opportunities for trade in the agriculture and food sectors (OECD Food, Agriculture and Fisheries Papers No. 122)*.

[24]. Kamble, S. S., Gunasekaran, A., & Gawankar, S. A. (2020). Achieving sustainable performance in a data-driven agriculture supply chain: A review for research and applications. *International Journal of Production Economics*, *219*, 179–194. https://doi.org/10.1016/j.ijpe.2019.05.022

[25]. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, *147*, 70–90. https://doi.org/10.1016/j.compag.2018.02.016

[26]. Klerkx, L., Jakku, E., & Labarthe, P. (2019). A review of social science on digital agriculture, smart farming and Agriculture 4.0: New contributions and a future research agenda. *NJAS – Wageningen Journal of Life Sciences*, *90–91*, 100315. https://doi.org/10.1016/j.njas.2019.100315

[27]. Kos, D., & Kloppenburg, S. (2019). Digital technologies, hyper-transparency and smallholder farmer inclusion in global value chains. *Current Opinion in Environmental Sustainability*, *41*, 56–63. https://doi.org/10.1016/j.cosust.2019.10.011

[28]. Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management: An empirical investigation. *The International Journal of Logistics Management*, *29*(2), 676–703. https://doi.org/10.1108/ijlm-06-2017-0153

[29]. Lee, J., Gereffi, G., & Beauvais, J. (2012). Global value chains and agrifood standards: Challenges and possibilities for smallholders in developing countries. *Proceedings of the National Academy of Sciences*, *109*(31), 12326–12331. https://doi.org/10.1073/pnas.0913714108

[30]. Liakos, K. G., Busato, P., Moshou, D., Pearson, S., & Bochtis, D. (2018). Machine learning in agriculture: A review. *Sensors*, *18*(8), 2674. https://doi.org/10.3390/s18082674

[31]. Liu, M., Min, S., Ma, W., & Liu, T. (2021). The adoption and impact of E-commerce in rural China: Application of an endogenous switching regression model. *Journal of Rural Studies*, *83*, 106–116. https://doi.org/10.1016/j.jrurstud.2021.02.021

[32]. Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial Management & Data Systems*, *111*(7), 1006–1023. https://doi.org/10.1108/02635571111161262
[33]. Maertens, M., & Swinnen, J. (2015). *Agricultural trade and development: A value chain perspective (WTO Staff Working Paper ERSD-2015-04)*.
[34]. Md Al Amin, K., & Md Mesbaul, H. (2023). Smart Hybrid Manufacturing: A Combination Of Additive, Subtractive, And Lean Techniques For Agile Production Systems. *Journal of Sustainable Development and Policy*, *2*(04), 174-217. https://doi.org/10.63125/7rb1zz78
[35]. Md Ariful, I., & Efat Ara, H. (2022). Advances And Limitations Of Fracture Mechanics–Based Fatigue Life Prediction Approaches For Structural Integrity Assessment: A Systematic Review. *American Journal of Interdisciplinary Studies*, *3*(03), 68-98. https://doi.org/10.63125/fg8ae957
[36]. Md Arman, H., & Md.Kamrul, K. (2022). A Systematic Review of Data-Driven Business Process Reengineering And Its Impact On Accuracy And Efficiency Corporate Financial Reporting. *International Journal of Business and Economics Insights*, *2*(4), 01–41. https://doi.org/10.63125/btx52a36
[37]. Md Foysal, H., & Aditya, D. (2023). Smart Continuous Improvement With Artificial Intelligence, Big Data, And Lean Tools For Zero Defect Manufacturing Systems. *American Journal of Scholarly Research and Innovation*, *2*(01), 254–282. https://doi.org/10.63125/6cak0s21
[38]. Md Hamidur, R. (2023). Thermal & Electrical Performance Enhancement Of Power Distribution Transformers In Smart Grids. *American Journal of Scholarly Research and Innovation*, *2*(01), 283–313. https://doi.org/10.63125/n2p6y628
[39]. Md Harun-Or-Rashid, M., Mst. Shahrin, S., & Sai Praveen, K. (2023). Integration Of IOT And EDGE Computing For Low-Latency Data Analytics In Smart Cities And IOT Networks. *Journal of Sustainable Development and Policy*, *2*(03), 01-33. https://doi.org/10.63125/004h7m29
[40]. Md Mesbaul, H., & Md. Tahmid Farabe, S. (2022). Implementing Sustainable Supply Chain Practices In Global Apparel Retail: A Systematic Review Of Current Trends. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 332–363. https://doi.org/10.63125/nen7vd57
[41]. Md Musfiqur, R., & Md.Kamrul, K. (2023). Mechanisms By Which AI-Enabled Crm Systems Influence Customer Retention And Overall Business Performance: A Systematic Literature Review Of Empirical Findings. *International Journal of Business and Economics Insights*, *3*(1), 31-67. https://doi.org/10.63125/qqe2bm11
[42]. Md Muzahidul, I., & Md Mohaiminul, H. (2023). Explainable AI (XAI) Models For Cloud-Based Business Intelligence: Ensuring Compliance And Secure Decision-Making. *American Journal of Interdisciplinary Studies*, *4*(03), 208–249. https://doi.org/10.63125/5etfhh77
[43]. Md Nahid, H. (2022). Statistical Analysis of Cyber Risk Exposure And Fraud Detection In Cloud-Based Banking Ecosystems. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *2*(1), 289–331. https://doi.org/10.63125/9wf91068
[44]. Md Sarwar Hossain, S., & Md Milon, M. (2022). Machine Learning-Based Pavement Condition Prediction Models For Sustainable Transportation Systems. *American Journal of Interdisciplinary Studies*, *3*(01), 31–64. https://doi.org/10.63125/1jsmkg92
[45]. Md. Abdur, R., & Zamal Haider, S. (2022). Assessment Of Data-Driven Vendor Performance Evaluation In Retail Supply Chains Analyzing Metrics, Scorecards, And Contract Management Tools. *Journal of Sustainable Development and Policy*, *1*(04), 71-116. https://doi.org/10.63125/2a641k35
[46]. Md. Al Amin, K., & Sai Praveen, K. (2023). The Role Of Industrial Engineering In Advancing Sustainable Manufacturing And Quality Compliance In Global Engineering Systems. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 31–61. https://doi.org/10.63125/8w1vk676
[47]. Md. Hasan, I., & Ashraful, I. (2023). The Effect Of Production Planning Efficiency On Delivery Timelines In U.S. Apparel Imports. *Journal of Sustainable Development and Policy*, *2*(04), 35-73. https://doi.org/10.63125/sg472m51
[48]. Md. Jobayer Ibne, S., & Md. Kamrul, K. (2023). Automating NIST 800-53 Control Implementation: A Cross-Sector Review Of Enterprise Security Toolkits. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *3*(1), 160–195. https://doi.org/10.63125/prkw8r07
[49]. Md.Akbar, H., & Farzana, A. (2021). High-Performance Computing Models For Population-Level Mental Health Epidemiology And Resilience Forecasting. *American Journal of Health and Medical Sciences*, *2*(02), 01–33. https://doi.org/10.63125/k9d5h638
[50]. Mohammad Mushfequr, R., & Ashraful, I. (2023). Automation And Risk Mitigation in Healthcare Claims: Policy And Compliance Implications. *Review of Applied Science and Technology*, *2*(04), 124–157. https://doi.org/10.63125/v73gyg14
[51]. Mohammad Mushfequr, R., & Sai Praveen, K. (2022). Quantitative Investigation Of Information Security Challenges In U.S. Healthcare Payment Ecosystems. *International Journal of Business and Economics Insights*, *2*(4), 42–73. https://doi.org/10.63125/gcg0fs06
[52]. Monteiro, J., & Barata, J. (2021a). Artificial intelligence in extended agri-food supply chain: A short review based on bibliometric analysis. Procedia Computer Science,
[53]. Monteiro, J., & Barata, J. (2021b). Artificial intelligence in extended agri-food supply chain: A short review based on bibliometric analysis. *Procedia Computer Science*, *192*, 3020–3029. https://doi.org/10.1016/j.procs.2021.09.074
[54]. Mortuza, M. M. G., & Rauf, M. A. (2022). Industry 4.0: An Empirical Analysis of Sustainable Business Performance Model Of Bangladeshi Electronic Organisations. *International Journal of Economy and Innovation*. https://gospodarkainnowacje.pl/index.php/issue_view_32/article/view/826

[55]. Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, *114*(4), 358–371. https://doi.org/10.1016/j.biosystemseng.2012.08.009
[56]. Nakasone, E., Torero, M., & Minten, B. (2014). The power of information: The ICT revolution in agricultural development. *Annual Review of Resource Economics*, *6*(1), 533–550. https://doi.org/10.1146/annurev-resource-100913-012714
[57]. Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. *The Electronic Journal of Information Systems Evaluation*, *14*(1), 110–121.
[58]. Pankaz Roy, S., & Md. Kamrul, K. (2023). HACCP and ISO Frameworks For Enhancing Biosecurity In Global Food Distribution Chains. *American Journal of Scholarly Research and Innovation*, *2*(01), 314–356. https://doi.org/10.63125/9pbp4h37
[59]. Rakibul, H., & Samia, A. (2022). Information System-Based Decision Support Tools: A Systematic Review Of Strategic Applications In Service-Oriented Enterprises. *Review of Applied Science and Technology*, *1*(04), 26-65. https://doi.org/10.63125/w3cevz78
[60]. Reardon, T., Barrett, C. B., Berdegué, J. A., & Swinnen, J. F. M. (2009). Agrifood industry transformation and small farmers in developing countries. *World Development*, *37*(11), 1717–1727. https://doi.org/10.1016/j.worlddev.2008.08.023
[61]. Rejeb, A., Rejeb, K., & Zailani, S. (2021). Big data for sustainable agri-food supply chains: A review and future research perspectives. *Journal of Data, Information and Management*, *3*, 167–182. https://doi.org/10.1007/s42488-021-00045-3
[62]. Reza, M., Vorobyova, K., & Rauf, M. (2021). The effect of total rewards system on the performance of employees with a moderating effect of psychological empowerment and the mediation of motivation in the leather industry of Bangladesh. *Engineering Letters*, *29*, 1-29.
[63]. Rodríguez-Crespo, E., & Martínez-Zarzoso, I. (2019). The effect of ICT on trade: Does product complexity matter? *Telematics and Informatics*, *41*, 182–196. https://doi.org/10.1016/j.tele.2019.05.001
[64]. Rony, M. A., & Ashraful, I. (2022). Big Data And Engineering Analytics Pipelines For Smart Manufacturing: Enhancing Efficiency, Quality, And Predictive Maintenance. *American Journal of Scholarly Research and Innovation*, *1*(02), 59–85. https://doi.org/10.63125/rze0my79
[65]. Rose, D. C., & Chilvers, J. (2018). Agriculture 4.0: Broadening responsible innovation in an era of smart farming. *Frontiers in Sustainable Food Systems*, *2*, 87. https://doi.org/10.3389/fsufs.2018.00087
[66]. Rotz, S., Duncan, E., Small, M., Botschner, J., Dara, R., Mosby, I., Reed, M., & Fraser, E. D. G. (2019). The politics of digital agricultural technologies: A preliminary review. *Sociologia Ruralis*, *59*(2), 203–229. https://doi.org/10.1111/soru.12233
[67]. Runck, B. C., Joglekar, A., Silverstein, K., Chan-Kang, C., Pardey, P. G., & Wilgenbusch, J. (2021). Digital agriculture platforms: Driving data-enabled agricultural innovation in a world fraught with privacy and security concerns. *Agronomy Journal*, *114*(4), 2635–2643. https://doi.org/10.1002/agj2.20873
[68]. Saba, A., Shaikat, B., & Tonoy Kanti, C. (2023). Integration Of Artificial Intelligence And Advanced Computing To Develop Resilient Cyber Defense Systems. *Journal of Sustainable Development and Policy*, *2*(04), 74-107. https://doi.org/10.63125/rxyc6y88
[69]. Saba, A., & Tonoy Kanti, C. (2023). Explainable Artificial Intelligence (XAI) Approaches For Cyber Risk Assessment In Financial Services. *American Journal of Interdisciplinary Studies*, *4*(03), 96-135. https://doi.org/10.63125/3gjcb322
[70]. Saikat, S. (2021). Real-Time Fault Detection in Industrial Assets Using Advanced Vibration Dynamics And Stress Analysis Modeling. *American Journal of Interdisciplinary Studies*, *2*(04), 39–68. https://doi.org/10.63125/0h163429
[71]. Saikat, S. (2022). CFD-Based Investigation of Heat Transfer Efficiency In Renewable Energy Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 129–162. https://doi.org/10.63125/ttw40456
[72]. Saiz-Rubio, V., & Rovira-Más, F. (2020). From smart farming towards Agriculture 5.0: A review on crop data management. *Agronomy*, *10*(2), 207. https://doi.org/10.3390/agronomy10020207
[73]. Scherer, R., Siddiq, F., & Tondeur, J. (2019). The technology acceptance model (TAM): A meta-analytic structural equation modeling approach. *Computers & Education*, *128*, 13–35. https://doi.org/10.1016/j.compedu.2018.09.009
[74]. Shaikh, S., & Aditya, D. (2021). Federated Learning-Driven Predictive Quality Analytics and Supply Chain Optimization In Distributed Manufacturing Networks. *Review of Applied Science and Technology*, *6*(1), 74-107. https://doi.org/10.63125/k18cbz55
[75]. Shaikh, S., & Md. Tahmid Farabe, S. (2023). Digital Twin-Driven Process Modeling For Energy Efficiency And Lifecycle Optimization In Industrial Facilities. *American Journal of Interdisciplinary Studies*, *4*(03), 65–95. https://doi.org/10.63125/e4q64869
[76]. Shaikh, S., & Sudipto, R. (2022). Multi-Objective Thermo-Economic and Supply Chain Optimization Modeling For Hydrogen Energy Integration In Smart Factories. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 163–193. https://doi.org/10.63125/p9y8p705
[77]. Sishodia, R. P., Ray, R. L., & Singh, S. K. (2020). Applications of remote sensing in precision agriculture: A review. *Remote Sensing*, *12*(19), 3136. https://doi.org/10.3390/rs12193136
[78]. Swinnen, J. F. M., & Maertens, M. (2007). Globalization, privatization, and vertical coordination in food value chains in developing and transition countries. *Agricultural Economics*, *37*(s1), 89–102. https://doi.org/10.1111/j.1574-0862.2007.00237.x
[79]. Talaviya, T., Shah, D., Patel, N., Yagnik, H., & Shah, M. (2020). Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides. *Artificial Intelligence in Agriculture*, *4*, 58–73. https://doi.org/10.1016/j.aiia.2020.04.002

[80]. Tonoy Kanti, C., & Shaikat, B. (2021). Blockchain-Enabled Security Protocols Combined With AI For Securing Next-Generation Internet Of Things (IOT) Networks. *International Journal of Scientific Interdisciplinary Research*, *2*(2), 98–127. https://doi.org/10.63125/pcdqzw41
[81]. van Klompenburg, T., Kassahun, A., & Catal, C. (2020). Crop yield prediction using machine learning: A systematic literature review. *Computers and Electronics in Agriculture*, *177*, 105709. https://doi.org/10.1016/j.compag.2020.105709
[82]. Verma, S., & Bhattacharyya, S. S. (2017). Perceived strategic value-based adoption of Big Data Analytics in emerging economy: A qualitative approach for Indian firms. *Journal of Enterprise Information Management*, *30*(3), 354–382. https://doi.org/10.1108/jeim-10-2015-0099
[83]. Wolfert, S., Ge, L., Verdouw, C., & Bogaardt, M.-J. (2017). Big data in smart farming – A review. *Agricultural Systems*, *153*, 69–80. https://doi.org/10.1016/j.agsy.2017.01.023
[84]. Yushkova, E. (2014). Impact of ICT on trade in different technology groups: Analysis and implications. *International Economics and Economic Policy*, *11*(1–2), 165–177. https://doi.org/10.1007/s10368-013-0264-5
[85]. Zamal Haider, S., & Hozyfa, S. (2023). A Quantitative Study On IT-Enabled ERP Systems And Their Role In Operational Efficiency. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 62–99. https://doi.org/10.63125/nbpyce10
[86]. Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. *Information Systems Research*, *16*(1), 61–84. https://doi.org/10.1287/isre.1050.0045