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# *Blockchain for Sustainable and Inclusive Agrifood Systems in Africa: Field Evidence and Country Readiness Assessment*

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# Contents

# General Introduction

The rapid evolution of agrifood systems lies at the intersection of many of the world's most pressing challenges: ensuring food security, fostering rural livelihoods, and promoting sustainable development amid intensifying environmental, economic, and social pressures. These challenges are particularly acute in Sub-Saharan Africa, where smallholder farmers remain central to food systems yet continue to face persistent constraints such as limited access to finance, market volatility, infrastructural deficits, and pervasive trust gaps (Fafchamps 2004; Ayim et al. 2022).

Digital innovations have increasingly been promoted as transformative tools for agricultural development, capable of overcoming long-standing barriers to market integration, traceability, and financial inclusion. Among these, *blockchain technology* has attracted growing attention for its theoretical capacity to address problems of transparency, accountability, and coordination within complex agrifood value chains (Casino et al. 2019; Kamilaris et al. 2018). Yet despite its promise, both the academic and policy debates on blockchain in agriculture remain fragmented and largely dominated by technological or pilot-specific perspectives.

Several critical knowledge gaps persist. First, there is limited synthesis of how the economic, social, and environmental implications of blockchain adoption have been theorised and empirically assessed in the scholarly literature. Second, while isolated case studies have documented blockchain applications in supply chains or certification processes, little is known about how *farmers themselves* perceive and experience these platforms, especially in developing-country contexts. Finally, there is a lack of systematic analysis of the *structural and institutional conditions* that shape a country's readiness to adopt and scale blockchain-enabled solutions in agriculture.

Blockchain in agrifood systems should be understood not merely as a technological innovation, but as a socio-technical and institutional one. It has the potential to redistribute information, authority, and incentives across value-chain actors, lowering coordination frictions and strengthening accountability, while also generating new governance and power asymmetries.

This perspective frames blockchain as part of broader trust reconfiguration processes, where cryptographic verification and traceability can complement, though never fully replace, institutional reliability and social capital. In this view, blockchain adoption is linked to classic technology-adoption frameworks—such as the Unified Theory of Acceptance and Use of Technology (UTAUT), the Technology–Organisation–Environment (TOE) model, and the Technology Acceptance Model (TAM)—reinterpreted for the constraints of smallholder agriculture. The thesis also draws conceptually on the Triple Bottom Line approach to sustainability, recognising that the economic, social, and environmental dimensions of innovation interact in context-specific and often unequal ways.

This dissertation is motivated by the need to address these interrelated gaps through an integrated, evidence-based analysis. Both personal and academic engagement with agricultural development in Nigeria—through fieldwork conducted within the AgriFi project—have provided first-hand insights into the promises and challenges of implementing blockchain-enabled innovation in low-resource environments. These experiences underscored the necessity of a multidimensional approach that links micro-level behavioural evidence with macro-structural enablers, while situating both within the wider theoretical and policy discourse on sustainable digital transitions.

Within this conceptual perspective, the thesis explicitly foregrounds inclusion, institutional readiness, and human capacity as essential complements to technological design and performance.

Accordingly, the overarching aim of this thesis is to assess the potential and limits of blockchain-based innovation in African agrifood systems by combining **conceptual review**, **empirical investigation**, and **comparative readiness analysis**. The research is guided by three broad questions that correspond to the structure of the dissertation:

1. **What is known?** To what extent, and with what methodological rigour, have the economic, social, and environmental dimensions of blockchain adoption been investigated in the existing literature?

2. **How is it experienced?** How do smallholder farmers engaged with a blockchain-enabled agricultural platform perceive its economic and social benefits, and what factors shape these perceptions?

3. **Where is it feasible?** Which African countries possess the enabling conditions required for the scaling of blockchain solutions in agriculture, and how can readiness be assessed systematically?

These questions reflect a cumulative logic: from theoretical consolidation to micro-level evidence and finally to macro-level contextualisation.

To answer these questions, the thesis adopts a **multi-method design** encompassing both qualitative and quantitative approaches.

- **Chapter 1** employs a *scoping review* of peer-reviewed literature on blockchain applications in the agrifood sector, systematically mapping how the *Triple Bottom Line* (TBL) dimensions—economic, social, and environmental sustainability—have been addressed. Using bibliometric and text-analysis tools (SciVal, VOSviewer) in conjunction with *Snowball Metrics* (Tricco et al.

2018; Arksey and O'Malley 2005), this chapter identifies knowledge clusters, theoretical models, and methodological gaps.

- **Chapter 2** turns to *primary field data* collected from 206 smallholder farmers in Nigeria across two contrasting implementation contexts—Niger State (private-investment model) and Katsina State (publicly funded model). Through descriptive and econometric analyses, it evaluates farmers' perceived economic and social benefits from participation in the AgriFi blockchain platform and isolates the socio-economic determinants of those perceptions.

- **Chapter 3** extends the analysis to the *macro-structural level*, developing a Blockchain Readiness Index for 48 Sub-Saharan African countries. Drawing on open-access secondary indicators covering digital connectivity, institutional capacity, inclusion, and infrastructure, it applies multiple weighting schemes and k-means clustering to derive comparative readiness profiles (OECD 2008; Nardo et al. 2005).

By integrating these methods, the dissertation bridges conceptual, micro-empirical, and macro-comparative perspectives within a coherent analytical framework.

The logic linking these three chapters is a commitment to understanding blockchain not merely as a technological artefact, but as a *context-dependent socio-institutional innovation* embedded in African agrifood systems. The thesis progresses from a critical assessment of the scholarly landscape (Chapter 1), through farmer-centred empirical investigation (Chapter 2), to a systems-level evaluation of enabling environments (Chapter 3).

This structure allows the work to address not only "what is known" about blockchain and sustainability in agrifood systems, but also "how it is experienced" by smallholder farmers and "where it is most feasible" to achieve inclusive and sustainable impacts.

The findings of this thesis contribute to several strands of academic and policy debate:

1. **Theoretical contribution.** By applying the TBL framework to blockchain in agrifood systems and linking it to both behavioural and structural dimensions, the thesis advances a more holistic understanding of *digital sustainability*.

2. **Empirical contribution.** The field evidence from Nigeria provides one of the first micro-level analyses of smallholder perceptions of a blockchain-enabled platform in Africa, highlighting the role of training, experience, and institutional context.

3. **Methodological contribution.** The Readiness Index offers a transparent, reproducible tool for cross-country comparison and for identifying enabling conditions for blockchain adoption.

4. **Policy relevance.** Collectively, the chapters provide evidence to inform national and regional strategies on digital agriculture, suggesting that blockchain's potential can only be realised when coupled with investments in human capacity, infrastructure, and trust-building mechanisms (World Bank 2024; GSMA 2023).

By adopting this multidimensional perspective, the thesis not only contributes to debates on blockchain and sustainability in agrifood systems but also engages with broader questions in development economics—how digital innovations interact with institutional structures, power asymmetries, and local capacities in low- and middle-income contexts. Such a cross-scalar approach, connecting technological design to human and institutional dimensions, responds to ongoing calls for more holistic analyses of digital transformation in the Global South.

Following this *General Introduction*, the thesis presents each of the three papers as stand-alone yet interconnected chapters:

- **Chapter 1** – *Multidimensional sustainability of agrifood blockchain applications: A scoping review of issues and potential.*
- **Chapter 2** – *Perceived Economic and Social Benefits of AgriFi: Early Evidence from a Blockchain-Enabled Platform in Nigeria.*
- **Chapter 3** – *Identifying Opportunities for Blockchain in African Agriculture: A Readiness Index and Cluster Analysis.*

The dissertation concludes with an integrative chapter summarising the main findings, discussing their implications for research, policy, and practice, and outlining avenues for future investigation.

# Chapter 1

# Multidimensional sustainability of agrifood blockchain applications: A scoping review of issues and potential


## Abstract

This paper presents a scoping review of scientific literature exploring current research on the sustainability of blockchain applications in the agri-food sector. The review follows the Triple Bottom Line (TBL) approach, which focuses on economic, social and environmental sustainability. The purpose is to map the state of the art on these topics and identify trends that can serve as good proxies to assess the interest of academics and research institutions in these topics. The Scopus database was used to conduct the literature search. The articles were analyzed using scoping review methodologies in combination with Snowball Metrics.

## 1.1 Introduction

Agrifood systems (AFS) are under pressure due to both internal and external factors. On the one hand, external shocks and stressors such as the increase of the frequency of extreme weather events due to climate change, supply chain disruptions due to conflicts such as the Russia-Ukraine war, and health systemic shocks such as Covid-19, all contributed to make the functioning of agrifood system riskier and uncertain and eventually led to an increase of food insecurity worldwide.[1] On the other hand, the credence good nature of agrifood products and the increasing complexity of agrifood supply chains under globalization (Christopher et al. 2011; Minarelli et al. 2016), with companies having less control of key processes and monitoring agencies having less ability to detect fraud, compound with the above mentioned external factors, further increasing food insecurity and the likelihood of food safety accidents and frauds (Rocchi et al. 2020)

Increased risks and uncertainties have sparked an increasing demand to make available to all AFS stakeholders information on production methods, product quality and composition, product area of origin, etc. Recently, public awareness and concern as well as scholarly interest towards such technical innovations has increased significantly, with blockchain technologies (BCT) becoming one of the most promising solutions also in the AFS. BCT are essentially a decentralized, immutable, and shared database that records any digital assets' movement. It is a connected distributed database managed among nodes in peer-to-peer networks and consists of network, protocol, ledger, and application layers. When applied to the agrifood supply chain, BCT enhances data disclosure and the accountability of all actors along the chain by providing a decentralized distributed ledger, time stamps, consensus structures, and cryptographic algorithms for secure information storage and verification. Furthermore, the immutability of blockchain guarantees that past data cannot be changed without notifying other users, which helps to prevent alterations to records and provides proof during enquiries (e.g. food recalls). In conclusion, agrifood blockchain applications promise to address information asymmetry, foster trust building, and improve agrifood supply chain visibility and transparency.

BCT can also decrease uncertainty and mitigate the impact of unforeseen external shocks. To deal with these issues, global value chains need to address issues such as resource scarcity, poor farm management, processing problems,

[1]The Economists' Global Food Security Index shows that the global food environment is deteriorating. After hitting its peak in 2019, the GFSI has since declined amid skyrocketing food prices and hunger on an unprecedented scale (*Global Food Security Index* 2022).

overproduction, food losses, unstable markets and barriers to cooperation between stakeholders (Timmermans et al. 2014; FAO 2019; FAO 2022). Challenges related to regulatory compliance also are of paramount importance and can constitute serious threats to free trade (Danezis et al. 2016; Pakseresht et al. 2022).

These issues have not only economic implications at different scales (individuals, communities and whole countries), but carries also important social and environmental implications (Barrientos et al. 2011). For instance, significant social implications concern the working conditions of agricultural and food processing labour force, an issue that is particularly relevant in global value chains that span across different legislation. Labour-intensive agricultural production is often associated with areas where work precarious, salaries are low and union protection is lacking (Burch and Lawrence 2009; Raynolds 2000). Furthermore, the concentration of power in the hands of large trade intermediaries and multinational corporations can undermine the ability of local communities to control their own food resources and access international markets (Bakewell et al. 2009). This, in turn, detrimentally impacts small-scale producers and local business. Eventually, rising economic instability in farming communities may lead to forced migration from rural to urban areas or even to foreign countries in search of better opportunities (Maertens and Swinnen 2009; Wittman 2009).

Consumer's awareness about environmental impact of agrifood supply chains is also increasing and the demand for sustainable food products is rising accordingly. Many consumers prefer products labelled organic, sustainably sourced, or environmentally responsible (Grunert et al. 2014; Rousseau 2015). This growing awareness is shown by the rising preference for supporting local food systems and environmentally sustainable farming and food processing practices (De Pelsmacker et al. 2005; Del Giudice et al. 2016). Thus, consumers seek out brands and companies dedicated to environmentally responsible practices, including reducing plastic packaging and regulating sustainable production practices, and are willing to pay a premium for such products (Kumar et al. 2017; Campbell et al. 2015).

In short, many authors have emphasized that BCT could in principle could contribute pursuing any of the three dimensions of sustainability, i.e. economic, social and environmental, in the AFS. From the economic viewpoint, it can improve traceability and efficiency along the agrifood value chains (Pun et al. 2021). In terms of environmental concerns, it provides detailed and accurate information on carbon emissions and other environmental challenges through on-time data uploading and sharing (Pan et al. 2019; Chohan 2019). From a societal standpoint, it encourages fair behaviours amongst stakeholders by discouraging fraudulent conduct trough data sharing, equalising also information accessibility throughout the supply chain (Upadhyay et al. 2021).

Therefore, this paper aims to assess what we know so far about the feasibility and effects of applying BCT to the agrifood system in terms of economic, social, and environmental sustainability. This assessment is carried out through a scoping review of existing evidence. In doing this, we give preference to papers providing empirical evidence. We will conduct the analysis on the most relevant papers using standard scoping review techniques together with Snowball Metrics to assess to what extent literature on BCT application in the agrifood system addressed economic, social and environmental sustainability problems. These three frameworks compose the so called "triple bottom line" (TBL) of sustainability (Elkington and Rowlands 1999).

The paper is organized into three main parts. Firstly, the theoretical framework supporting the BCT adoption in the AFS is outlined. Secondly, the methodology employed in selecting papers to be analyzed in the scoping review is discussed, followed by an analysis of the results. The final section concludes.

## 1.2 Blockchain multidimensional sustainability as applied to agrifood systems

One of the primary benefits of blockchain technology in the agrifood sector is its ability to ensure traceability and transparency in the supply chain while simultaneously simplifying transaction processes. The rationale for implementing BCT in the AFS is twofold. Firstly, it helps ensuring food product quality and safety, thus contributing to enhancing consumers' health. Secondly, it mitigates issues such as inadequate social responsibility and poor environmental performance (Cappelletti et al. 2023).

BCT has the capability to gather data from the agricultural sector with utmost security, encompassing details such as the origin and quality of agricultural products and the production methods employed. Data collection security can be enabled through the creation of a digital ledger, allowing the production chain of agricultural products to be traced from source to final destination. As a result, consumers can be certain of the provenance and quality of their purchases, whilst farmers can exhibit the long-term viability of their cultivation techniques. Further, blockchain can also be used to securely collect and store data on water, soil quality, pesticide and fertiliser use. Such data can significantly enhance sustainable agricultural practices and ensure the adherence of food producers to quality and safety requirements. Moreover, blockchain has been implemented in smart farming complementing internet of things

(IoT) systems [2] to gather and manage data from sensors using communication technologies, which allows for the extraction of meaningful information to make sounder-based decisions. This facilitates the implementation of precision agriculture, enhancing the efficiency of natural resources use and crop yields. This approach minimizes errors caused by human factors and improves the accuracy and efficiency of data collection.

Blockchain platforms offer significant advantages for data analysis. Many of the issues existing within the agricultural supply chain, particularly among cooperatives, farmers, and consumers, arise from inadequate information and communication tools among these stakeholders. BCT-based solutions contribute addressing these issues. The analysis on time of the supply chain flows is a crucial component leading to sustainable agricultural models. BCT could also help in managing the supply chain and process payment transactions for farmers' agricultural requirements through logistics of stocks as well as raw materials and distribution chain pricing. BCT can mitigate issues such as stock price fluctuations, unfavourable exchange rates for farmers due to complex distribution channels, and food spoilage (Putri et al. 2020).

### 1.2.1 Conceptual frameworks for the analysis of blockchain adoption

The AFS entails a variety of actors including farmers, agrifood producers, distributors, retailers, and final sellers. They utilise private databases and several communication channels to oversee vital product safety and the origin of data. Often this information conform solely to regional regulations and are particularly difficult to verify. Direct consequence of this are misinterpretations and likely safety hazards. Additionally, these systems may prove susceptible to breaches or data loss being characterized by a single point of failure [3]. (Cappelletti et al. 2023; Sendros et al. 2022).

In addition, the complexity of AFS substantially reduces the opportunity of consumers' conscious choices, which is an increasingly important from both a socio-economic and environmental point of view.

BCT have the potential to overcome these challenges, but BCT adoption faces various hurdles. For instance, from the socio-economic viewpoint it has

[2]The IoT is a vast interconnected network of devices and systems, facilitating data transfer and communication on a global scale. The objectivity of this interconnectedness excludes any subjective evaluations, by using a clear and concise binary (or Boolean) language.

[3]In an agri-food chain, data is typically collected by a single entity throughout the entire process, from production to sale, and then archived. This creates a central and unique location for all supply chain information, including sensitive data, which poses a security risk in the event of a breach. This type of data storage is known as a 'single point of failure'.

been reported that the low scalability nature of these technologies or the medium-small businesses' inability to afford the initial investment might be a problem (Alimohammadlou and Alinejad 2023; Ruzza et al. 2022). At the same time, some actors seem to be reluctant to innovate, possibly due to insufficient technological skills, the lack of BCT comprehension, or the perception that BCT is not useful.

Several analytical frameworks have been proposed to assess the factors influencing the adoption of BCT by potential users. These frameworks are the same proposed in the broader context of technology adoption studies, that can be referred to the so-called (i) Unified Theory of Acceptance and Use of Technology (UTAUT), (ii) Technology-Organization-Environment (TOE) framework, and (iii) Technology Acceptance Model (TAM).

The UTAUT theoretical framework posits that the employment of technology is hinged upon an individual's behavioural intention. The prospect of embracing the technology is contingent upon four primary constructs: performance expectancy, effort expectancy, social influence, and facilitating conditions. The impact of these predictors is governed by age, gender, experience, and the voluntary nature of the technology's use (Venkatesh et al. 2003; Marikyan and Papagiannidis 2021).

Queiroz and Wamba (2019) use UTAUT to examine the implementation of BCT in the US-India supply chain project design [4]. The research identifies the enabling conditions (e.g. perceived ease of use, perceived usefulness, clear regulations), social influences ( e.g. subjective norms), and performance expectations (e.g. discomfort, insecurity), and how these factors influence the adoption (intention to use) of blockchain technology in these contexts. In a later paper, (Wamba and Queiroz 2022) broaden the theoretical framework by incorporating numerous theories such as diffusion of innovations (DOI), resource-based view (RBV), dynamic capability, technology acceptance model (TAM) and institutional approach to present a multi-stage (intention, adoption, and routinisation) model for BCT diffusion in India-US contexts. They demonstrate that significant differences arise between the countries for each stage of adoption, showing how important social-economic variables are.

A second important approach is the TOE framework developed in the field of information systems to assess how different elements influence the acceptance and employment of new technologies. These elements include the nature of the technology, its organizational context and the external environment within

[4] This study involves a population of 738 individuals, approximately half of whom are Indian and half are from USA. All of these individuals work within supply chains that use blockchain systems. The involved supply chains are diverse, ranging from Agriculture, Forestry and Fishing to Wholesale and Retail Trade or Professional, Scientific and Technical Activities. The purpose of the paper is to investigate the adoption behaviour of blockchain in the supply chain management field, with a focus on adopters from India and the USA.

which the organization is situated. The TOE framework comprises three key components: technology, organization, and environment. The first one pertains to the technology's features, comprising its functionality, sophistication, compatibility with existing systems, and ease of use. Organization concerns the technology's use within the internal context of an organization, incorporating factors like the organization's size, structure, culture, and resources. The environment denotes the external setting in which an organization functions, encompassing market circumstances, regulatory prerequisites, and social and cultural conventions.

Wong et al. (2020) employed the TOE to survey the adoption of BCT by small- to medium-size enterprises (SMEs) in Malaysia. Their results illustrate that cost, relative advantage, complexity, and competitive pressure significantly impact the intention to adopt blockchain. Also Oguntegbe et al. (2022) applies the TOE framework and Behavioural Reasoning Theory (BRT) to examine the behavioural antecedents that lead to the implementation of BCT in managing the agrifood supply chain. The study primarily employs qualitative methodologies to demonstrate that the implementation of BCT is significantly impacted by three factors. Firstly, a thorough comprehension of the technological benefits by supply chain decision-makers has a positive influence. Secondly, environmental barriers, such as a lack of technological skills among supply chain actors, scalability issues, and lack of clear legal framework have a negative impact. Finally, the implementation of BCT is significantly influenced by the organizational adoption strategies of supply chain entities. Largely, these findings come from AFS chain contexts.

Sachin Kamble and Arha (2019) propose a model for the analysis of user attitudes towards the adoption of BT in the Indian supply chain context. The model incorporates three adoption theories, namely the Technology Acceptance Model (TAM), Technology Readiness Index (TRI), and the Theory of Planned Behaviour (TPB). Supply chain professionals were surveyed in India, and the proposed model was validated using structural equation modelling. They found that perceived usefulness, attitude, and perceived behavioural control on BCT usage have an impact on behavioural intention, while the impact of subjective norm is negligible.

For a comprehensive analysis of the theoretical models involved in the implementation of BCT within supply chain management, refer to Taherdoost (2022). What emerges from the empirical studies is that implementation of blockchain-based systems is determined by four fundamental aspects. Firstly, technology readiness is crucial, meaning that the BC infrastructure must be adaptable to various contexts and existing technologies. Secondly, potential users' level of understanding and awareness of the benefits and functionalities of BCT is key. Thirdly, the regulatory environment is a crucial factor in the successful implementation of blockchain technology. Clear regulations and legal frameworks that support or at least do not hinder the use of blockchain technology are necessary. Additionally, the initial cost of implementing blockchain solutions is often prohibitive for small businesses, making scalability a crucial aspect to consider.

In agrifood-related contexts, the implementation of blockchain solutions depends on various factors beyond those mentioned above. It is crucial to ensure that the benefits of blockchain are passed on to the consumer. To ensure profitability of implementation, it is essential to make the concepts of traceability, food safety, and quality improvement linked to the implementation of BCT easy to read and transmit. Moreover, the literature indicates that it is crucial to emphasise the capacity of BCT to verify and promote sustainable and ethical practices throughout agri-food chains, in order to impact on consumers willingness to pay (WTP).

### 1.2.2 The Triple Bottom line of blockchain implementation in agrifood systems

When considering specifically the sustainability of implementing a new technology in production, current literature advocates for a three-dimensional analysis of economic, social, and environmental aspects. The assessment of these three factors is known as the 'Triple bottom line' analysis.

#### Economic Dimension

In economic terms, logistics and supply chains coordination play a crucial role in farming and food processing by ensuring the efficient movement of products from producers to consumers. The literature suggests that the improvement in transparency and traceability enhance cooperation among stakeholders (trust-building), help reducing food loss, and can improve resource utilization (Park and H. Li 2021; Y. Li et al. 2020) by providing a decentralized and transparent system that allows for real-time updates and easy access to transaction records. BCT-based platforms for data recording and management reduce traceability time and costs and enhances trust in case of food recalls, enabling stakeholders to have a better knowledge of product flows, enhancing their response, and reducing unnecessary waste by narrowing down the recall range.

BCT are able to improve resource utilization in the food supply chain by providing real-time data collection, accurate monitoring of resource utilization as well as efficient stock and delivery management (K. Li et al. 2023). Integration with other digital solutions, such as the Internet of Things (IoT), can further optimize resource utilization (Saurabh and Dey 2021; Chen et al. 2021). Machine learning can be coupled with BCT to enhance data network effectiveness and efficiency by leveraging the power of data and algorithms to generate forecasts, improve decision-making, and promote not only economic but also ecologically sustainable choices (Caro et al. 2018; Balamurugan et al. 2021; Viriyasitavat et al. 2019).

Examples of BCT applications in agrifood supply chains include tracking food, real-time food traceability using Hazard Analysis and Critical Control Points (HACCP), and verifying product quality (Tian 2017). Companies like IBM and Walmart have explored blockchain technology for food tracking and safety issues, with mixed fortunes. In 2016, Walmart and IBM collaborated in a pilot study of a blockchain-based traceability system. They traced mangoes from farm to store. The existing traceability system took nearly seven days to gather all the information on mango movements, which needs all stakeholders to get in touch with each other to obtain the necessary information. Through implementation of blockchain technology, the need for time-consuming communication with other stakeholders can be eliminated, thus improving efficiency [5] reducing the trace time to only 2.2 seconds (Yiannas 2018).

### Social Dimension

The social dimension of sustainability in the food supply chain emphasizes fair treatment of workers, community development, and ensuring consumer health and safety. BCT can enhance social sustainability in two ways. Firstly, implementing blockchain for end-to-end tracking to verify and authenticate the origin and conditions of agrifood production, thus making the supply chain transparent. This can provide incentives for fair labor practices and ethical sourcing, verifing also adherence to fair trade principles within the entire production process. Secondly, through the automatic activation of its algorithm smart contracts can automate and validate fair trade practices and transactions, ensuring just and verifiable compensation to all stakeholders, contributing to rebalance the power relationships along the supply chain (Mangla et al. 2021; Dutta et al. 2020).

A clear and immutable record of food production, processing, and distribution contributes directly to the well-being of consumers by ensuring the quality and safety of the products they use. BCT can enable customers by offering them effortless access to detailed information regarding the products they buy. This comprises details about the source of the product, its pathway through the supply chain, and its impact on social and environmental issues (Silva and Moro 2021).

[5] According to Verhoeven et al. (2018), in the Walmart tracing mangoes study the reduction in traceability time was probably due to the removal of the manual validation process rather than a shift to a more efficient platform.

The introduction of such technological paradigm can also empower local communities involved in food production by providing a platform that enhances fair trade practices. Data disclosure and immutability creates the opportunity for interested stakeholders to verify if these communities are properly compensated and involved in decision-making processes relating to the supply chain. The disclosure of such information reduce informational asymmetries and ultimately improve the production chain reputation (Viano et al. 2022; Wan et al. 2020).

**Environmental Dimension**

The environmental aspect of sustainability focuses on the reduction of potentially negative impacts on the environment of agrifood production, processing, transportation, and consumption. BCT can help in supporting and improving sustainability initiatives within this sphere. It can be used to monitor sustainability performance by recording emissions at each stage of the supply chain and ensuring the accuracy of carbon emissions reporting, due to its immutable and transparent nature. These features improves transparency and trust in claims on environmental sustainability practices along the food supply chain (Park and H. Li 2021; Ferdousi et al. 2020).

Pakseresht et al. (2022) review evidences that implementation of BCT within the food industry has a significant potential to prevent food loss, adopt organic farming practices, maintain soil health, reduce environmental impacts, safeguard biodiversity and enhance the resilience of ecosystem services. Pre-production (input) traceability can improve sustainable practices, conserve natural resources and identify greenhouse gas emissions. Post-production (output) traceability increases food safety monitoring and product tracking in the event of incidents(Singh et al. 2023).

From a consumer perspective, besides enhancing food safety, traceability systems ought to provide details on external factors, covering the societal and ecological effects of a given product, in order to enable the client to make more informed purchasing decisions (Chopra et al. 2022).

## 1.3 Methods

### 1.3.1 Scoping review methodology

A scoping review, that is a systematic review of a rapidly growing body of knowledge, offers a suitable method to charting the quickly expanding literature about sustainability dimensions of BCT applications in the AFS. It takes stock of the knowledge to date while pinpointing gaps in research. It also provides structure to the analysis by meeting the pre-determined eligibility criteria outlined in the scoping review protocol, limiting biases that may arise due to author preference or prior familiarity with the work. The scoping review of BCT applications to AFS has been conducted according to the *Preferred Reporting Items for Systematic Reviews and Meta-Analyses* (PRISMA) protocol extension for essential reporting items for scoping reviews (PRISMA-ScR) (Tricco et al. 2018). We follow Arksey and O'Malley (2005) five-stage methodological framework, as modified by Levac et al. (2010):

1. identifying our research question,
2. identifying relevant studies,
3. performing study selection,
4. charting the data,
5. collating, summarizing, and reporting the results.

Figure 1.1 presents an overview of the procedure adopted to choose the papers for our analysis. The adopted approach moves from a more general scope - i.e., contributions relating BCT applications to AFS - to our specific area of interest - i.e., the impact of BCT implementation to the AFS - measured across the triple bottom line of sustainability - i.e., economic, social and environmental sustainability dimensions. The process consisted of three rounds: the first aims to identify common papers across all three sustainability dimensions, the second extracts papers that focus on two out of the three dimensions; and the third specifically refers to papers that focus only to one sustainability dimension.

### 1.3.2 Data sources and searches

Our scoping review used has been applied to the Elsevier's Scopus dataset, that is a an abstract and citation database including peer-reviewed journals, but also book series and trade journals. The items included in the Scopus database are generally considered to be meeting the requirement for peer review quality[6]. Trying to answer our research question - namely "what we know so far about the feasibility and effects of applying BCT to the agrifood system in terms of economic, social, and environmental sustainability?" - we focus only on peer-reviewed papers and book chapters, i.e. not including grey literature contributions.

[6]We decided to use Scopus instead of the Reuters-Thompson's Web of Science (WOS), because the former is easier to navigate, and makes possible some preliminary analysis of the database contents. Although neither resource is all-inclusive, some studies reported a 80-90% overlap in coverage between WoS and Scopus for the period between 1990 and 2020.

### 1.3.3 Eligibility criteria

The study's selection criteria comprised papers presenting empirical evidence of the impact of blockchain-based applications to agrifood contexts or review of existing research on blockchain as applied to AFS. Therefore, the keywords initially used to address the above-mentioned question are: blockchain, DLT [7], sustainability, agrifood, agribusiness, food supply chain, and Triple Bottom Line. To enhance the query accuracy, we imposed also subject area restrictions, excluding items belonging to mathematics, physics, chemistry (and related sciences such as biochemistry), earth sciences, energy, medicine and veterinary (and their subcategories and related sciences such as pharmacy, nursery, etc.), and arts. Furthermore, items including as keywords words not directly linked to the AFS were excluded as well, such as bitcoin, criptocurrencies, crime, cybersecurity, edge computing, ethereum, etc. Additionally, we selected only full-text research journal articles or book chapters written in English over the period 2015-2023 as the literature on BCT applications to AFS was largely not existent prior 2015. The results reported in the next subsections refer to research findings published as per December 15th, 2023.

### 1.3.4 Process description

We first retrieved a larger set of items dealing with blockchain (or DLT) as related to the agrifood system, simply looking for all items (i.e. any contributions on the topic, not only peer reviewed journal articles and book chapters) that deal with BCT and AFS, using the following query:

[1]

TITLE-ABS-KEY ((blockchain*) OR ( DLT) OR ("distributed ledger technology")) AND ( ( FSC ) OR ( "food supply chain" ) OR (agr*) OR ("food system")) AND PUBYEAR > 2015 AND PUBYEAR < 2024 AND ( LIMIT-TO ( LANGUAGE,"English" ) )

identifying 13,433 items. The next step restricts the analysis to BCT applications and their impact in the AFS by including a specification (in boldface) to the original query as follows:

[2]

[7] DLT stands for Distributed Ledger Technologies. Blockchain technology is a subset of them.

TITLE-ABS-KEY ((blockchain*) OR ( DLT) OR ("distributed ledger technology")) **AND (("triple bottom line") OR ( impact*) OR (implement*) OR (aspect))** AND ( ( FSC ) OR ( "food supply chain" ) OR ( agr*) OR("food system")) AND PUBYEAR > 2015 AND PUBYEAR < 2024 AND ( LIMIT-TO ( LANGUAGE,"English" ) )

retrieving 10,007 items. Then, we focus upon each of the three dimensions encompassing the Triple Bottom Line, namely the economic, social, and environmental sustainability aspects of BCT applications in AFS. We did it by adding to the previous query specific strings per each of the three dimensions thus matching the query on Scopus with each category (Figure 1.2).

- *Economic valuation*

[3.1]

TITLE-ABS-KEY ((blockchain*) OR ( DLT) OR ("distributed ledger technology")) **AND ((econom*) OR (financ*)** OR ("triple bottom line")) AND ((aspect*) OR (impact*)) AND ( ( FSC ) OR ( "food supply chain" ) OR ( agr*) OR ("food system")) AND PUBYEAR > 2015 AND PUBYEAR < 2024 AND ( LIMIT-TO ( LANGUAGE,"English" ) )

This query identifies 4,806 items.

- *Social impact*

[3.2]

TITLE-ABS-KEY ((blockchain*) OR ( DLT) OR ("distributed ledger technology")) **AND ((social*) OR ("socio-economic") OR (inclus*)** OR ("triple bottom line")) AND ((aspect*) OR (impact*)) AND ( ( FSC ) OR ( "food supply chain" ) OR ( agr*) OR ("food system")) AND PUBYEAR > 2015 AND PUBYEAR < 2024 AND ( LIMIT-TO ( LANGUAGE,"English" ) )

This query identifies 3,994 items.

- *Environmental assessment*

[3.3]

TITLE-ABS-KEY ((blockchain*) OR ( DLT) OR ("distributed ledger technology")) AND ((impact*) OR (implement*) OR (aspect*) OR ("triple bottom line")) **AND ((environment*) OR (sustainab*) OR (green) OR (ecologic*))** AND (( FSC ) OR ( "food supply chain" ) OR ( agr*) OR ( "food system")) AND PUBYEAR $>$ 2015 AND PUBYEAR $<$ 2024 AND ( LIMIT-TO ( LANGUAGE,"English" ) )

This query identifies 7,700 items.

Finally, we skimmed the set of items dealing with BCT applications/impact analyses to the AFS, filtering out subject areas ("SUBJAREA") and keywords ("EXACTKEYWORD") that do not relate to our research question as well as document types ("DOCTYPE") that are not suitable for our scoping review, i.e. grey literature contributions. This skimming process yielded 1,801 journal articles/book chapters dealing with the economic dimension, 1,489 journal articles/book chapters with the social dimension, and 2,310 journal articles/book chapters with the environmental dimension.

On this pool of papers, we implemented a two-step procedure to identify the articles/chapters that deal with all three aspects, those that deals with any combination of sustainability dimensions pairs, and those dealing with only one dimensions, respectively. The two steps include first the identification of papers belonging to each of the three groups and then performing a visual check of their contents to select the papers actually relevant for our research purpose, i.e. empirical papers assessing economic, social and environmental sustainability of blockchain applications to the agrifood system. This process, as described in the next sections, led to the selection of 219 relevant journal articles and book chapters.

### Papers dealing with all three sustainability dimensions

To obtain papers dealing with all three dimensions of sustainability we begin with introducing a string in our query that includes all dimensions linked by using an "AND" connector between them (Figure 1.3). We thus found 852 journal articles and book chapters. On this set of papers, we performed a visual check of titles, keywords and abstracts in order to include only those papers that are truly relevant for our research question. As a result, the number of papers reduced from 852 to 102.

### Papers dealing with sustainability dimensions pairs

The scientific contributions focusing on only two dimensions of sustainability each have been identified by using the "AND" connector in pairs and specifying via the

"AND NOT" connector to exclude papers from the third group as follows (Figure 1.3):

- economic AND social aspect (AND NOT environmental): 106 journal articles and book chapters;
- economic AND environmental assessment (AND NOT social): 271 journal articles and book chapters;
- social AND environmental assessment (AND NOT economic): 88 journal articles and book chapters.

Also in this case we proceeded with a visual check of titles, keywords and abstract contents. Through this process we significantly reduced the amount of papers to the ones actually relevant to our research. Only 8 journal articles and book chapters resulted suitable for our analysis out of the 106 dealing with economic and social aspects. The set of scientific contributions examining economic and environmental aspects reduced from 271 to 45 relevant sources. Finally, the 88 journal articles and book chapters that investigate social and environmental aspects plummeted to only 2 after visual inspection of their contents.

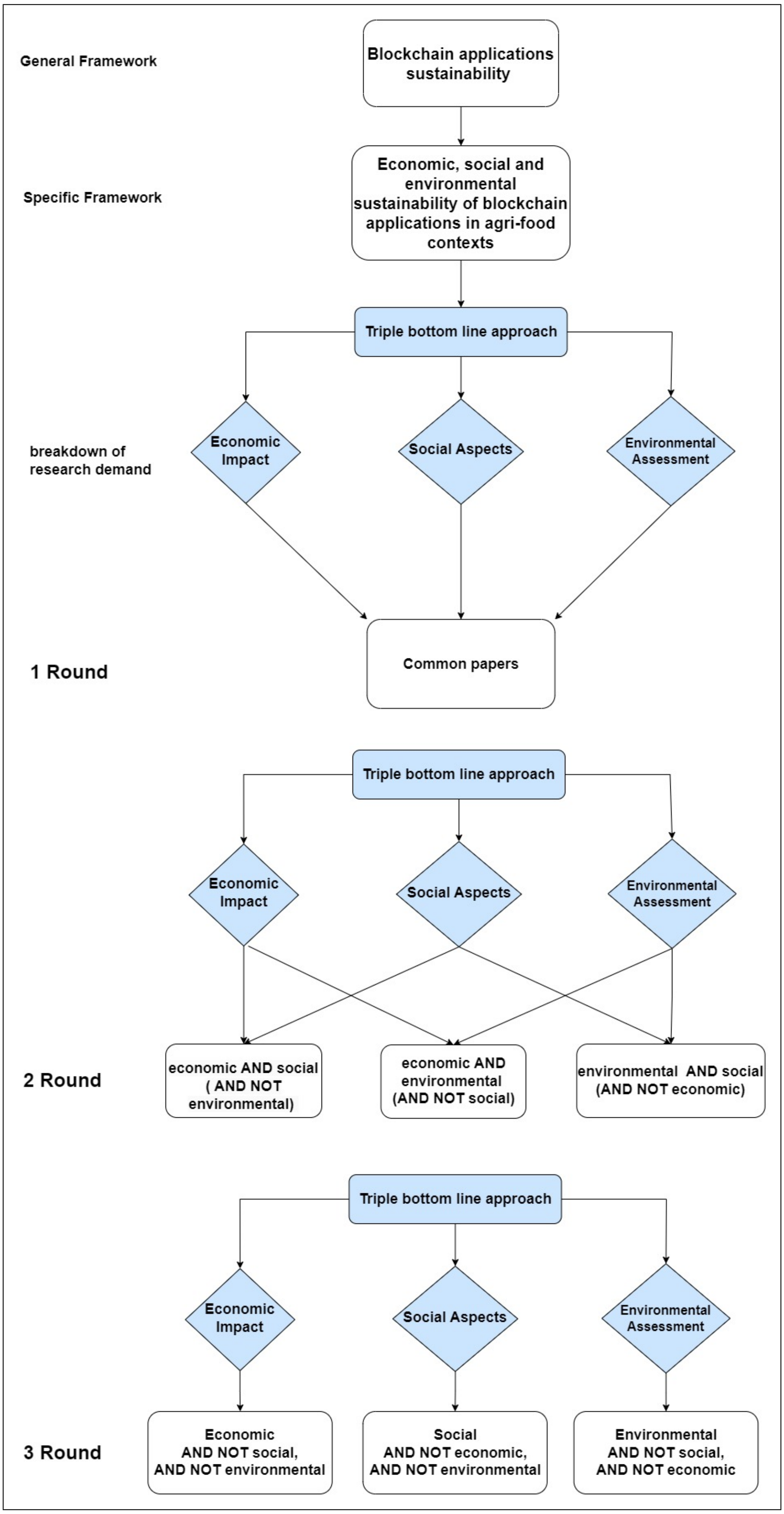


**Figure 1.1:** Selection process overview

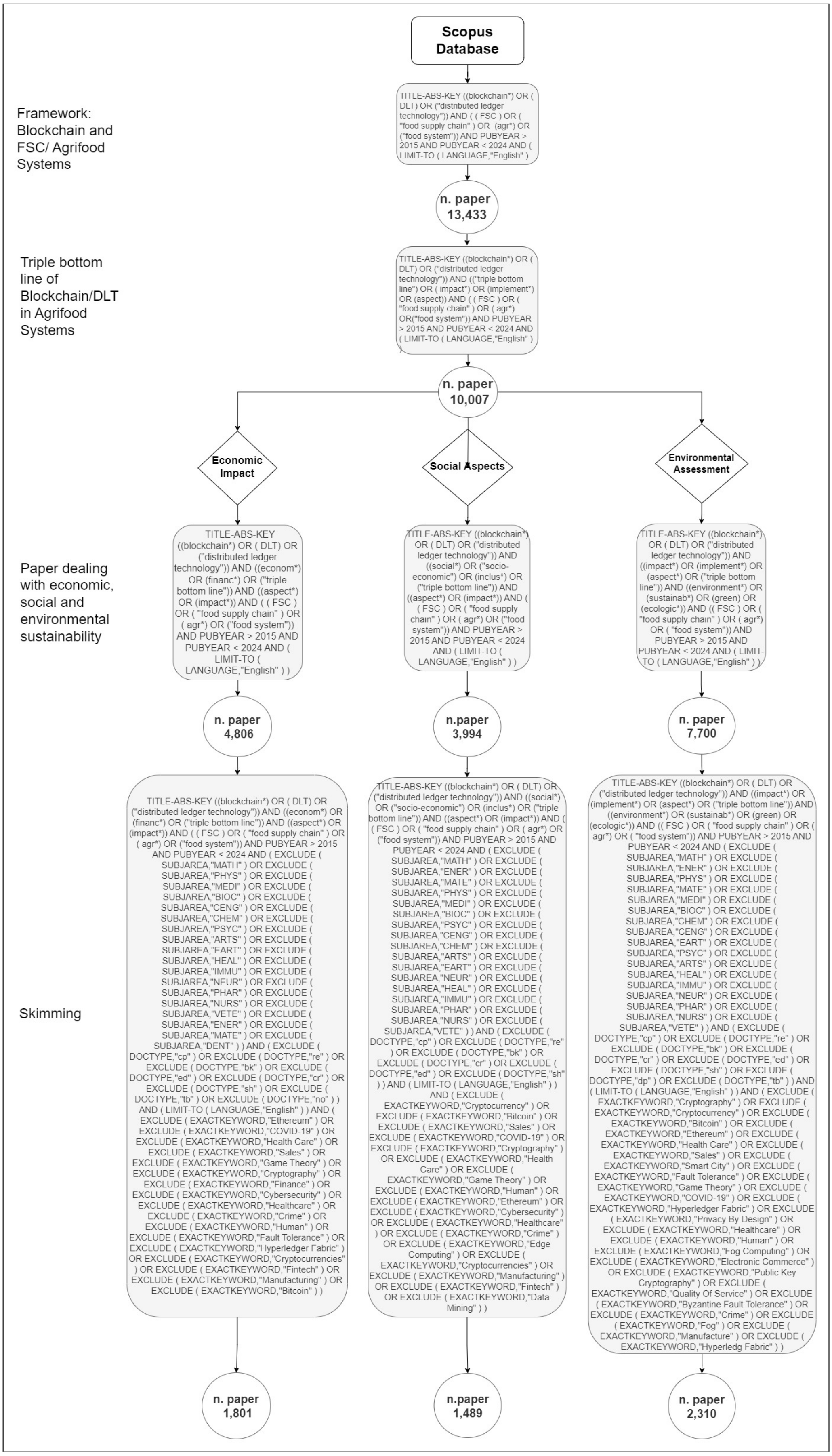


**Figure 1.2:** Selection process


**Figure 1.3:** Flow Chart: Paper in common

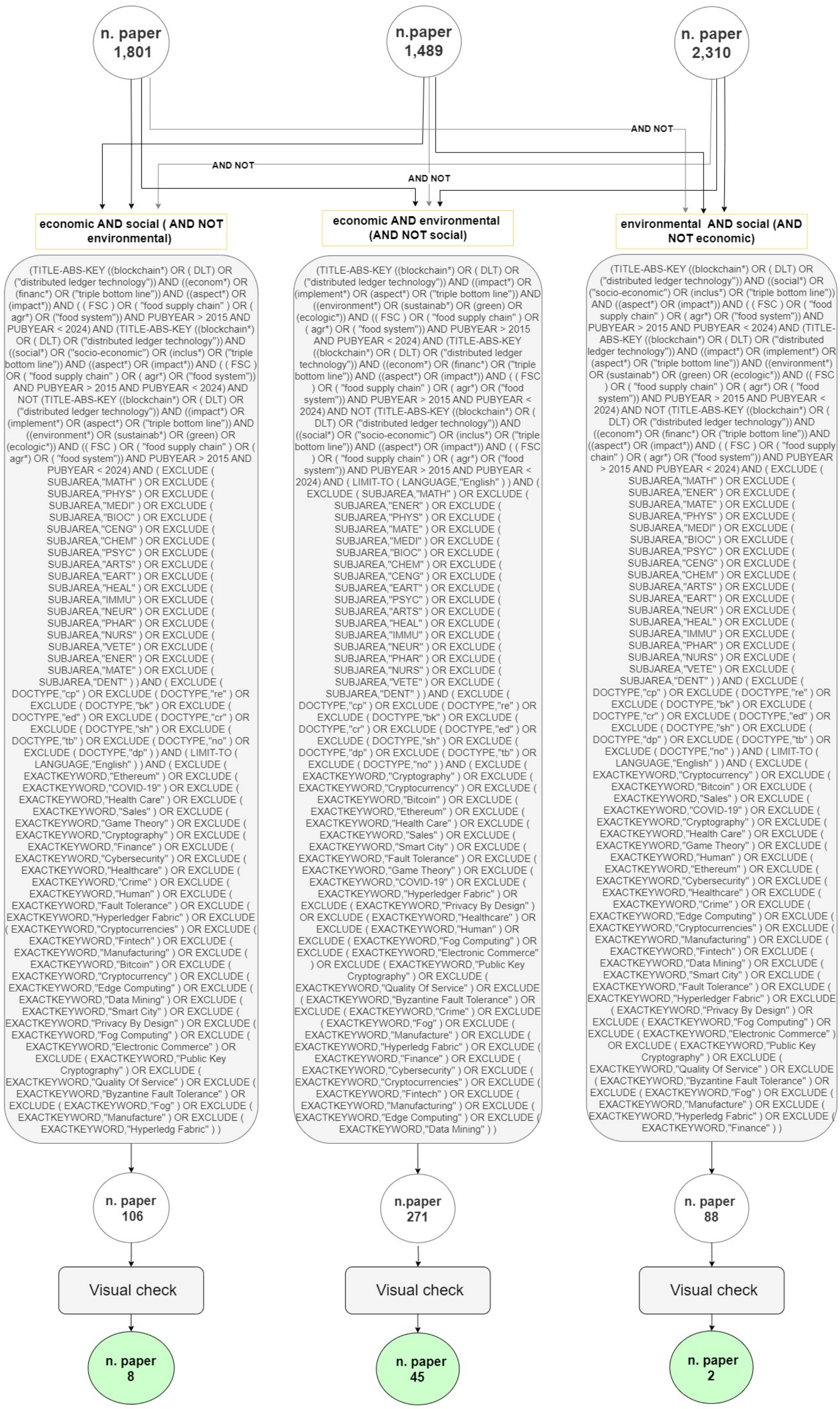


**Figure 1.4:** Flow chart: Paper dealing with two out of three dimensions

### Papers dealing with only one sustainability dimension

Finally, we identified the journal articles and book chapters that focus only on one sustainability dimension - economic, social, or environmental - excluding those that address more than one of these dimensions. To achieve this, we search for contributions that address solely one dimension and not the other two. This was done the "AND NOT" connector as follows (Figure 1.4):

- economic AND NOT social, AND NOT environmental: 95 journal articles and book chapters;
- social AND NOT economic, AND NOT environmental: 11 journal articles and book chapters;
- environmental AND NOT economic AND NOT social: 628 journal articles and book chapters.

After visual inspection of titles, keywords and abstracts, we extracted 13 contributions out of the 95 that originally dealt with economic aspects only, only 2 contributions dealing exclusively with social aspects out of 11, and 47 journal articles and book chapters out of the 628 contributions dealing with environmental aspects only as resulting from the previous steps.


**Figure 1.5:** Flow Chart: Paper dealing with only one dimension

## 1.4 Analysis and results

Publications on BCT in the AFS have been steadily increasing over the last years (Figure 1.6). This is a clear sign of interest in the field by both practitioners and scholarly circles. In this section, we analyze these publications adopting a two-step procedure. First, we look at the broader set of **2081** unique titles[8] resulting from our search prior to visual inspection of titles, keywords and abstracts. Then, we analyze the restricted set of 219 papers selected after the visual inspection.

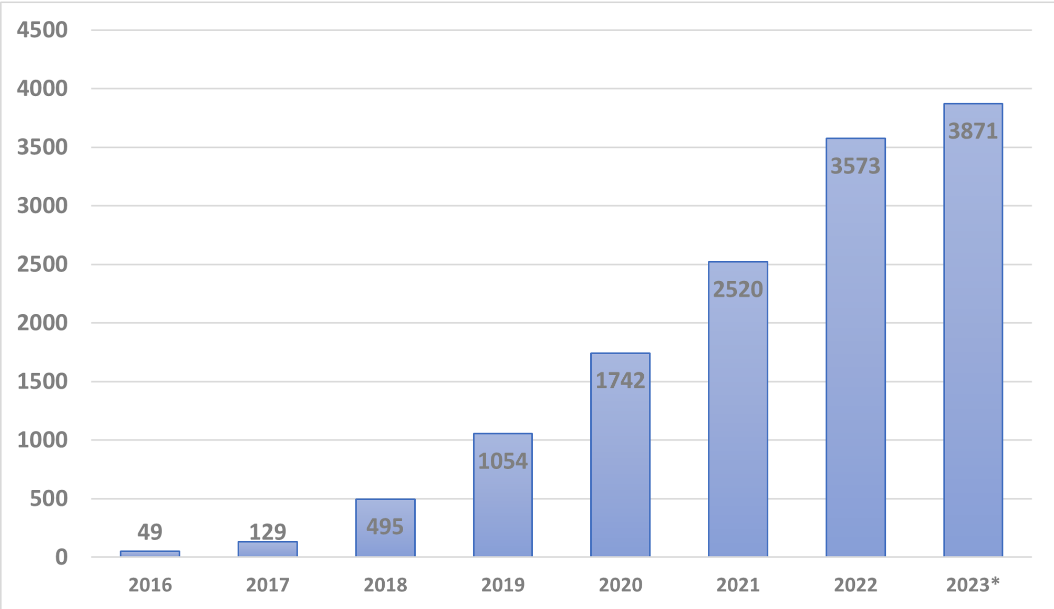


**Figure 1.6:** Blockchain in Food Supply Chain: Publications by Year.
* Update 31st of December 2023

### 1.4.1 Text analysis of the larger dataset

The set of 2081 publications has been analyzed using the SciVal bibliometric software that is an integrated modular platform created by Elsevier for the bibliometric analysis of research items indexed in the the Scopus database. The components upon which the analysis can be carried out comprise the title, the abstract, the keywords, the funding sponsor, the author's country of origin, and the affiliated institution's name. Details on subject areas, citation statistics, and journal ranking information are also available.

The interest in the use of blockchain technology in agrifood systems is widespread and covers various subject areas (Figure 1.7). By and large, the titles published

[8]The number of unique titles is composed of papers resulting from the research process before visual check

in social science related areas (i.e. business, management and accounting, social sciences, and economics, econometrics and finance) account for half the publications (44.2%). The share of social science is considerably lower if we adopt the approach suggested by SciVal, that is by assigning weight to the significance of the subject area indexed on Scopus, based on four metrics that should all be taken into account for a more comprehensive view of the importance of each area, namely: the scholarly output[9], the number of citations, the average number of citations per publication, and the number of authors. In this case, titles published in social science related areas accounts for 38.1% of total. These figures could be contrasted with the very tiny share of publications specifically indexed in the subject area of Agricultural Sciences, accounting for only 2.6% of total publications and 1.9% of the weighted average. These data indicate that the interest in applying the blockchain paradigm to the agrifood industry is mainly driven by economic factors[10]. At the same time they also hint at a significant heterogeneity of the various perspectives related to BCT applications in the AFS.

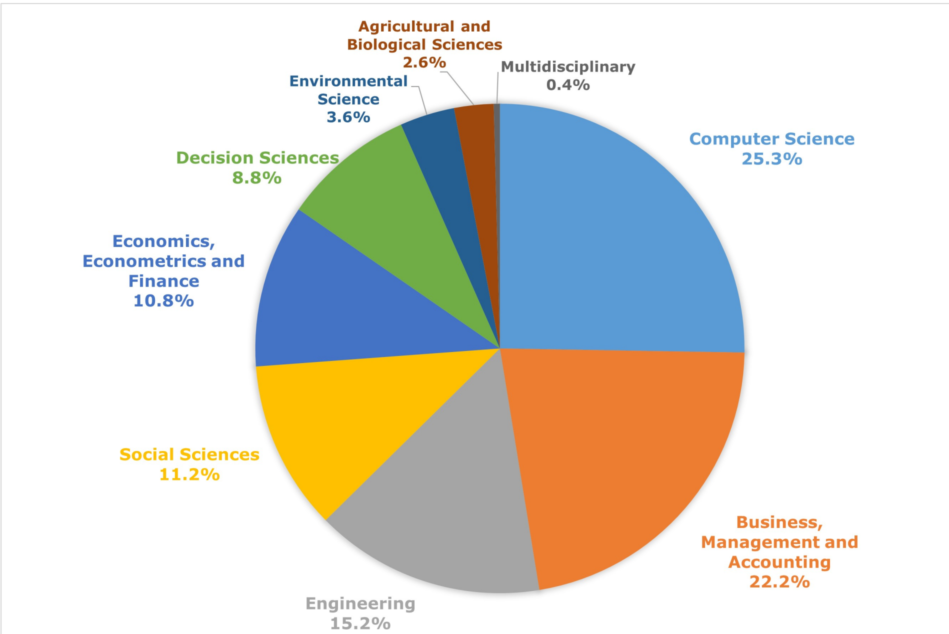


**Figure 1.7:** Share of publications on blockchain applications in the agrifood sector by subject area.

Heterogeneity features not only contents, but also the authors' country of origin (Figure 1.8). India stands in a dominant position with more than 500 publications in the period of analysis, reflecting the high dynamism of this country in both

[9]Scholarly output denotes the tally of publications catalogued in Scopus concerning the specified subject matter.

[10]See section 1.2.2 for a discussion of factors driving the interest in BCT applications in AFS.

the agrifood sector and the development of technical innovations, especially ICT innovations as applied to agrifood. Other countries ranking in top positions include agrifood and ICT giants such as China and USA as well as other countries such as European countries - Italy[11], France, and Germany - other developed countries, such as Australia and the UK, and middle income countries such as Malaysia and Saudi Arabia. Data shows that authors from over one hundred countries have published in the BCT in AFS field, indicating a widespread global interest in the topic. Furthermore, the research demonstrates a clustering pattern in the research on BCT applications to AFS in Asia,where these topics appear to be more extensively covered than in other areas.

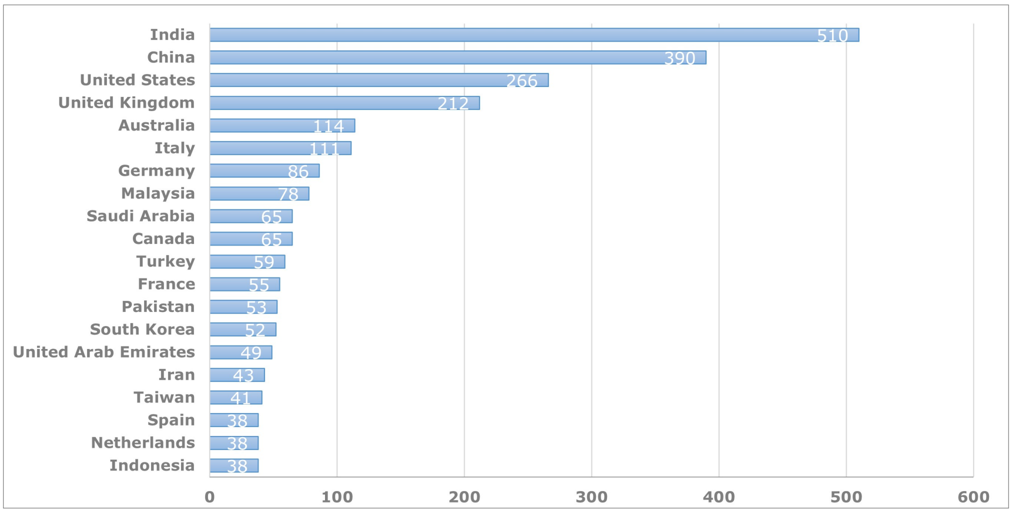


**Figure 1.8:** Blockchain in Food Supply Chain: Publications by country

In terms of primary funding sponsors, not surprisingly governmental bodies play a prominent role. What is rather surprising, instead, is that the first twenty positions in the rank are all governmental bodies (Figure 1.9). There are basically two big players that stand up by far as funding agencies, namely the European Union, through the European Commission's Horizon 2020 Programme and European Regional Development Fund, and China with several funding bodies such as the National Natural Science Foundation of China, National Key Research and Development Program of China, National Office for Philosophy and Social Sciences, the Ministry of Education of the People's Republic of China, etc. USA also play an important role through its National Science Foundation, though less importantly than the EU and China. Contrasting the authors' countries of origin with the nationality of the

[11]In the case of Italy, the academic literature has emphasized the potential BCT as a remedy to contrast counterfeiting and specifically the so-called "Italian sounding" that is the act of using Italian terms, colors (like those of the Italian flag), and names to give a product an Italian appearance, regardless of its country of origin or production method, in order to promote it (Scuderi et al. 2019; Adamashvili et al. 2021).

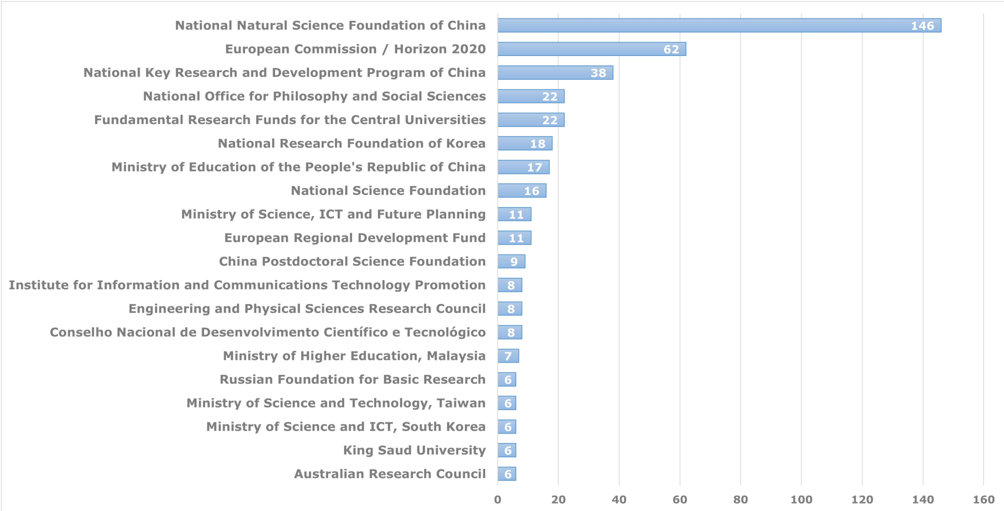


**Figure 1.9:** Blockchain in Food Supply Chain: Publications by Funding Sponsor

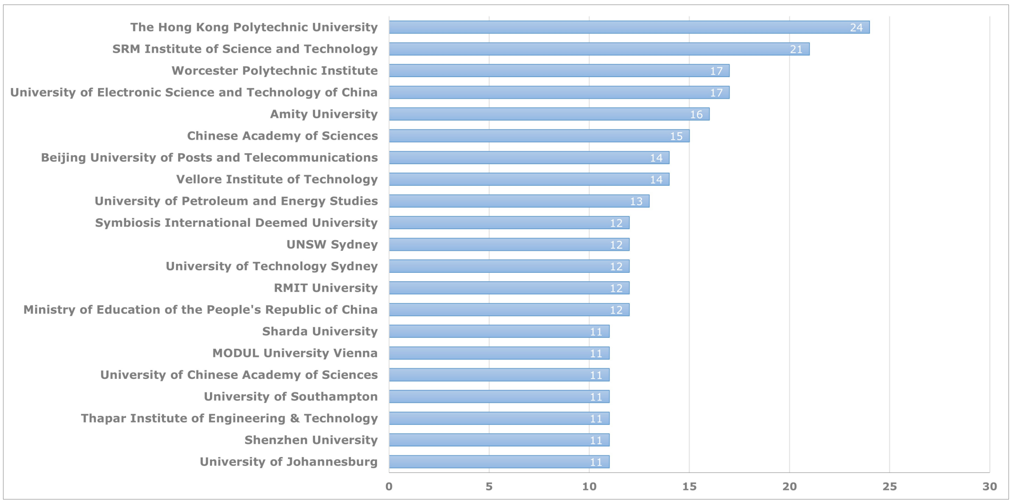


**Figure 1.10:** Blockchain in Food Supply Chain: Publications by Affiliation

funding agencies there is generally a consistency for China and to a lesser extend EU. Vice versa, it is noteworthy that in the case of India the country ranks first in terms of publications by country, while there is no Indian funding agency among the top twenty positions.

In terms of affiliation (Figure 1.10), as expected from the data presented in Figure 1.8, Indian and Chinese universities and research bodies hold a very clear prominent position, being present 14th times among the top twenty ranked entities (Eight Indian Institutions, six Chinese entities). Two universities from the UK ranks among the top 20th positions (Worcester Polytechnic Institute, University of Southampton), which is in line with the UK's high standing in terms of both publications by country and publications by funding sponsor [12]. A similar argument

[12]It is useful to recall that United Kingdom could benefit from participating in the Horizon 2020 program of the European Union over the considered years.

can be made for Australia.

### Assess the quality of the selected publications

So far we just looked at some raw data statistics. Now we delve into a more detailed analysis looking at the publication outlets and impact of the selected papers. To do this, we assess the ratio of publications in our dataset that appear in the top percentiles of globally cited publications, field-weighting our results. Furthermore, we analyse the percentage of publications featured in top-ranking journals.

About one third of the total of selected publications (31%) are in the top 10% of the most cited papers in their field and 8% are in the top 1%. Looking at the evolution over time (Figure 1.11), we can observe a decrease in the share of publications featuring in both the top 10%, 5% and 1% from 2018 to 2023 [13]. This result could be biased by the exponential increase in publications on the Covid-19 pandemic from 2021 onwards.

Quite a large share of the selected publications (36.2%) are published in the top 10% journals as ranked by CiteScore, and 7.2% in the top 1%. Figure 1.12 shows a slight upward trend, with a peak in 2020. The analysis of this trends reveal that since 2020, over one-third of papers on our analysed topics have been published in the top 10% of Scopus Sources, with approximately one in four appearing in the top 5% of Scopus Sources with the highest ranking by CiteScore index.

It is noteworthy that until 2019 there were almost no publications on blockchain applied to agrifood in the top 1% journals. However, from 2020 onwards the publications in the first percentile (top 1% journal) range between 4.8% and 11.3%. The Covid-19 could have constrained these trends too.

Looking at the Scopus-indexed keywords for each paper in our dataset, and omitting the term "blockchain" and related synonyms because of their ubiquitous presence in the selected literature, the most commonly indexed terms include "Supply Chain","Traceability", "Food Supply", and "Internet of Things","Artificial Intelligence" which is expected considering our selection process (Figure 1.13). However, other keywords are also prominent, such as "Trust", "Transparency" and "Smart contract", all hinting at the interest for the asymmetric information issue and related risks. Vice versa, "Agriculture" as farming appears in a marginal position in the word cloud, in line with the share of publications directly dealing with agriculture that account for only a tiny share of total (cf. Figure 1.7).

[13] The graph starts from 2018 because there are very few publications before this date in our dataset, and including them would distort the results.

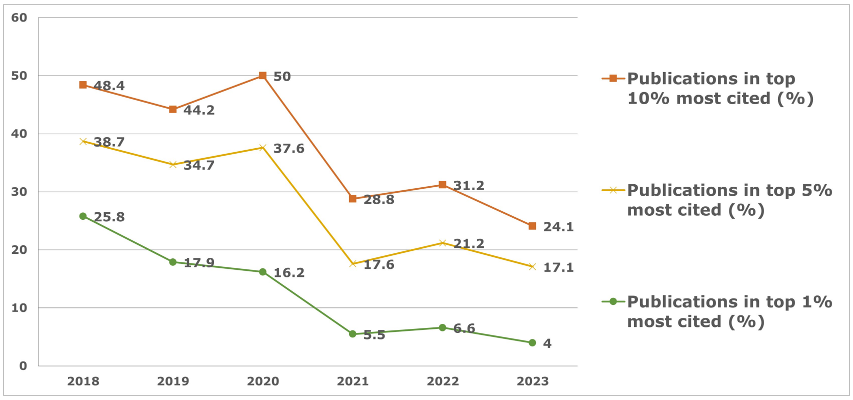


**Figure 1.11:** Blockchain in Food Supply Chain: Publications by Top Citation Percentiles

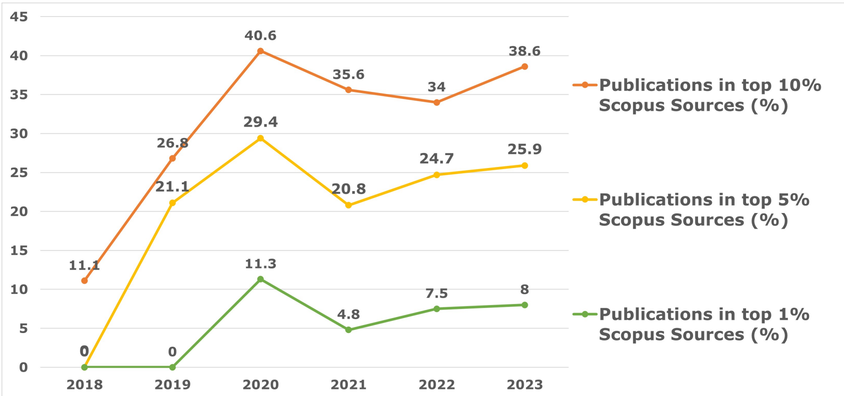


**Figure 1.12:** Blockchain in Food Supply Chain: Publications in Top Journal Percentiles.

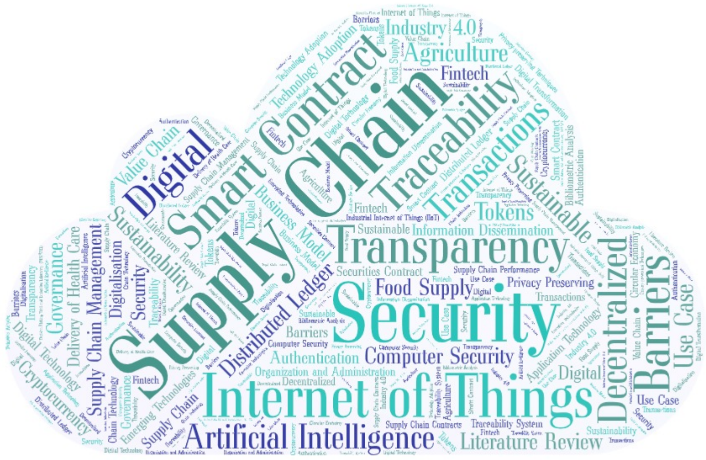


**Figure 1.13:** Blockchain in Food Supply Chain:Top 50 key-phrases by relevance

### 1.4.2 Analysis of the three sustainability dimensions

In this section we investigate how the introduction of a blockchain-based tracking and data management system impacts the environmental, social, and economic sustainability of a agrifood systems. In order to proceed, it is necessary to retrieve the publications that specifically deal with each of the three sustainability dimensions that consists of 117 journal articles and book chapters[14]. In addition, other papers identified via snowballing during content examination of these 117 publications have been included. This resulted in a total of 185 publications. Out of the three main categories analysed, 88 focus on the economic effects of blockchain within the agrifood system, while 63 concern its impact on the environment, and 34 examine its social impact.

The criteria used for assessing the academic community's interest in the sustainability dimensions of BCT applications to AFS include the analysis of publication references, the number of citations and the number of views that selected papers received over time. The metric selection process was based on the recommendations provided by Snowball Metrics[15]).

First of all, we look at the View Counts as resulting from the Scopus database. The metric is the number of abstract/full-text views at the publisher's website[16]. It can be considered as a good *prima facie* proxy of the interest of the whole research community, i.e. researchers, undergraduate and graduate students, etc., showing a preliminary interest by inspecting a given publication that is usually not captured by citation-based metrics. Views begin to accumulate as soon as an output is available online and captures more promptly than citations the interest in a publication.

We take into account 3 dimensions related to views, namely, Average Views per Publications, Views Count and Field- Weighted Views Impact (FWVI). The latter indicates how the number of views received by a given publications compares with the average number of views received by all other similar publications. Similar publications are those publications in the Scopus database that have the same publication year, publication type, and discipline, as represented by the Scopus classification system. A FWVI of 1.00 indicates that the publication has been viewed

[14]This number corresponds to the sum of round 2 and round 3 selected papers after visual inspection.

[15]Snowball Metrics is a collaborative endeavour led by globally renowned research universities to produce standardised metrics to evaluate research performance. The aim of these metrics is to establish worldwide standards that facilitate institutional benchmarking for the entire spectrum of research activities. The Snowball Metrics website is owned and operated by Elsevier (more information on https://snowballmetrics.com

[16]The Views Count metric is updated every two weeks. It shows the number of views/visits a document has received in the current year, alongside the count for the previous year and the last 10 years.

exactly as would be expected based on the global average for similar publications in the same database. A FWVI higher (lower) than 1.00 indicates that the publications have been viewed more (less) than would be expected based on the global average for similar publications[17].

Figure 1.14 presents the cumulative number of views on the x-axis and views per publication on the y-axis. The size of each bubble corresponds to the FWVI. Our analysis begins in 2018 when we had a limited number of publications in our set, and ends in December 2023. Each segment of the dotted line indicates one year. It is worth noting that papers focusing on the environmental dimension receive more views, both in absolute terms and on average, compared to those focusing on economic and social impact. This is particularly significant considering that there are fewer papers dealing with this dimension respect to the economic ones. In terms of views per publication, papers on social and economic impact have similar values. However, papers focusing on economic impact receive more views, which is to be expected due to the larger number of papers in our selection.

The recent years trend for these metrics is declining in all three dimensions. The number of views has risen, as anticipated due to growth in the volume of publications. However, views per publication have declined. This tendency is less marked with regard to social sustainability articles. The dimension of the bubble, which indicate the field-weighted impact of views, is also interesting. It exceed 1 in each of the 3 sectors, ranging between 4.1 of the economic sustainability dimension and 7.6 of the economic sustainability, indicating that these publications receive on average between 310% and 660% more views than comparable works in the same domain, respectively.

The citation metrics we use is the Field Weighted Citation Impact (FWCI) over time, which indicates the number of citations received by a publication in comparison to the worldwide average number received by all other similar publications. Also in this case FWCI of 1.00 indicates that the publication has been cited exactly as would be expected based on the global average for similar publications, while a FWCI higher (lower) than 1.00 indicates that the publication has been cited more (less) than would be expected based on the global average for similar publications.

This metric over the years has been consistently above 1.00 for all three dimensions since year 2020 [18], averaging between 3.51 for economic impact papers and 5.62 for papers focusing on the environmental impact (Figure 1.15). The three sub-groups show different trends. Considering that the number of publication has

[17] For example, a Field- Weighted Views Impact of 3.87 means 287% more views than world average. On the other way around if it is 0.55 means 45% fewer views than world average within the same database.

[18] Before 2020 there are only a few papers published.

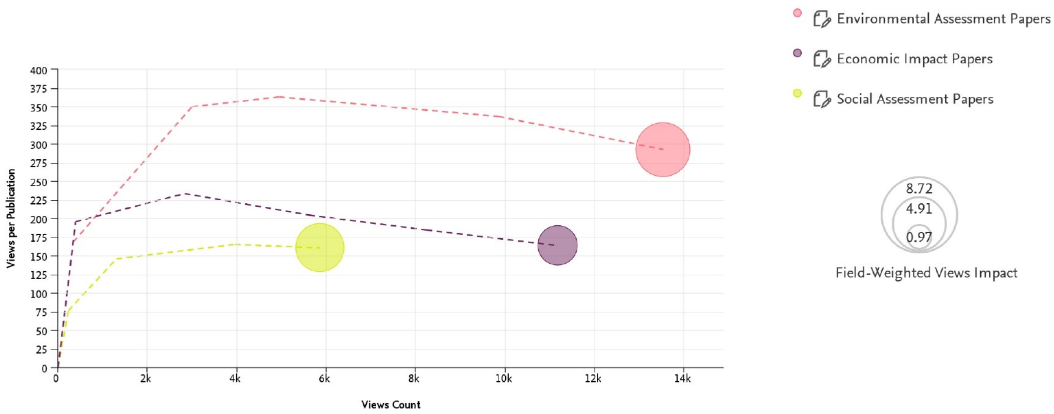


**Figure 1.14:** Blockchain multidimensional sustainability in Food Supply Chain: Benchmarking the Views Count, Views per Publication, and Field-Weighted Views Impact

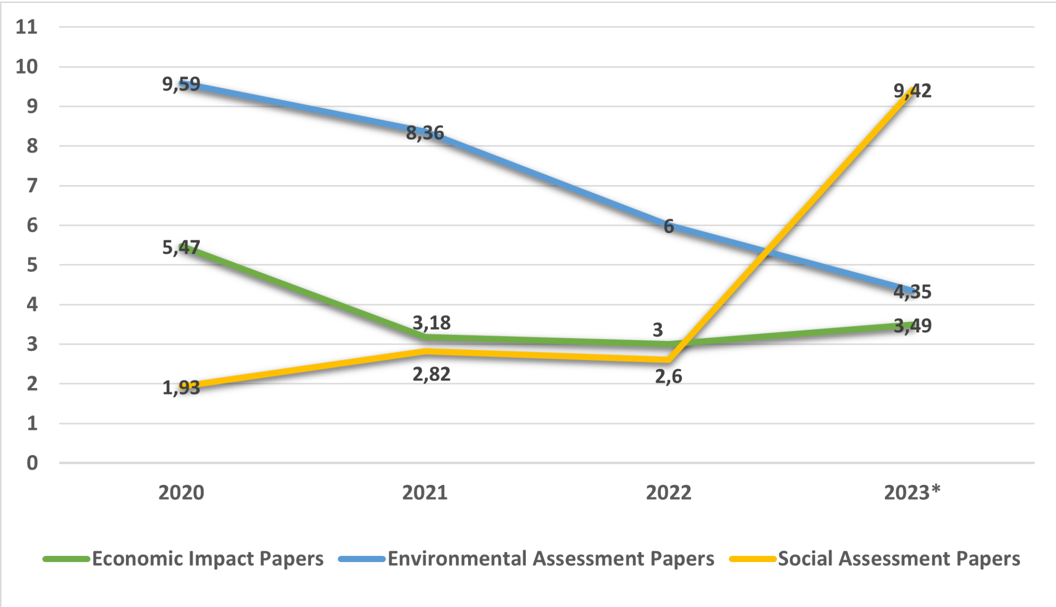


**Figure 1.15:** Blockchain multidimensional sustainability in Food Supply Chain: Field-Weighted Citation Impact (FWCI) trend over past 5 years. Self-citation excluded. *incomplete year

been increasing over time in each of these groups, we would expect a decline in the FWCI over time. However, it is so only for papers addressing environmental aspects. Nevertheless, to date these papers are cited, on average, 335% more frequently than similar publications in their field (FWCI of 4,35). Publications dealing with economic sustainability show a somewhat declining FWCI. However, in recent years, it has been consistently above 3, indicating that these papers are cited on average 200% more than similar publications. In contrast, papers dealing with the social sustainability show an increasing trend. This area was generally under-explored in literature before year 2020. The surge in FWCI, along with the

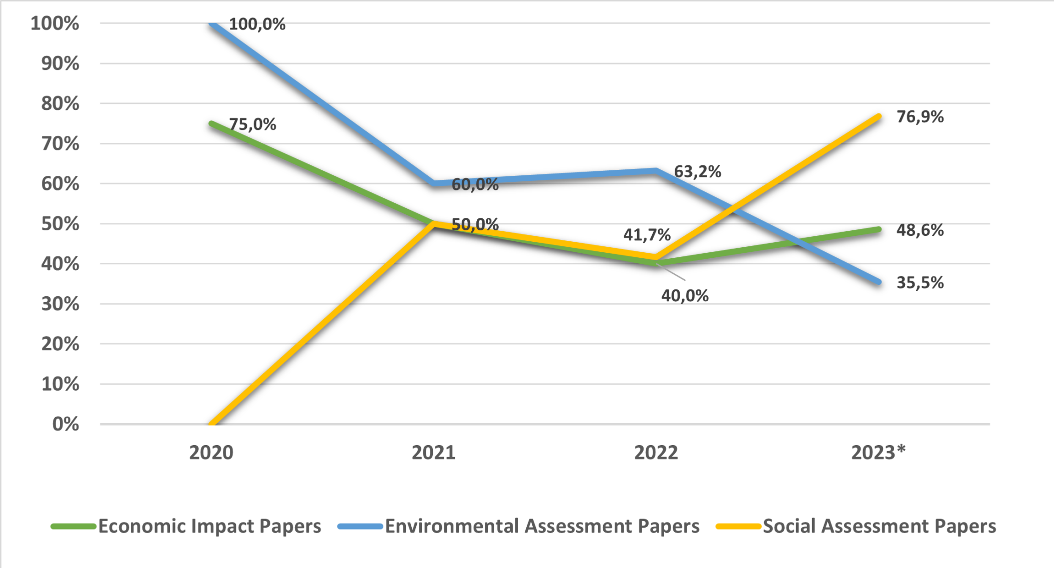


**Figure 1.16:** Blockchain multidimensional sustainability in Food Supply Chain: Publications in Top 10% Journal Percentiles *incomplete year

increase in the number of published papers focusing on this dimension, reflect a heightened interest in this field in recent years[19], peaked in 2023 with a FWCI of 9.42.

According to CiteScore metric, more than 95% of journal articles and book chapters were published between 2020 and 2023. Therefore, we limit our analysis to this period. Almost half of the considered publications (47.55%) were published in the top 10% of most cited journals indexed by Scopus. These papers are equally divided into the three subcategories. Figure 1.16 shows the proportion of articles from our dataset that appear in the highest decile of journals based on the CiteScore metric from 2020 to 2023.. We can observe trends similar to those found in the analysis of the FWCI. These trends, along with the significant increase in the number of papers on the topic in recent years, indicate the rising interest of the academic community on blockchain sustainability in agrifood context.

### 1.4.3 Cluster Analysis

To conclude our analysis, we would like to assess whether there is any clustering pattern emerging from our dataset. We do this building a map displaying the linkages between keywords indexed throughout the selected papers. This analysis has been conducted on a larger set of papers, namely the 185 papers analyzed in the previous section plus the paper in common to all these three subcategories

[19]However, the FWCI in 2023 for social assessment papers is likely to be biased, because of three highly cited papers that could have a significnat impact considering the limited number of publications in this group relative to the other two groups.

found in round (102 papers). These set of 287 journal articles and book chapters represent the larger set of relevant papers dealing with the economic, social, and environmental sustainability implications of implementing blockchain solutions within the agrifood supply chain.

Figure 1.17 shows the resulting clustering map developed using the VOSviewer (freely available at www.vosviewer.com) software to create a bibliometric map. Terms that frequently appear together in publications are situated in close proximity to one another on the map. Less strongly related terms, with lower co-occurrence rates, are positioned further apart. Each term on the map is represented by a circle whose size reflects the number of relevant publications in which the term appears in the title, abstract or keywords. Different colours represent the terms belonging to different clusters. The clustering membership is determined by the frequency of co-occurrence amongst the keywords.

Five major clusters can be identified though the analysis. As one might expect the *trait d'union* across the keywords is the term "blockchain", which appears 184 times and is associated with 41 other keywords. The total link strength (TLS)[20] of this word is very high (544), indicating its presence across all five clusters. "Supply chain" is another important keyword, occurring 77 times and connected to 41 other keywords. Its TLS is 290. The other recurring key terms are "food supply", "traceability", "Internet of Things", "transparency", and "smart contracts".

The five clusters represent specific thematic areas. The blue cluster comprises the keywords that relate to the aspects which are most affected by the adoption of blockchain within any supply chain. The purple cluster contains keywords related to the food supply industry, primarily concerning the safety of the final product (the closeness with terms like traceability and digital storage is noteworthy). The biggest cluster is the red one, whereby many topics are interconnected, largely due to the literature reviews' comprehensive nature. The green cluster pertains to innovations in agriculture technology, with the presence of architecture based terms like smart contracts, agricultural robots, internet of things, information management. Finally, the yellow cluster is mainly about the environmental sustainability of employing blockchain technology in the agrifood sector.

[20]Total Link Strength (TLS) represents the sum of all links generated by each keyword. A higher TLS indicates a significant co-occurrence of that keyword across clusters. Conversely, a lower TLS suggests a greater weight of occurrence within the cluster in which it occurs.

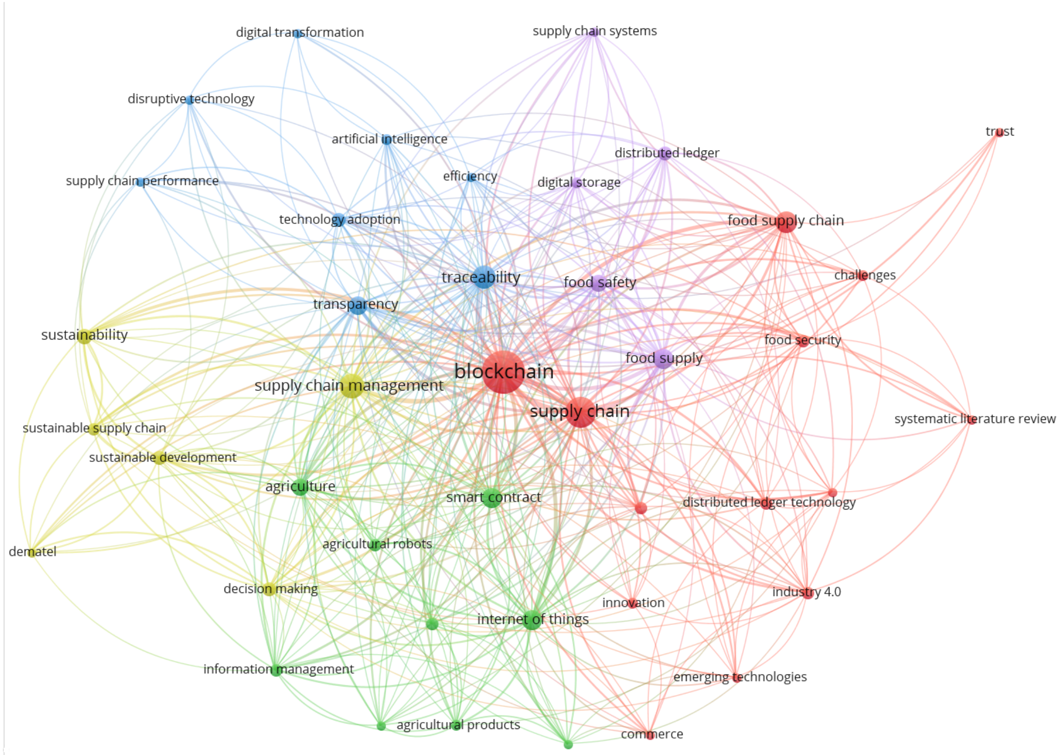


**Figure 1.17:** Blockchain Multidimensional Sustainability: Clustering maps of Key Words (Made with VOSviewer).

## 1.5 Conclusions

External threats, such as climate crises, wars or health shocks like Covid-19, play a significant role in agri-food systems, increasing risks and uncertainties. This is coupled with increasing stakeholder demand for sustainable production methods and quality products. Therefore, there is a growing interest in technological solutions that meet these new requirements and social contexts. Among the available solutions, blockchain is one of the most promising and has been extensively studied by scholars in recent years. This paper explores the current state of the art and trends in the literature on the environmental, economic, and social sustainability of blockchain in agri-food supply chain contexts, following the Triple Bottom Line approach. The analysis was conducted using the Scopus database. A scoping review methodology was employed to extract all relevant literature on the topic, and the most significant works were selected for our interests. We then investigated these databases using metrics provided by Snowball Metrics and classical analysis methodologies.

As we expected, interest of scholars on this subject is constantly increasing over last years. The publications cover a wide range of fields, with half of them relating to social science. The country with the most publications and affiliations is India, while China is the largest funding sponsor in this database. Out of the 2051 papers in our database, approximately one-third fall within the top citation percentiles. Just over 8 % of the papers fall within the top 1% of the most cited papers (field weighted). The trend appears to be increasing in absolute terms but decreasing in relative terms. This is likely due to the exponential growth of papers on Covid-19 related topics, which has significantly raised the threshold for accessing the top rankings in terms of citations. A comparable argument can be made regarding publications in the top journal percentiles, although the trend is less clear.

Regarding the analysis of the three components that comprise the triple bottom line,namely economic, social and environmental, the results are highly indicative. They demonstrate a strong interest in the subject according to all the metrics used, particularly in relation to the growing focus on the environmental and social sustainability aspects of BCT.

# References

Adamashvili, Nino et al. (2021). «Blockchain-based wine supply chain for the industry advancement». In: *Sustainability* 13.23, p. 13070.

Alimohammadlou, Moslem and Saeed Alinejad (Apr. 2023). «Challenges of blockchain implementation in SMEs' supply chains: an integrated IT2F-BWM and IT2F-DEMATEL method». In: *Electronic Commerce Research*. ISSN: 1572-9362. DOI: 10.1007/s10660-023-09696-3. URL: https://doi.org/10.1007/s10660-023-09696-3.

Arksey, Hilary and Lisa O'Malley (2005). «Scoping studies: towards a methodological framework». In: *International Journal of Social Research Methodology* 8.1, pp. 19–32. DOI: 10.1080/1364557032000119616. eprint: https://doi.org/10.1080/1364557032000119616. URL: https://doi.org/10.1080/1364557032000119616.

Bakewell, Oliver et al. (2009). «South-South migration and human development: reflection on African experiences». In.

Balamurugan, S et al. (2021). «IoT-Blockchain driven traceability techniques for improved safety measures in food supply chain». In: *International journal of information technology*, pp. 1–12.

Barrientos, Stephanie et al. (2011). «Economic and social upgrading in global production networks: A new paradigm for a changing world». In: *International Labour Review* 150.3-4, pp. 319–340.

Burch, David and Geoffrey Lawrence (2009). «Towards a third food regime: behind the transformation». In: *Agriculture and human values* 26, pp. 267–279.

Campbell, Colin L et al. (2015). «Consumers' reaction to fair trade motivated price increases». In: *Journal of Retailing and Consumer Services* 24, pp. 79–84.

Cappelletti, Giulio et al. (July 2023). «Harnessing the Power of Blockchain in the Agri-Food Sector: A Meta-Analysis of Current Research and Best Practices». In: *Applied Mathematical Sciences* 17, pp. 477–501. DOI: 10.12988/ams.2023.917473.

Caro, Miguel Pincheira et al. (2018). «Blockchain-based traceability in Agri-Food supply chain management: A practical implementation». In: *2018 IoT Vertical and Topical Summit on Agriculture-Tuscany (IOT Tuscany)*. IEEE, pp. 1–4.

Chen, Huilin et al. (2021). «Effective management for blockchain-based agri-food supply chains using deep reinforcement learning». In: *IEeE Access* 9, pp. 36008–36018.

Chohan, Usman W (2019). «Blockchain and Environmental Sustainability: Case of IBM's Blockchain Water Management». In: *Notes on the 21st Century (CBRI)*.

Chopra, Muskaan et al. (2022). «Analysis & prognosis of sustainable development goals using big data-based approach during COVID-19 pandemic». In: *Sustainable Technology and Entrepreneurship* 1.2, p. 100012.

Christopher, Martin et al. (Jan. 2011). «Approaches to managing global sourcing risk». In: *Supply Chain Management: An International Journal* 16.2. ZSCC: 0000591, pp. 67–81. ISSN: 1359-8546. DOI: 10.1108/13598541111115338. URL: https://doi.org/10.1108/13598541111115338 (visited on 09/07/2023).

Danezis, Georgios P. et al. (Dec. 2016). «Food authentication: Techniques, trends & emerging approaches». In: *TrAC Trends in Analytical Chemistry* 85. ZSCC: 0000513, pp. 123–132. ISSN: 01659936. DOI: 10.1016/j.trac.2016.02.026. URL: https://linkinghub.elsevier.com/retrieve/pii/S0165993615301291 (visited on 09/07/2023).

De Pelsmacker, Patrick et al. (2005). «Do consumers care about ethics? Willingness to pay for fair-trade coffee». In: *Journal of consumer affairs* 39.2, pp. 363–385.

Del Giudice, Teresa et al. (2016). «Anti-waste labeling and consumer willingness to pay». In: *Journal of International Food & Agribusiness Marketing* 28.2, pp. 149–163.

Dutta, Pankaj et al. (2020). «Blockchain technology in supply chain operations: Applications, challenges and research opportunities». In: *Transportation research part e: Logistics and transportation review* 142, p. 102067.

Elkington, John and Ian H Rowlands (1999). «Cannibals with forks: The triple bottom line of 21st century business». In: *Alternatives Journal* 25.4, p. 42.

*The State of Food and Agriculture 2019. Moving forward on food loss and waste reduction* (2019). DOI: https://doi.org/10.4060/ca6030en. URL: https://www.fao.org/documents/card/en/c/ca6030en.

*The State of Food and Agriculture 2022. Leveraging agricultural automation for transforming agrifood systems* (2022). DOI: https://doi.org/10.4060/cb9479en. URL: https://www.fao.org/3/cb9479en/online/cb9479en.html.

Ferdousi, Tanvir et al. (2020). «A Permissioned Distributed Ledger for the US Beef Cattle Supply Chain». In: *IEEE Access* 8, pp. 154833–154847. DOI: 10.1109/ACCESS.2020.3019000.

*Global Food Security Index* (2022). URL: https://impact.economist.com/sustainability/project/food-security-index/.

Grunert, Klaus G et al. (2014). «Sustainability labels on food products: Consumer motivation, understanding and use». In: *Food policy* 44, pp. 177–189.

Kumar, Bipul et al. (2017). «Purchasing behaviour for environmentally sustainable products: A conceptual framework and empirical study». In: *Journal of Retailing and Consumer Services* 34, pp. 1–9.

Levac, Danielle et al. (2010). «Scoping studies: advancing the methodology». In: *Implementation science* 5, pp. 1–9.

Li, Kunpeng et al. (2023). «Blockchain in food supply chains: A literature review and synthesis analysis of platforms, benefits and challenges». In: *International Journal of Production Research* 61.11, pp. 3527–3546.

Li, Ying et al. (2020). «The impact of digital technologies on economic and environmental performance in the context of industry 4.0: A moderated mediation model». In: *International Journal of Production Economics* 229, p. 107777.

Maertens, Miet and Johan FM Swinnen (2009). «Trade, standards, and poverty: Evidence from Senegal». In: *World development* 37.1, pp. 161–178.

Mangla, Sachin Kumar et al. (2021). «Using system dynamics to analyze the societal impacts of blockchain technology in milk supply chainsrefer». In: *Transportation Research Part E: Logistics and Transportation Review* 149, p. 102289.

Marikyan, M and P Papagiannidis (2021). «Unified theory of acceptance and use of technology». In: *TheoryHub book*.

Minarelli, Francesca et al. (2016). «Asymmetric information along the food supply chain: a review of the literature». In: *12th European International Farming Systems Association (IFSA) Symposium, Social and Technological Transformation of Farming Systems: Diverging and Converging Pathways*, pp. 12–15.

Oguntegbe, Kunle Francis et al. (2022). «Behavioural antecedents to blockchain implementation in agrifood supply chain management: A thematic analysis». In: *Technology in Society* 68, p. 101927. ISSN: 0160-791X. DOI: https://doi.org/10.1016/j.techsoc.2022.101927. URL: https://www.sciencedirect.com/science/article/pii/S0160791X22000689.

Pakseresht, Ashkan et al. (2022). «The intersection of blockchain technology and circular economy in the agri-food sector». In: *Sustainable Production and Consumption*.

Pan, Yuting et al. (2019). «Application of blockchain in carbon trading». In: *Energy Procedia* 158, pp. 4286–4291.

Park, Arim and Huan Li (2021). «The Effect of Blockchain Technology on Supply Chain Sustainability Performances». In: *Sustainability* 13.4. ISSN: 2071-1050. DOI: 10.3390/su13041726. URL: https://www.mdpi.com/2071-1050/13/4/1726.

Pun, Hubert et al. (2021). «Blockchain adoption for combating deceptive counterfeits». In: *Production and Operations Management* 30.4, pp. 864–882.

Putri, AN et al. (2020). «Smart agriculture using supply chain management based on hyperledger blockchain». In: *IOP Conference Series: Earth and Environmental Science*. Vol. 466. 1. IOP Publishing, p. 012007.

Queiroz, Maciel M and Samuel Fosso Wamba (2019). «Blockchain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA». In: *International Journal of Information Management* 46, pp. 70–82.

Raynolds, Laura T (2000). «Re-embedding global agriculture: The international organic and fair trade movements». In: *Agriculture and human values* 17, pp. 297–309.

Rocchi, Benedetto et al. (2020). «Assessing the economy-wide impact of food fraud: A SAM-based counterfactual approach». In: *Agribusiness* 36.2, pp. 167–191.

Rousseau, Sandra (2015). «The role of organic and fair trade labels when choosing chocolate». In: *Food Quality and Preference* 44, pp. 92–100.

Ruzza, Daniel et al. (2022). «Blockchain Application to the SMEs in the Food Industry: Trusty Case Study». In: *Blockchain Technology Applications in Businesses and Organizations*. Ed. by Pietro De Giovanni. Hershey, PA, USA: IGI Global, pp. 19–42. ISBN: 978-1-79988-014-1. DOI: 10.4018/978-1-7998-8014-1.ch002. URL: https://services.igi-global.com/resolvedoi/resolve.aspx?doi=10.4018/978-1-7998-8014-1.ch002.

Sachin Kamble, Angappa Gunasekaran and Himanshu Arha (2019). «Understanding the Blockchain technology adoption in supply chains-Indian context». In: *International Journal of Production Research* 57.7, pp. 2009–2033. DOI: 10.1080/00207543.2018.1518610.

Saurabh, Samant and Kushankur Dey (2021). «Blockchain technology adoption, architecture, and sustainable agri-food supply chains». In: *Journal of Cleaner Production* 284, p. 124731.

Scuderi, Alessandro et al. (2019). «The supply chain value of pod and pgi food products through the application of blockchain». In: *Calitatea* 20.S2, pp. 580–587.

Sendros, Andreas et al. (2022). «Blockchain applications in agriculture: a scoping review». In: *Applied Sciences* 12.16, p. 8061.

Silva, Catarina Ferreira da and Sergio Moro (2021). «Blockchain technology as an enabler of consumer trust: A text mining literature analysis». In: *Telematics and Informatics* 60, p. 101593.

Singh, Ashish et al. (2023). «Redefining food safety traceability system through blockchain: findings, challenges and open issues». In: *Multimedia Tools and Applications* 82.14, pp. 21243–21277.

Taherdoost, Hamed (2022). «A Critical Review of Blockchain Acceptance Models: Blockchain Technology Adoption Frameworks and Applications». In: *Computers* 11.2. ISSN: 2073-431X. DOI: `10.3390/computers11020024`. URL: `https://www.mdpi.com/2073-431X/11/2/24`.

Tian, Feng (2017). «A supply chain traceability system for food safety based on HACCP, blockchain & Internet of things». In: *2017 International conference on service systems and service management*. IEEE, pp. 1–6.

Timmermans, A.J.M. et al. (2014). *Food losses and waste in the context of sustainable food systems*. English. HPLE report / High Level Panel of Experts on Food Security and Nutrition 8. CFS Committee on World Food Security HLPE.

Tricco, Andrea C et al. (2018). «PRISMA extension for scoping reviews (PRISMA-ScR): checklist and explanation». In: *Annals of internal medicine* 169.7, pp. 467–473.

Upadhyay, Arvind et al. (2021). «Blockchain technology and the circular economy: Implications for sustainability and social responsibility». In: *Journal of cleaner production* 293, p. 126130.

Venkatesh, Viswanath et al. (2003). «User acceptance of information technology: Toward a unified view». In: *MIS quarterly*, pp. 425–478.

Verhoeven, Peter et al. (2018). «Examples from blockchain implementations in logistics and supply chain management: exploring the mindful use of a new technology». In: *Logistics* 2.3, p. 20.

Viano, Cristina et al. (2022). «Blockchain tools for socio-economic interactions in local communities». In: *Policy and Society* 41.3, pp. 373–385.

Viriyasitavat, Wattana et al. (2019). «When blockchain meets Internet of Things: Characteristics, challenges, and business opportunities». In: *Journal of industrial information integration* 15, pp. 21–28.

Wamba, Samuel Fosso and Maciel M Queiroz (2022). «Industry 4.0 and the supply chain digitalisation: a blockchain diffusion perspective». In: *Production Planning & Control* 33.2-3, pp. 193–210.

Wan, Paul Kengfai et al. (2020). «Blockchain-enabled information sharing within a supply chain: A systematic literature review». In: *IEEE access* 8, pp. 49645–49656.

Wittman, Hannah (2009). «Reworking the metabolic rift: La Vía Campesina, agrarian citizenship, and food sovereignty». In: *The journal of peasant studies* 36.4, pp. 805–826.

Wong, Lai-Wan et al. (2020). «Time to seize the digital evolution: Adoption of blockchain in operations and supply chain management among Malaysian SMEs». In: *International Journal of Information Management* 52, p. 101997.

Yiannas, Frank (2018). «A new era of food transparency powered by blockchain». In: *Innovations: Technology, Governance, Globalization* 12.1-2, pp. 46–56.

# Chapter 2

# Perceived Economic and Social Benefits of AgriFi: Early Evidence from a Blockchain-Enabled Platform in Nigeria

## Abstract

This study investigates the early-stage impacts of AgriFi, a blockchain-enabled agricultural platform, on smallholder farmers in Nigeria. Drawing on survey data from 206 participants across two contrasting business models—Niger State (private investment) and Katsina State (government-supported)—the research explores farmers' perceived economic and social benefits, as well as the socio-economic factors predicting those perceptions. Findings show that farmers widely associate AgriFi with improved market access, financial inclusion, and profitability, while social benefits such as community dynamics and labor coordination remain less consistent. Dynamic enablers—particularly training quality and long-term farming experience—consistently drive positive perceptions, whereas age, gender, and education play more limited or unexpected roles. The analysis also highlights how implementation modality shapes outcomes: farmers in Niger, where the platform integrates blockchain-backed financial services, report stronger perceived gains than those in Katsina. Despite early-stage limitations and reliance on self-reported data, this study contributes new evidence to the literature on digital agriculture, emphasizing the importance of training, extension, and farmer-centered design for inclusive adoption. The paper concludes by calling for longitudinal research, platform co-design, and policy strategies that integrate digital innovation with local trust-building and capacity development.

## 2.1 Introduction

Agriculture remains a cornerstone of economic activity across West Africa, yet systemic constraints continue to limit the potential of smallholder farmers. Among the most pressing challenges are limited access to credit, volatile markets, inadequate infrastructure, and persistent trust deficits within agricultural value chains (Fafchamps, 2004). These constraints not only hinder productivity but also reduce farmers' ability to engage in resilient, market-oriented farming systems.

Building on the conceptual insights and research gaps identified in the preceding review, this chapter shifts from theory to evidence, examining how blockchain-based innovation is experienced by farmers themselves

Access to finance remains particularly limited for rural farmers, many of whom cannot invest in critical inputs such as seeds, fertilizer, or machinery (World Bank, 2019). Meanwhile, poor infrastructure—especially in transportation and storage—contributes to post-harvest losses and market isolation (Jayne & Ameyaw, 2016). A less visible but equally constraining barrier lies in the erosion of trust between farmers, intermediaries, and institutions, which manifests through side-selling, delayed payments, and lack of transparency (Barrett et al., 2012).

In this context, digital technologies—particularly blockchain—are gaining attention for their ability to address trust, coordination, and accountability challenges in agriculture. Blockchain's decentralized, transparent, and tamper-proof architecture has been promoted as a mechanism to reconfigure how farmers access inputs, credit, and markets, while reducing reliance on intermediaries (Casino et al., 2019). Recent studies highlight blockchain's potential in enhancing traceability, transparency, and trust within agri-food supply chains, thereby addressing systemic inefficiencies and fostering sustainable agricultural practices.

Despite the theoretical promise of blockchain in agriculture, empirical research on how such platforms are experienced and perceived by farmers remains limited. Much of the existing literature has focused on technical feasibility, scalability, and use cases in logistics (Treiblmaier & Beck, 2019), while neglecting farmers' own evaluations—particularly in low-income, rural contexts.

Key questions remain unanswered: Do farmers perceive blockchain-based platforms as beneficial? What socio-economic factors condition their engagement? How do trust, training, and digital access shape their experiences?

In Nigeria, where rural infrastructure gaps, low digital literacy, and high institutional uncertainty prevail, these questions are particularly urgent. While platforms such as AgriFi—a blockchain-enabled digital system that integrates traceable input delivery, credit profiling, and smart contracts for pre and post-harvest transactions—offer integrated solutions, there is limited evidence on how intended users, such as smallholder farmers, evaluated those tools. (See 2.3 for a detailed description of AgriFi's architecture and business model.)

This study addresses this knowledge gap by examining perceived benefits and the users' characteristics that are associated with those perceived benefits. It delves into primary data collected from 206 farmers in two regions in Nigeria featuring different business models—i.e., Niger State (private investment-driven) and Katsina State (publicly funded)—offering a comparative lens into how platform design and local context shape adoption dynamics.

Specifically, the paper investigates the two following research questions:

- **RQ1: What perceived economic and social advantages do smallholder farmers report from their involvement in the AgriFi platform?**
  → This includes perceived improvements in market access, income stability, community relations, and access to finance.

- **RQ2: Which socioeconomic characteristics (e.g., training, cooperative membership, digital literacy) predict more favorable perceptions of AgriFi's benefits?** This helps identify which categories of farmers are most likely to benefit and what factors may limit perceived value.

This research contributes to the emerging field of farmer-centered digital agriculture by shifting attention from the technological promise of blockchain to the lived experience of those who use it. It provides new evidence on how smallholder farmers in Nigeria assess digital platforms, what shapes their perceptions, and where gaps in engagement remain.

For practitioners and researchers, the findings highlight the importance of enabling conditions—particularly training and extension support—in converting technical innovation into perceived value. For policymakers, the study underscores that platform design must be tailored to local realities, with attention to inclusivity, literacy, and trust-building.

Ultimately, by disentangling farmer perceptions, this research offers a grounded view of blockchain's potential to transform agricultural value chains in low-trust, resource-constrained environments. It contributes not only to the literature on ICT adoption in agriculture but also to practical debates on how to design scalable, inclusive, and trust-enabling agri-tech solutions.

## 2.2 Literature Review

### 2.2.1 ICT Innovations in African Agriculture

Information and communication technologies (ICTs) are significantly transforming the ways in which smallholder farmers in Africa access markets, information, and financial resources. The historical evidence indicates that various tools—such as mobile phones, digital platforms, and radio—have enhanced agricultural productivity and resilience among farmers in Sub-Saharan Africa. The widespread deployment of mobile phones has effectively bridged the communication gap between rural farmers and critical information sources, including market prices, weather forecasts, and agronomic advice.

However, substantial gaps persist in the movement toward the structural digitalization of agriculture. The underutilization of advanced technologies is particularly pronounced due to existing infrastructure deficits, low levels of digital literacy, and high costs associated with technology adoption. Moreover, inequities are exacerbated in underserved rural areas that feature limited access to cost-effective broadband internet connectivity, which further restricts farmers' ability to leverage more sophisticated tools and platforms (Aker & Mbiti, 2010). Addressing these underexploited capabilities is essential for unlocking the potential of ICT-enabled agriculture at both societal and economic levels.

The adoption of ICT among farmers is correlated with increased agronomic productivity and improved access to markets and financial services, supported by empirical evidence. The development of ICT platforms enables smallholder farmers to obtain timely and reliable market information, agricultural practices, and pricing strategies, thus facilitating informed decision-making regarding input utilization while simultaneously reducing transaction costs and enhancing profitability (Jack & Suri, 2014; Aker & Mbiti, 2010). Furthermore, the proliferation of mobile money services, exemplified by M-PESA payment system across several African - and not African- countries, along with digital credit options, has broadened access to finance, enabling farmers to invest in essential inputs such as fertilizers, drought-resistant seeds, and modern equipment.

ICT tools also contribute to enhanced transparency and the reduction of information asymmetry, thereby fostering more efficient value chains in the long term. Numerous platforms facilitate direct interactions among farmers, input suppliers, and buyers, streamlining operations, ensuring fair pricing, and bolstering traceability within the agricultural supply chain (Barrett et al., 2012). Nonetheless, for these initiatives to scale effectively and achieve meaningful impacts, challenges such as the lack of digital skills and the digital divide must be addressed.

### 2.2.2 West African Agriculture and Blockchain: Challenge of Trust

Trust deficits represent a longstanding and critical challenge for agriculture in many developing countries, particularly in Sub-Saharan Africa. Farmers often encounter issues such as side selling, wherein they bypass cooperatives to market their produce independently, thus undermining collective bargaining efforts. Delays in adjudication and asymmetric information regarding knowledge between farmers and buyers further exacerbate the imbalance of power, eroding trust and diminishing the effectiveness of cooperatives (Barrett et al., 2012; Lee et al., 2022). This trust deficit, compounded by weak institutional frameworks and inadequate enforcement mechanisms, results in inefficiencies that hinder local markets from maximizing their impact on rural livelihoods.

In this context, blockchain technology emerges as a potential solution. It provides a decentralized and transparent trust framework in regions characterized by weak institutional structures and conventional trust mechanisms that are easily overwhelmed. The immutable and tamper-resistant nature of blockchain ensures verifiable transactions, thereby reducing opportunities for fraud and promoting fairer interactions among smallholder farmers, cooperatives, and other stakeholders within the agricultural value chain (Casino et al., 2019; Nakamoto, 2008).

In cooperatives commonly found in rural West Africa, trust-building mechanisms typically rely on either social enforcement (peer monitoring, reputation) or third-party enforcement (audits, contracts). While these mechanisms may function effectively in certain contexts, they often fall short in fostering the growth of larger cooperatives or accommodating a diverse array of stakeholders with conflicting interests (Bijman et al., 2011). The weak enforcement of contracts, coupled with a lack of transparency and high monitoring costs, impedes cooperatives' ability to fulfill their intended function of promoting equitable resource sharing among members, highlighting the increasing demand for a reliable and scalable trust solution.

The decentralized trust layer offered by blockchain has the potential to address enduring challenges, ranging from side selling to opaque profit-sharing systems. By maintaining an immutable ledger and automating operations through decentralized applications (DApps), blockchain can facilitate equitable resource allocation and enhance collective bargaining power. When trust is established through code rather than traditional means, farmers may evolve to embody sustainable practices in water and cultivation management, as well as inclusive rural development, particularly in contexts where conventional trust structures are financially or logistically burdensome to establish and maintain.

Empirical studies from West African and East African contexts have begun to validate these theoretical propositions. Lawal et al. (2025) discovered that blockchain-based solutions significantly enhanced accountability and reduced instances of side selling in Kenyan farmer cooperatives. Blockchain-enabled platforms afforded cooperative members visibility across the entire value chain, thereby fostering a sense of collective ownership and trust among participants.

A notable pilot project in Ghana demonstrated that blockchain technology enabled cocoa farmers to transact directly with international clients, eliminating intermediaries and consequently increasing the proportion of the overall price received by farmers. These case studies highlight the extent to which blockchain technology can serve as a trust substitute, facilitating transparency and accountability within agricultural settings.

Nevertheless, the literature reveals that significant obstacles to blockchain adoption persist. Challenges related to infrastructure, digital literacy, and high implementation costs remain pronounced, particularly in lower-income and rural communities (Tripathi et al., 2022). While blockchain technology possesses substantial potential, its widespread adoption and scaling will necessitate context-specific adjustments and supplementary interventions, including training in digital literacy and infrastructure development.

In the context of agricultural value chains, blockchain technology not only serves as a trust substitute but also addresses issues related to resource optimization and market integration. The emergence of blockchain-powered platforms facilitates streamlined interactions among farmers, suppliers, and buyers within decentralized systems, automating critical transactions—such as payment transfers and input deliveries—through the use of smart contracts. This increases operational efficiencies and ensures timely and equitable exchanges (Tripathi et al., 2022).

The real-time traceability afforded by blockchain technology addresses the challenge of information asymmetry. By providing farmers with verified data on market prices, demand forecasts, and buyer requirements, blockchain enables informed decision-making and access to more favorable market opportunities. Moreover, the use of immutable financial records enhances farmers' creditworthiness and access to essential financial services.

### 2.2.3 The AgriFi Platform

The AgriFi platform employs blockchain technology to address significant deficiencies in trust and inefficiencies in agricultural value chains, particularly in developing economies. By establishing a decentralised system, AgriFi facilitates connections between stakeholders, including smallholder farmers, input suppliers, investors, financial institutions, and insurance providers. This enhances transparency, accountability, and operational efficiency. At the core of the platform is a secure digital profiling system that records data on farming activities, financial transactions, and geolocation for each registered farmer in a manner that is resistant to manipulation.

#### Verification and Onboarding Processes

The onboarding process undertaken by AgriFi is characterised by a meticulous multi-stage verification procedure, the objective of which is to ascertain the eligibility and reliability of participants. The selection process prioritises cooperatives or farmer groups based on environmental risk assessments, regional security, and the availability of essential infrastructure, such as mobile connectivity and storage facilities. The verification of farmers entails the utilisation of satellite imagery, field visits, and the collation of pertinent documentation, including identity proof and land ownership records. Upon verification, farmers are registered on the AgriFi app and grouped into clusters according to crop type, geographic location, and risk profile. The clustering approach facilitates optimal monitoring, mitigates risks such as side-selling and environmental hazards, and ensures targeted resource distribution.

#### Blockchain-Enabled Architecture

The AgriFi platform is underpinned by blockchain technology, which serves as the foundation for all operational aspects. The distributed ledger technology guarantees the transparency and traceability of all transactions, including those related to input receipt, credit access, and produce sale. Smart contracts, which are self-executing agreements encoded on the blockchain, automate key processes such as the distribution of payments and the delivery of inputs. Such contracts serve to minimise reliance on intermediaries, thereby ensuring timely and fair transactions while simultaneously reducing operational costs. Investor-funded pools are created based on comprehensive farmer profiles, enabling the efficient allocation of financial resources, which are then subjected to rigorous monitoring through a combination of technological and field-based surveillance.

### Clustering for Efficiency and Impact

The clustering of farmers is a fundamental aspect of AgriFi's operational strategy. It serves to optimise the allocation of resources and to foster collective action among farmers. The platform's ability to group farmers with similar characteristics allows for more efficient monitoring of compliance and coordination of logistical activities. During the growing season, private extension service providers conduct regular monitoring using GPS tracking and physical inspections to ensure adherence to recommended farming practices. Following the harvest, the produce is aggregated at designated warehouses or collected directly from farms, thus ensuring efficient post-harvest management. The distribution of payments to farmers and other stakeholders is conducted through the use of smart contracts, which guarantee the fair and efficient allocation of revenues.

### Innovative Input Delivery and Revenue Distribution

Essential agricultural inputs are delivered through AgriFi's network of trusted suppliers, often in the form of in-kind donations, thereby ensuring that farmers receive the necessary materials for cultivation. This approach serves to mitigate the inherent risks associated with cash-based transactions, whilst simultaneously promoting transparency. Once the harvest is complete, the blockchain-enabled system guarantees the fair distribution of revenue. Typically, the majority of the proceeds are allocated to the farmers, while the investors and platform operators receive their compensation through pre-agreed returns and fees. This system not only fosters confidence among participants but also addresses long-standing inefficiencies in revenue sharing within traditional agricultural systems.

The integration of blockchain technology by AgriFi represents a scalable solution to the systemic challenges inherent to agricultural systems, promoting trust, efficiency, and financial inclusion. By integrating trust into its technological infrastructure, the platform enables smallholder farmers to indirectly benefit from advanced digital tools without requiring extensive technical knowledge. This approach is consistent with broader efforts to enhance digitalisation in agriculture, particularly in rural and low-income contexts.

### 2.2.4 Factors influencing Perceived Benefits

Understanding the factors that shape farmers' perceptions of the benefits associated with blockchain-enabled platforms is critical to evaluating the efficacy and scalability of initiatives like AgriFi. Drawing on the literature and the conceptual framework presented in Section 2.3, this section explores the socio-economic, technological, and contextual variables that condition farmers' engagement and their assessment of digital agriculture tools.

#### Socio-Economic Characteristics and Farm-Level Dynamics

Farmer-specific characteristics such as education, experience, and demographic profile interact with farm-level constraints and opportunities to shape adoption patterns and perceived value.

- **Education and Experience:** While education often facilitates technology adoption by improving digital literacy and comprehension of platform features, recent findings suggest that secondary education may also correlate with more critical assessments, potentially due to higher expectations. Conversely, farming experience—particularly beyond 10 years—emerges as a consistent positive correlate of perceived economic and resilience benefits. Experienced farmers may be more adept at translating new tools into practical advantages, particularly in credit management and market participation (Wossen et al., 2017).

- **Farm Size:** The relationship between farm size and digital engagement is complex. Larger farms may benefit from economies of scale and greater capacity to engage with blockchain platforms, but smallholders may perceive relatively greater marginal benefits from improved access to inputs and markets. The heterogeneity in outcomes across farm size categories underscores the need for tailored onboarding strategies.

- **Gender and Age:** Although frequently included in adoption studies, these demographic variables do not appear as robust predictors once project-level interventions—particularly training and extension—are accounted for, as our models later confirm. However, gender disparities in access to digital tools and financial services remain relevant constraints in many contexts and may affect baseline levels of engagement.

#### Training and Extension Access

Among the most important enabling conditions for positive perceptions of AgriFi are training and extension support. The composite Training Index used in this study—accounting for both access to and quality of training—demonstrates strong positive associations with perceived market access, financial inclusion, and overall economic benefits. These results align with the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), both of which highlight the role of facilitating conditions in promoting digital tool adoption (Venkatesh et al., 2003).

Extension services, particularly when delivered regularly, also play a critical role. Beyond conveying technical knowledge, extension agents serve as brokers of trust and accountability, guiding farmers through onboarding processes and problem-solving. Literature on peer influence and knowledge diffusion in agriculture (Feder & Slade, 1984; Conley & Udry, 2010) emphasizes the role of extension systems in lowering uncertainty and shaping adoption behavior, particularly in early-stage or unfamiliar technologies. Their presence is especially significant for domains like resilience and financial access, where risk perception and procedural understanding are central.

### Access to Credit and Digital Finance

Access to credit is both a direct benefit of AgriFi and a key enabler of downstream impacts. The platform's integration of blockchain-backed credit mechanisms allows for more transparent financial profiling and verifiable repayment histories. These tools enhance farmer creditworthiness, reduce lender risk, and contribute to perceived economic stability. As previous studies show, financial inclusion is essential for unlocking investment in productivity-enhancing inputs and improving household resilience (Jack & Suri, 2014; Aker & Mbiti, 2010).

### Digital Devices and Smartphone Usage

The smartphone is the primary interface through which farmers interact with AgriFi. Although mobile phone penetration in Nigeria has grown steadily, disparities persist—particularly among the poorest or most remote farmers. This digital divide can limit the uptake and full use of platform features, especially those requiring real-time engagement. Efforts to ensure equitable access to smartphones and mobile connectivity are essential for maximizing platform inclusiveness and functionality (Global Findex, 2022).

### Perceptions of Blockchain Functionality

Finally, perceived benefits tied to the blockchain infrastructure itself—namely transparency, traceability, and efficiency—are crucial for long-term platform engagement. In contexts marked by institutional fragility and corruption, farmers may value the immutable recordkeeping and automated transactions enabled by blockchain as a way to overcome past experiences of fraud, favoritism, or inefficiency (Casino et al., 2019). Positive experiences with these features may translate into higher trust in the system, greater adoption, and broader recommendations within farmer networks.

In summary, the formation of perceived benefits is shaped less by fixed demographic attributes and more by a set of dynamic enablers: training, experience, credit access, and extension support. These findings have critical implications for the design of inclusive and effective digital agriculture programs and highlight the importance of contextualizing technology within local socio-economic realities.

### 2.2.5 Gaps in the Literature

While the literature on blockchain applications in agriculture is expanding rapidly, significant gaps remain—particularly regarding the technology's capacity to address the socio-economic realities of rural smallholder systems. Much of the current research focuses on the technical feasibility of blockchain in logistics and supply chain management, emphasizing issues such as data integration, scalability, and interoperability (Casino et al., 2019; Treiblmaier & Beck, 2019). These studies, while valuable, often overlook the actual experiences and structural constraints faced by smallholder farmers—arguably the primary stakeholders in any inclusive digital agriculture transformation.

Existing literature highlights several well-known barriers to blockchain adoption, including infrastructural deficits, technical complexity, and low levels of digital literacy among rural populations (Tripathi et al., 2022). These challenges not only limit adoption but also obscure the broader systemic benefits that blockchain might enable—such as expanded market access, enhanced financial inclusion, and more efficient resource allocation. Furthermore, these potential benefits are frequently examined in isolation, rather than as interacting elements shaping the smallholder livelihoods.

An important underexplored area concerns the socio-economic factors that condition farmers' interaction with blockchain platforms. Variables such as cooperative membership, access to training, and levels of digital literacy are often mentioned but rarely analyzed in a systematic, empirically grounded way. This gap is especially salient in developing countries, where community-based structures and informal networks are crucial to overcoming institutional weaknesses and facilitating collective technology adoption.

Furthermore, a significant research gap relates to the *perceived* benefits of blockchain from the perspective of end users. While much of the literature highlights theoretical advantages—transparency, accountability, decentralization—empirical studies on how farmers actually experience and evaluate these features remain rare. Therefore, farmer's evaluations remain marginal in debates about design, usability, and the conditions required for scaling blockchain-based interventions.

## 2.3 Conceptual Framework

### 2.3.1 Theoretical Underpinnings

This study draws upon interdisciplinary theoretical frameworks to examine how the blockchain-enabled AgriFi platform shapes perceived economic and social benefits among smallholder farmers in Nigeria. Our approach integrates insights from digital trust theory, technology adoption models, and rural development literature, aligning our analytical strategy with proven academic foundations.

**Blockchain as a Trust Substitution Mechanism:** In settings where institutional trust is limited, blockchain technologies can substitute for interpersonal trust by offering immutable, transparent, and auditable records. This is particularly valuable in agricultural systems where informal agreements dominate and where side-selling, credit default, and fraud are prevalent (Casino et al., 2019).

In Niger State, AgriFi operates as a private investment-driven model, combining blockchain-led financing, input traceability, and contract enforcement. In Katsina State, the platform is used primarily for input logistics and subsidy distribution under a government-supported program.This dual implementation provides a natural contrast for understanding blockchain's role in either fostering trust-based exchanges or streamlining public distribution systems.

**Technology Adoption Frameworks:** To evaluate how farmers engage with AgriFi, we use the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) as reference theoretical frameworks. These models suggest that technology adoption depends on:

- **Perceived usefulness** (e.g., efficiency and market access)
- **Ease of use** (e.g., platform simplicity)
- **Facilitating conditions** (e.g., training and extension)
- **Social influence** (e.g., peer and government endorsement)

These constructs are reflected in our model through variables like the **Training Index**, **Extension Access**, and state-level implementation differences. Prior research in African agricultural systems underscores the importance of facilitation mechanisms (Aker et al., 2016).

**Farmer Experience and Adaptive Capacity:** Experience-based learning is central to decision-making and innovation in agriculture (Barrett et al., 2010). Experienced farmers tend to possess stronger adaptive strategies, better credit histories, and more extensive social capital. Our analysis tests whether farming experience correlates with higher perceived benefits, especially in profit and resilience outcomes (Wossen et al., 2017).

**Collective Action and Cooperative Structures:** Rural systems in West Africa are deeply embedded in community-based structures. Cooperatives facilitate information sharing, credit access, and collective bargaining (Bernard et al., 2010; Ostrom, 1990). AgriFi leverages this logic through clustering cultivation and group-based training, aiming to strengthen institutional capacity from below.

### 2.3.2 Conceptual Model

This study builds a conceptual model that integrates digital infrastructure, farmer engagement, and individual heterogeneity to explain the formation of perceived benefits from the AgriFi platform. Drawing on the theoretical perspectives outlined above, the model proposes that perceptions of benefit are driven by a combination of digital trust mechanisms, enabling conditions for adoption, and socio-demographic characteristics.

At its core, blockchain technology functions as a digital trust infrastructure, ensuring transparency, traceability, and accountability throughout the value chain. When paired with appropriate engagement mechanisms—specifically training and extension services—this infrastructure becomes more accessible and impactful for smallholder farmers. However, the effectiveness of these interventions varies based on farmer heterogeneity, including factors such as education level, years of experience, and geographic context.

We examine six outcome domains to operationalize this framework:

- Market Access
- Profitability
- Economic Stability
- Access to Financial Services
- Resilience to Economic Shocks
- Perceived Economic Benefit Index (PEBI), a continuous composite indicator

Hypotheses:

- H1: Higher **training access and quality** (Training Index) are positively associated with perceived improvements in market access, financial services, and overall benefits (PEBI).
- H2: Farmers with more **experience** are more likely to perceive improvements in profitability, resilience, and overall benefit.
- H3: Regular **extension services access** is positively associated with perceived improvements in financial access and resilience.
- H4: Farmers in Niger State, operating under a **private investment model**, are more likely to report improved access to financial services due to stronger integration of credit and traceability tools. This effect is amplified by widespread perceptions of corruption in public systems, which may undermine trust in government-led subsidy mechanisms.

## 2.4 Methodology

This section outlines the methodological approach employed to explore the factors influencing smallholder farmers' engagement with the AgriFi platform, the perceived benefits, and the systemic challenges encountered. The methodology integrates insights from the mixed-methods framework established in the conceptual framework, balancing quantitative rigor with qualitative depth.

### 2.4.1 Study Area and Project Context

The research focuses on two distinct contexts within Nigeria: Niger and Katsina States. Both regions have implemented the AgriFi project under the management of Toronet(nota), but the operational models differ significantly, reflecting variations in funding mechanisms and strategic priorities.

**Niger State:** AgriFi in Niger State is driven by private investment. The project focuses on enhancing financial inclusion and improving access to agricultural inputs through blockchain- based platform. Verification processes include several identity checks and monitoring is based on satellite imagery and field visits ensuring eligibility based on specific risk factors. The private funding model aims to foster accountability and efficiency, providing a testbed for evaluating blockchain's potential as a trust substitution mechanism in agriculture.

**Katsina State:** In Katsina State, the AgriFi project operates on a larger scale, supporting approximately 50,000 farmers under a government-funded project. The primary objective is logistical optimization, with a focus on subsidizing fertilizer distribution. Verification processes are similar to those in Niger but are tailored to streamline administrative functions and ensure compliance. Unlike Niger, Katsina's model has yet to integrate additional agricultural services, making it a suitable context for exploring only blockchain's role in logistical enhancements.

### 2.4.2 Data Collection and Sources

Primary data were gathered between June and September 2024 through structured questionnaires and semi-structured interviews with smallholder farmers in Niger and Katsina States. In total, 206 farmers were surveyed: 118 in Niger State and 88 in Katsina State. The questionnaires captured socio-demographic characteristics (age, education, farm size, years of experience), farming practices (crop choices, input use), access to resources (credit, extension, digital tools), and perceptions of AgriFi's economic and social benefits.

### Niger State (n = 118):

In Niger, AgriFi operates under a privately funded model, serving roughly 500 farmers at the time of the study. We sampled more than 20 % of this population (118 farmers) to ensure strong representativeness. Farmers were selected across multiple villages to reflect geographic and demographic diversity—balancing gender, age groups, and cropping systems. Because AgriFi's blockchain platform in Niger integrates financing (through smart contracts), input distribution, and post-harvest transactions, the dataset allows for a detailed evaluation of how training, farm experience, and blockchain-mediated services influence perceived outcomes such as market access and income stability.

### Katsina State (n = 88):

In Katsina, AgriFi is implemented via a government-supported subsidy scheme that reaches approximately 50,000 farmers. Security concerns in certain areas—namely, sporadic banditry and restricted access roads—limited our ability to conduct a more extensive or stratified survey. Despite these constraints, we interviewed 88 farmers drawn from different administrative zones to capture variation in how the government-led model leverages blockchain primarily for logistical coordination (e.g., input distribution and record-keeping). Given this smaller, non-probability sample, findings from Katsina are used primarily for comparative, descriptive insights rather than for multivariate inference.

Although some details (e.g., representativeness percentages, village distribution) overlap between the two states, the key distinctions lie in:

- Implementation model:
  - Private investment model (Niger): Emphasizes financial inclusion through blockchain-enabled credit profiling, smart contracts that release inputs upon meeting predefined milestones, and automated record-keeping.
  - Government subsidy model (Katsina*):* Prioritizes large-scale input distribution, with blockchain used to track delivery and reduce leakages; financial services are not yet fully integrated.
- Sampling constraints and security issues:
  - In Katsina, ongoing concerns about rural insecurity (e.g., armed banditry) prevented access to some farming communities, limiting sample size and geographic coverage.
  - In Niger, by contrast, the more contained operational footprint of a private consortium allowed safer, systematic sampling across villages.

These primary data were supplemented with secondary sources to contextualize our findings and enrich the analysis:

- **National and State-level agricultural statistics:** Annual crop production and input usage data from the Nigerian Bureau of Statistics (NBS) and Katsina and Niger State Ministries of Agriculture.

- **Demographic and socioeconomic indicators:** Data from the Nigerian Demographic and Health Survey (NDHS) 2023, which provided baseline information on rural livelihoods, household composition, and digital access.

- **Geospatial and infrastructure data:** Open-source GIS layers showing road networks, market locations, and mobile-network coverage (sourced from Nigeria's National Space Research and Development Agency and Humanitarian Data Exchange).

Altogether, the design—combining purposive sampling based on distinct implementation contexts, a robust questionnaire, and triangulation with secondary datasets—aimed to capture both the heterogeneity of farmer experiences and the key operational differences between the private (Niger) and public (Katsina) AgriFi models.

In addition to the purposive sampling described above, the study design specifically considered how AgriFi's blockchain functionality shapes farmers' experiences. In Niger State, where AgriFi's private investment model integrates supply-chain actors via self-enforcing smart contracts, the dataset allows us to assess how features such as milestone-based input delivery (e.g., automatic release of inputs once off-takers confirm receipt of produce) and automated payments foster transparency, efficiency, and trust. Because these smart contracts activate upon predefined triggers—such as confirmation of harvest quantities—the resulting data provide a foundation for evaluating whether farmers perceive improvements in key areas like input distribution and financial inclusion.

In Katsina State, although the sample (n=88) is smaller and primarily exploratory, it highlights the early logistical and administrative enhancements achieved through blockchain. Here, the government-subsidy model leverages the platform to track and streamline large-scale input distribution—reducing leakages and improving record-keeping—but does not yet fully integrate credit profiling. Data from these initial interviews offer insights into how blockchain-enabled record management and digital verification impact operational efficiency, even before broader financial services are embedded.

Overall, the combined sampling approach captured not only the diversity of implementation contexts (private vs. public) but also enabled a focused analysis of how specific blockchain features—self-enforcing contracts in Niger and large-scale input tracking in Katsina—translate into perceived benefits for smallholder farmers.

### 2.4.3 Analytical Approach

The analytical framework developed for this study reflects both the early-stage nature of the AgriFi project and the operational divergence between its two primary implementation contexts—Niger and Katsina. Given the constraints of project maturity and the structure of available data, this phase of research relies exclusively on quantitative methods to generate early evidence on farmers' perceptions of AgriFi's economic value.

To address the research questions, we developed a set of regression models tailored to the structure of each dependent variable. These include:

- **Ordinal logistic regression (POLR)** for multi-level ranked outcomes (e.g., perceived market access)
- **Logistic/probit regression** for dichotomous outcomes (e.g., increased profitability, financial access, or economic stability, etc.)
- **Ordinary Least Squares (OLS)** for a composite **Perceived Economic Benefit Index (PEBI)**, which aggregates key economic outcomes into a continuous measure reflecting farmers' overall satisfaction

Each model incorporates a core set of predictors: demographic variables (age, gender, education), farm characteristics (size, experience), and platform-related features (training quality, extension support, geographic context). Model fit was evaluated using standard diagnostics, including AIC and residual deviance.

The selection and construction of variables are informed by the conceptual framework presented in Section 2.3 and supported by contextual references (e.g., Global Findex Database 2022) to better situate observed farmer behaviors within broader financial inclusion patterns in Nigeria.

The explanatory variables are organized into three conceptual blocks: socio-economic characteristics, household-level attributes, and project-specific factors (Table 2.1). The dependent variables are shown in Table 2.2.

**Table 2.1:** Independent Variables Used in the Analysis

| **Variable** | **Type** | **Categories / Coding** | **Reference Category** | **Notes** |
|---|---|---|---|---|
| **Panel A: Socio-Economic Characteristics** | | | | |
| Age | Categorical | 1 = 18–25<br>2 = 26–40<br>3 = 41–55<br>4 = 56+ | 18–25 (1) | Four-level ordinal variable. |
| Gender | Binary | 0 = Female<br>1 = Male | Female (0) | |

*Continued on next page*

| Variable | Type | Categories / Coding | Reference Category | Notes |
|---|---|---|---|---|
| Education | Categorical | 0 = No formal education<br>1 = Primary<br>2 = Secondary<br>3 = Higher | No formal education (0) | |
| Cooperative Membership | Binary | 0 = No<br>1 = Yes | No (0) | |
| **Panel B: Household and Farm Characteristics** | | | | |
| Farm Size | Categorical | 1 = $<$ 1 ha<br>2 = 1–5 ha<br>3 = $>$ 5 ha | $<$ 1 ha (1) | Three-level ordinal variable. |
| Farming Experience | Categorical | 1 = $<$ 5 years<br>2 = 5–10 years<br>3 = $>$ 10 years | $<$ 5 years (1) | Three-level ordinal variable. |
| Labor Availability | Continuous | Number of hired workers (integer $\geq$ 0) | – | Household's hired-labor capacity. |
| **Panel C: Project-Specific Factors** | | | | |
| Extension Access | Categorical | 0 = None or Infrequent<br>1 = Regular | None or Infrequent (0) | Frequency of extension service usage. |
| Training Index | Continuous (0–3.5) | Access:<br>3 = "Thorough"<br>2 = "Need more"<br>1 = "No training"<br>0 = "N/A"<br>Quality:<br>4 = "Excellent"<br>3 = "Good"<br>2 = "Fair"<br>1 = "Poor"<br>0 = "Very Poor"/No training | – | Row-wise mean of Access and Quality. Range $\in$ [0, 3.5]. Higher scores = better training access/quality. |

*Continued on next page*

| **Variable** | **Type** | **Categories / Coding** | **Reference Category** | **Notes** |
|---|---|---|---|---|
| State | Binary | 1 = Niger State (private-investment model)<br>0 = Katsina State (government subsidized) | Katsina (0) | Captures two implementation contexts: private vs. public. |

**Table 2.2:** Dependent Variables: Perceived Economic and Social Outcomes

| Variable | Type | Original Survey Coding | Final Coding / Levels | Regression Approach / Notes |
|---|---|---|---|---|
| Market Access | Ordinal | 1 = Improvement<br>2 = No improvement<br>3 = Uncertain | Ordered factor with 3 levels | Ordered logit/ ordinal regression |
| Profitability | Binary | 1 = Profit increase<br>0 = No change or profit decrease | Factor with levels:<br>0 - 1 | Logistic regression (logit) |
| Economic Stability | Binary | 1 = Increased stability<br>0 = Otherwise | Factor with levels:<br>0 - 1 | Logistic regression (logit) |
| Access to Financial Services | Binary | 1 = Improved access to credit/ insurance<br>0 = Otherwise | Factor with levels:<br>0 - 1 | Logistic regression (logit) |
| Resilience | Binary | 1 = More resilient to shocks<br>0 = Otherwise | Numeric:<br>0 - 1 | Probit regression (probit) |

### Perceived Economic Benefit Index (PEBI)

A separate discussion must be held for PEBI. The Perceived Economic Benefit Index (PEBI) is a continuous measure that captures each farmer's overall assessment of AgriFi's economic impact by aggregating five distinct dimensions: market access, profitability, economic stability, access to financial services, and resilience to shocks. Each dimension was originally recorded on a discrete scale through survey questions. To ensure consistent interpretation—so that higher values always denote greater perceived benefit—we reverse-coded every component before aggregation. Specifically:

- **Market Access Impact** (originally 1 = Improvement, 2 = No improvement, 3 = Uncertain) was recoded a 1–3 scale where 3 signifies a clear improvement.
- **Profitability Impact** and **Economic Stability Impact** (both originally on a 1–5 scale, where 1 indicates strong positive change and 5 indicates strong negative change) were recoded as a 1–5 scale in which 5 represents the greatest benefit.
- **Access to Financial Services** (originally 1 = Improved, 2 = No change, 3 = Worse) was reversed resulting in a 1–3 scale with 3 indicating improved access.
- **Resilience Against Economic Shocks** (originally 1 = More resilient, 2 = Not more resilient) was recoded producing a 1–2 scale where 2 denotes full resilience.

After reverse-coding, each variable ranges from its minimum (1, indicating absent or negative perceived change) to its maximum (3 or 5, indicating the strongest positive perception). The PEBI is then calculated as the arithmetic mean of these five reverse-coded scores for each farmer:

$$PEBI_i = \frac{\text{MarketAccess}_i + \text{Profitability}_i + \text{EconomicStability}_i + \text{AccessFinancialServices}_i + \text{Resilience}_i}{5}$$

Because the five dimensions have different individual maxima—five for profitability and stability, three for market access and financial access, and two for resilience—the combined index ranges continuously between 1.00 (if a farmer perceives no benefit on any dimension) and 3.60 (if a farmer reports the highest benefit across all five dimensions).

In empirical analysis, PEBI functions as the dependent variable in an ordinary least squares (OLS) regression, with covariates such as training access, farming experience, extension support, and state as predictors. The continuous nature of PEBI allows us to interpret each regression coefficient as the expected change in a farmer's average perceived-benefit score per unit change in the predictor. For example, a coefficient of 0.15 on "training access" indicates that farmers who receive high-quality training have, on average, a 0.15-point higher PEBI—reflecting more uniformly positive perceptions of AgriFi's economic impact. By condensing multiple discrete economic outcomes into a single, interpretable index, PEBI provides a robust and parsimonious summary of farmers' overall economic sentiments toward the platform.

### 2.4.4 Empirical Strategy and Theoretical Rationale

To evaluate farmers' perceptions of AgriFi's economic impact, we employ a two-step modeling approach:

1. **Dimension-Specific Models:**
   We estimate separate regression models for each of five economic outcomes—market access, profitability, financial services, economic stability, and resilience—using ordered logistic regression for ordinal outcomes and logit/probit models for binary outcomes. Formally, for farmer *i*:

$$PB_i = \alpha + \beta_I I_i + \beta_H H_i + \beta_P P_i + \varepsilon_i$$

Where:

- $PB_i$ represents perceived benefit (either binary, ordinal, or continuous depending on the model).

- $I_i$: Vector of **individual characteristics** (age, gender, education).
- $H_i$: Vector of **household/farm characteristics** (farming experience, farm size).
- $P_i$: Vector of **project-specific variables**, including **Training Index**, **Extension Access**, and **State** (to control for regional differences in implementation).
- $\varepsilon_i$: The error term.

This disaggregated approach allows us to identify which socio-economic and project variables are associated with each distinct perception. By exploring heterogeneity—across age groups, gender, education levels, and farming experience—we mirror best practices in agricultural technology adoption research (Feder et al., 1985; Di Falco & Veronesi, 2013).

1. **Composite Index Model:**

To capture the overall perceived economic benefit, we construct the Perceived Economic Benefit Index (PEBI) as the mean of the five reverse-coded outcomes (market access, profitability, financial services, economic stability, resilience). Each component was coded so that higher values denote stronger positive perception; the raw index therefore ranges from 1.00 (minimal perceived benefit on all dimensions) to 3.60 (maximal benefit across every dimension). We then estimate:

$$PEBI_i = \alpha + \beta_I I_i + \beta_H H_i + \beta_P P_i + \varepsilon_i$$

Where:

- $PEBI_i$ is the **Perceived Economic Benefit Index**, created as the standardized mean of five binary or ordinal perceived outcomes: market access, profitability, financial services, economic stability, and resilience.
- Predictors ( $I_i, H_i,\ P_i$) are the same as in Model 1.

Here we use ordinary least squares (OLS). In this way, each coefficient represents the expected change in a farmer's average perceived-benefit score associated with a one-unit change in the predictor. Equal weighting of the five dimensions aligns PEBI with multidimensional well-being frameworks (Alkire & Foster, 2011), where multiple functionings (market access, income, stability, financial inclusion, resilience) jointly inform overall welfare. By summarizing five discrete outcomes into a single continuous measure, PEBI facilitates detection of broad patterns in perception formation that individual models might miss.

### 2.4.5 Theoretical Foundation, Model Assumptions, and Analytical Constraints

Our study rests on two complementary theoretical pillars—Sen's capability approach and multidimensional well-being measures—to justify the focus on farmers' perceptions, and it proceeds with explicit recognition of methodological assumptions and data limitations.

**Capability Approach:** Drawing on Sen's notion of well-being as the freedom to achieve valued functionings (Sen, 1999), we treat farmers' self-reported perceptions of economic improvement (e.g., market access, income stability, resilience) as legitimate, policy-relevant outcomes. In an early-stage intervention such as AgriFi—where objective behavioral or market data are not yet observable—perceived changes reflect shifts in farmers' capability sets (for instance, the ability to access credit or withstand shocks). Empirical evidence indicates that these perceptions can directly influence future investments, adoption decisions, and long-term welfare trajectories (Lybbert & Wydick, 2018; Lybbert & Sumner, 2012). By centering on perception-based outcomes, our analysis remains theoretically coherent under a capability framework and pragmatically necessary when objective indicators lag behind implementation.

**Multidimensional Well-Being Measures:** We operationalize these insights through the Perceived Economic Benefit Index (PEBI), which aggregates five reverse-coded economic dimensions—market access, profitability, financial access, economic stability, and resilience—into a single continuous score. This approach parallels Alkire and Foster's multidimensional poverty methodology (Alkire & Foster, 2011), where multiple indicators (e.g., health, education, living standards) are combined to capture overall well-being. By equally weighting each domain, PEBI offers a holistic gauge of farmers' perceived benefits from AgriFi, enabling us to identify broad patterns that individual outcome models might miss.

#### Model Assumptions

1. **Associational (Non-Causal) Inference:**
   Because our data are observational and lack a randomized control group, we do not claim causal effects. Instead, we focus on associations between covariates (demographics, farm characteristics, TrainingIndex, Extension Access, and State) and perceived outcomes. Including a rich set of controls and disaggregating models by state (private-investment in Niger vs. government-subsidy in Katsina) helps mitigate, but cannot fully eliminate, omitted variable bias and selection concerns (Imbens & Wooldridge, 2009).

2. **Perception-Based Outcomes:**
   In the absence of long-term yield or income data, farmers' self-assessments serve as provisional proxies for potential future impacts. Early-stage evaluations often rely on this strategy (Van den Broeck & Dercon, 2011), since perceptions can

directly shape subsequent behavior, technology uptake, and investment decisions (Lybbert & Wydick, 2018).

3. **Heterogeneity Exploration:**
   We explicitly examine how perceived benefits vary by age, gender, education, farming experience, and geographic context. This aligns with recent guidance on targeting digital and financial inclusion initiatives, which emphasize that impacts frequently differ across demographic and experiential subgroups (Suri & Jack, 2016; Beaman et al., 2014).

## Limitations and Data Constraints

While the mixed-model strategy provides early evidence on farmers' perceived economic benefits, several constraints affect analytical scope and inference quality:

- **State-Specific Sample** Size and Implementation Stage:
  - Katsina State: Only 88 valid responses (from 100 distributed) were obtained, and financial services remain minimally integrated. Consequently, Katsina's data are primarily used for descriptive contrasts rather than multivariate inference. The government-led model emphasizes large-scale fertilizer distribution rather than integrated financial services, limiting depth of perceived benefit at this stage.
  - Niger State: A larger sample (118 out of ~500 eligible farmers) permits more robust multivariate analysis of perceptions linked to AgriFi's combined financial and logistical offerings. However, even this dataset reflects early-stage rollout, so findings capture short-term perceptions rather than long-term outcomes.
- **Survey-Related Biases**: Farmers' self-reports may be affected by recall bias or social desirability bias—recall errors can distort past experiences, and respondents may overstate benefits to align with perceived enumerator expectations. Though enumerator training and questionnaire design aimed to minimize these biases, they cannot be fully eliminated.
- **Digital Divide and Access Constraints**: Limited access to smartphones, internet connectivity, and digital literacy—especially in remote or low-literacy areas—may inhibit both true engagement with the AgriFi platform and accurate reporting of perceived benefits. We capture basic measures of digital access, but residual measurement error remains possible.
- **Short-Term vs. Long-Term Outcomes**: Given that AgriFi's rollout began only months before data collection, our analysis reflects farmers' immediate impressions rather than verified economic outcomes (e.g., actual yield increases or income

gains). Longitudinal follow-up studies will be necessary to assess whether early perceptions translate into sustained improvements in productivity and welfare.

Despite these constraints, our theoretically grounded, multi-model approach provides a credible baseline for evaluating perceived benefits of digital agriculture platforms. It highlights the importance of treating farmers' perceptions as meaningful indicators of capability enhancement and lays the groundwork for future longitudinal and causal analyses as AgriFi matures

## 2.5 Results

In this section, we present a detailed analysis of the data to answer the two research questions (RQ1 and RQ2). We draw upon both descriptive statistics and econometric models (binary and ordinal logistic) to capture the nuanced factors underpinning farmers' self-reported economic and social benefits from AgriFi.

### 2.5.1 Perceived Economic and Social Benefits (RQ1)

*Table 2.3* offers a window into who engaged with AgriFi in Katsina and Niger—and what that means for interpreting our findings. First, the age profile skews toward the "prime" farming years: roughly three-quarters of respondents in both states fall between 26 and 55. This focus on mid-career farmers is a strength—these are the individuals most likely to make investment decisions—but it leaves us with little insight into the youngest entrants (18–25) and more seasoned producers (56+), whose needs and perceptions may differ sharply.

Education varies dramatically between the two sites. In Katsina, nearly seven in ten report "higher" (upper-secondary or beyond) schooling, whereas in Niger only one in seven does. Conversely, over a third of Niger's respondents say they have no formal education—compared with under 5 percent in Katsina. Because these levels are all **self-reported**, we must be cautious: farmers may overstate or understate their own schooling depending on how they think it will be received.

Similarly, the frequency of extension contact differs markedly: 72 percent of Niger farmers say they have "regular" service visits, versus 44 percent in Katsina. Again, these are **perceptions**—and likely influenced by recall bias or social desirability (farmers eager to please enumerators may exaggerate their engagement with extension agents).

The distribution of farm experience and size is more balanced: roughly one-third each are under 5 years, 5–10 years, and over 10 years of farming; and about half cultivate 1–5 ha, with the rest split between smaller and larger holdings. This spread is useful for testing whether newer or larger operators perceive AgriFi differently.

Finally, gender remains heavily male-dominated (84 percent in Katsina; 77 percent in Niger), a reminder that women's voices—key to any agricultural intervention—are under-represented in our data.

Taken together, *Table 2.3* paints a picture of a self-selected group of mid-career, predominantly male farmers with wide variation in schooling and extension access. These self-reported anecdotes set the stage for our next step—examining how these characteristics translate into perceived economic benefits—and remind us to interpret the results in light of potential reporting biases and sample imbalances

**Table 2.3:** Sample Characteristics by State – Key Categorical Predictors (%)

| **Variable** | **Category** | **Katsina (%)** | **Niger (%)** |
|---|---|---|---|
| **Panel A: Socio-Demographic** | | | |
| Age | 18–25 | 10.2 | 6.8 |
| | 26–40 | 35.2 | 49.2 |
| | 41–55 | 38.6 | 33.1 |
| | 56+ | 15.9 | 11.0 |
| Education | No formal | 4.5 | 36.4 |
| | Primary | 11.4 | 17.8 |
| | Lower Secondary | 15.9 | 32.2 |
| | Higher | 68.2 | 13.6 |
| Gender | Male | 84.1 | 77.1 |
| | Female | 15.9 | 22.9 |
| **Panel B: Extension, Farm, and Household** | | | |
| Extension Access | None/Infrequent | 23.9 | 14.4 |
| | Occasional | 31.8 | 13.6 |
| | Regular | 44.3 | 72.0 |
| Farm Experience | $< 5$ yrs | 22.7 | 22.9 |
| | 5–10 yrs | 44.3 | 29.7 |
| | $> 10$ yrs | 33.0 | 47.5 |
| Farm Size | $< 1$ ha | 29.5 | 24.6 |
| | 1–5 ha | 54.5 | 55.1 |
| | $> 5$ ha | 15.9 | 20.3 |

**Table 2.4:** Raw Distributions of Economic Outcome Categories (Full Sample, n = 206)

| Economic Outcome | Response Category | Full Sample (%) |
|---|---|---|
| Market Access | Improved | 59.2 |
| | No improvement | 28.2 |
| | Uncertain | 12.6 |
| Profitability | Greatly increased | 26.2 |
| | Slightly increased | 35.0 |
| | No change | 27.2 |
| | Slightly decreased | 7.3 |
| | Greatly decreased | 0.5 |
| Access to Fin. Services | Better access | 82.0 |
| | No change | 15.0 |
| | Worse access | 3.0 |
| Economic Stability | Significantly increased | 31.0 |
| | Slightly increased | 23.4 |
| | Remained the same | 36.4 |
| | Slightly decreased | 8.6 |
| | Greatly decreased | 0.5 |
| Resilience | More resilient | 56.8 |
| | Not more resilient | 43.2 |
| Labor Practices | Improved working conditions | 67.0 |
| | No change | 23.3 |
| | Worsened conditions | 6.5 |
| | Not applicable/Other | 3.2 |

*Table 2.4* reports the full-sample distribution of farmers' self-reported economic outcomes across six key domains. In the Market Access domain, 59.2 % of respondents indicated an improvement in linkages to buyers, while 28.2 % saw no change and 12.6 % remained uncertain. Profitability perceptions follow a similarly positive pattern: 61.2 % of farmers experienced either "greatly" or "slightly" increased net income, whereas fewer than 8 % reported any decline. Access to Financial Services is the most uniformly positive domain, with 82.0 % of participants noting enhanced credit or insurance options. Economic Stability improvements were reported by 54.4 % of the sample, compared to 36.4 % who observed no change and 9.1 % who experienced a decrease. Resilience against shocks was affirmed by 56.8 %, leaving 43.2 % feeling no greater preparedness. Finally, 67.0 % of respondents reported improved labor practices on their farms, with only 6.5 % indicating worsened conditions. These aggregate figures establish a baseline for the subsequent state-level analyses in Section 2.5.1.

### Descriptive Overview of Economic Variables

We begin by examining key economic variables—Market Access Impact, Profitability Impact, Access to Financial Services, Economic Stability, and Resilience Against Shocks—disaggregating responses by Katsina ($n$ = 88) and Niger ($n$ = 118) to account for contextual differences.

1. **Market Access.** Across the full sample, **59.2%** of farmers reported improvements in their ability to access better-paying buyers and more reliable outlets, while **28.2%** perceived no clear change and **12.6%** were unsure. Disaggregating by state, **59.1%** of Katsina farmers and **59.3%** of Niger farmers indicated positive changes, with slightly higher stability in Niger. Qualitative feedback suggests that Niger farmers often attributed improvements to access to credit-backed inputs, whereas some Katsina farmers noted that **limited local infrastructure** remained a constraint.

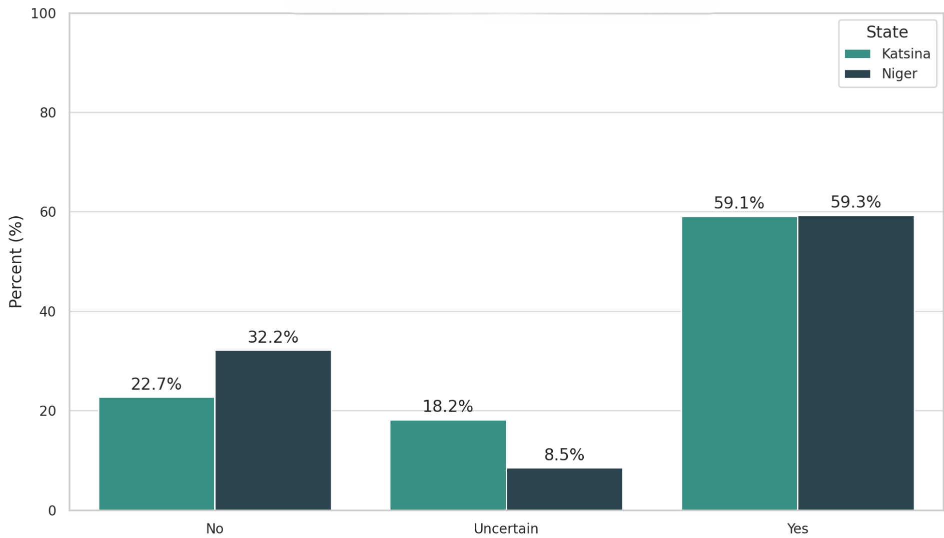


**Figure 2.1:** Market Access Impact by State

1. **Profitability.** About **61.2%** of respondents perceived at least a moderate increase in net farm income or operational profits, while **27.2%** saw minimal gains, and only **0.5%** reported negative impacts. The results were consistent across both states: **60.2%** of Katsina farmers and **61.9%** of Niger farmers experienced profitability improvements, suggesting that AgriFi had **no major financial burden** but also that **adaptation and market linkages are ongoing challenges.**

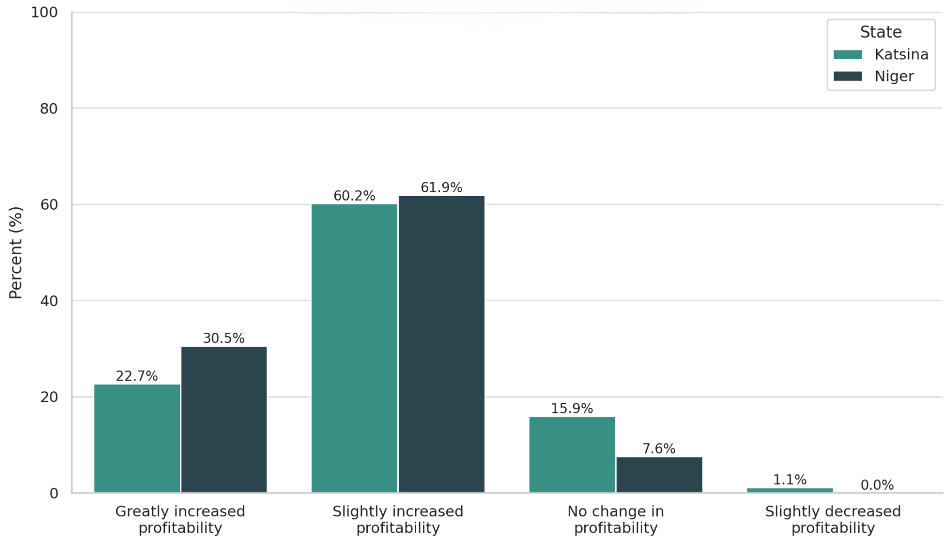


**Figure 2.2:** Profitability Impact by State

1. **Access to Financial Services.** A substantial **82%** of respondents believed that AgriFi had either already broadened or would soon broaden their **credit and insurance options.** This aligns with expectations that **blockchain-backed transparency boosts trust in external financing.** However, state-wise differences were notable: while **89.8%** of Niger farmers confirmed access improvements, the figure was slightly lower in Katsina (**71.6%**), likely reflecting different **implementation priorities.**

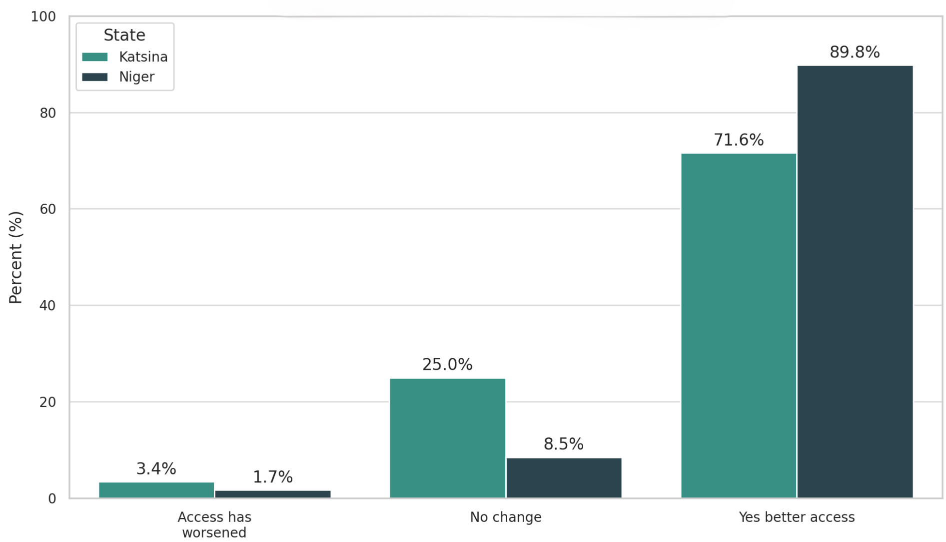


**Figure 2.3:** Financial Services Access by State

1. **Economic Stability.** Over **54.4%** of farmers perceived improvements in their overall **economic stability**, particularly in terms of income stability, reduced price

volatility, and more stable transaction environments. However, **36.4%** saw no clear difference, and a small portion (**0.5%**) reported a negligible impact. The stability factor was slightly more pronounced in Niger, where **55.9%** of respondents cited economic gains, compared to **52.3%** in Katsina.

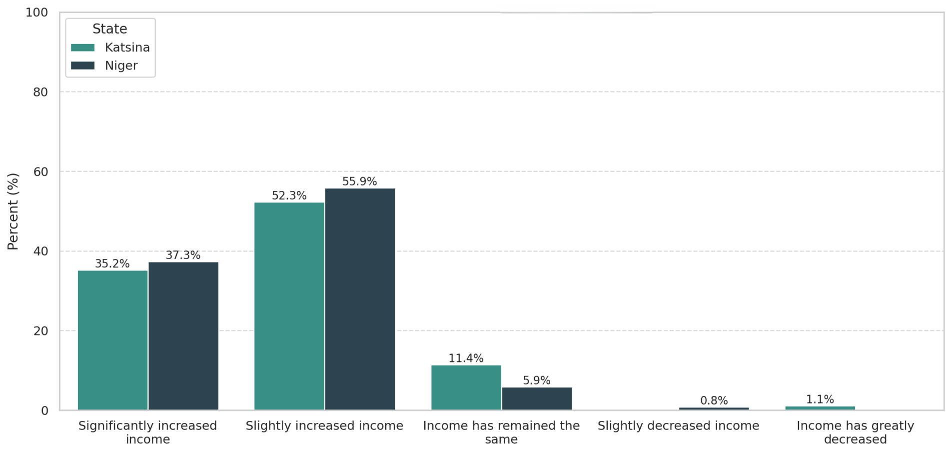


**Figure 2.4:** Economic Stability Impact by State

1. **Resilience Against Shocks.** Approximately **56.8%** of farmers felt **better equipped to handle price fluctuations or climate variability**, while **43.2%** indicated no significant changes. Breaking it down by state, **58%** of Katsina farmers and **55.9%** of Niger farmers believed that AgriFi improved their resilience, with qualitative interviews reinforcing this. Notably, over 70% of those responding positively attributed their resilience to enhanced access to **insurance** provisions.

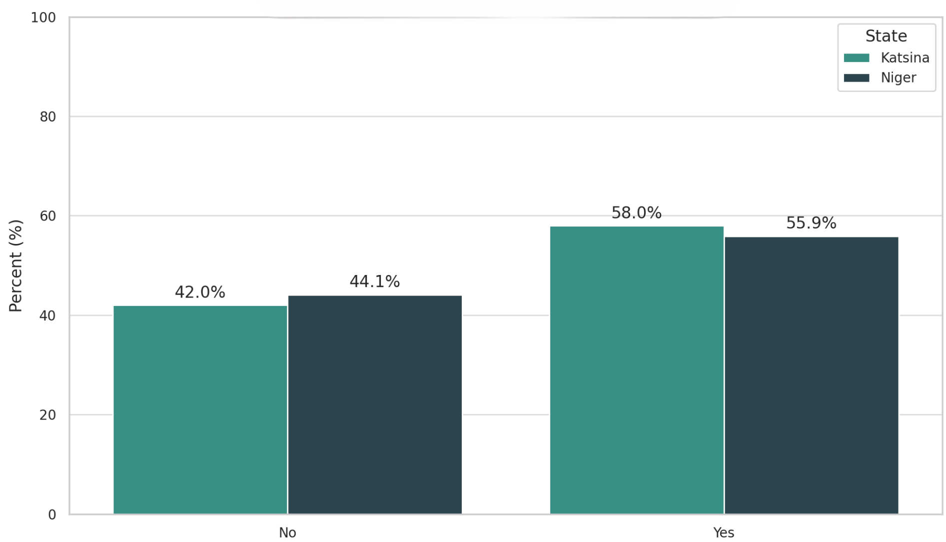


**Figure 2.5:** Resilience Against Shocks by State

### Descriptive Overview Social Variables

This section analyzes the social dimensions of AgriFi's impact on participating smallholder farmers. We focus on three key indicators: **Community Dynamics, Interaction with New Local Actors, and Labor Practices Impact**, disaggregating responses by state (Katsina: $n \approx 89$; Niger: $n \approx 118$).

**1. Community Dynamics.** A significant proportion of respondents (approximately **58.7%**) indicated that their involvement in AgriFi contributed to **improved community relationships**, with **60.2%** of farmers in Katsina and **57.6%** in Niger reporting a positive impact. Meanwhile, **28.6%** (**21.6%** in Katsina, **35.6%** in Niger) perceived no change in their community interactions. A small fraction (**7.8%**) noted **strained relationships**, with slightly higher reports in Katsina (**11.4%**) than in Niger (**4.2%**). Finally, some respondents remained uncertain (**6.8%** in Katsina, **2.5%** in Niger).

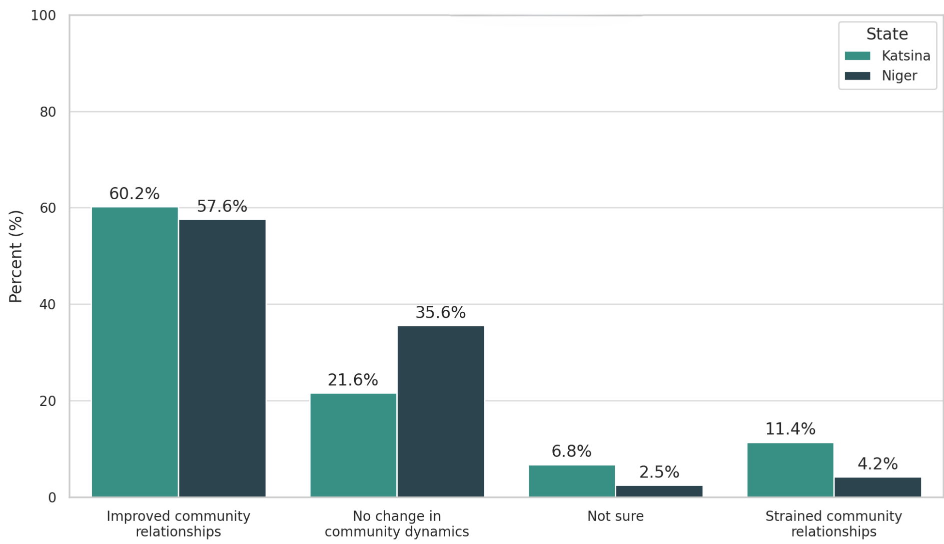


**Figure 2.6:** Community Dynamics by State

These results suggest that while AgriFi has generally fostered **positive social ties**, the extent of these changes varies by location, with Niger participants perceiving improved dynamics in community relations. Interview insights suggest that the clustering of farmers played a role in enhancing cooperative behavior, particularly in Niger, whereas in Katsina, logistical challenges and subsidy-driven engagement may have limited broader social integration.

**2. Interaction with New Local Actors.** When asked whether their participation in AgriFi expanded their interaction with **new buyers, traders, or agricultural stakeholders**, only **36%** of farmers affirmed this outcome, with higher positive responses in Katsina (**52.3%**) than in Niger (**24.6%**). However, a notable **63.2%** (**75.4%** in Niger, **47.7%** in Katsina) stated that their engagement with local actors remained unchanged. This suggests that while some farmers—particularly in Katsina—have gained access to new networks, a majority are yet to experience meaningful shifts in external engagement.

**3. Labor Practices Impact.** In terms of labor conditions, **67%** of farmers across both states reported improvements in working conditions, including more structured labor management and better coordination in farming activities. Katsina exhibited a higher positive response (**78.4%**) compared to Niger (**58.5%**), indicating that logistical optimizations and cooperative structures in Katsina may have contributed to more efficient labor organization. Conversely, **23.3%** (**17%** in Katsina, **29.7%** in Niger) observed no changes, while **6.5%** reported worsened conditions (**10.2%** in Niger, **1.1%** in Katsina).

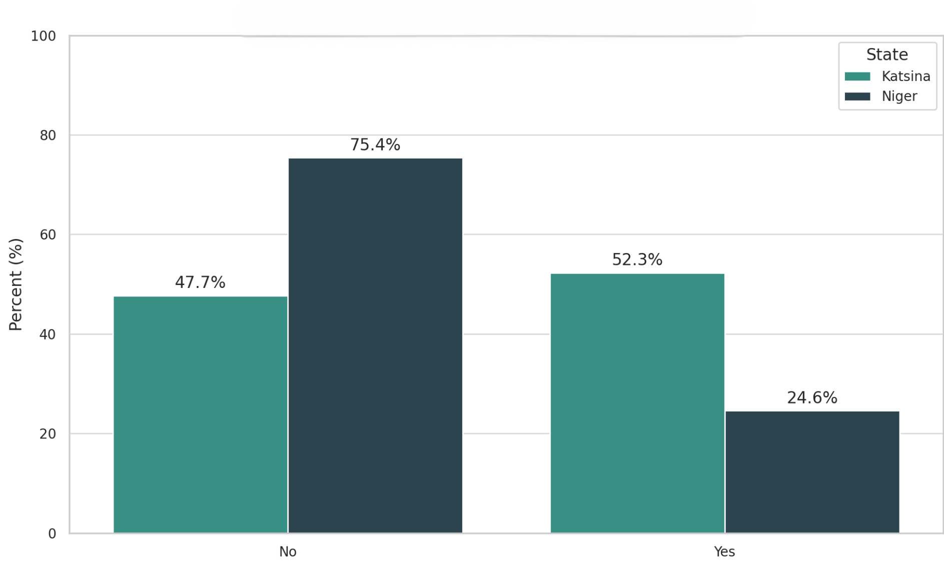


**Figure 2.7:** Interaction with Local Actors by State

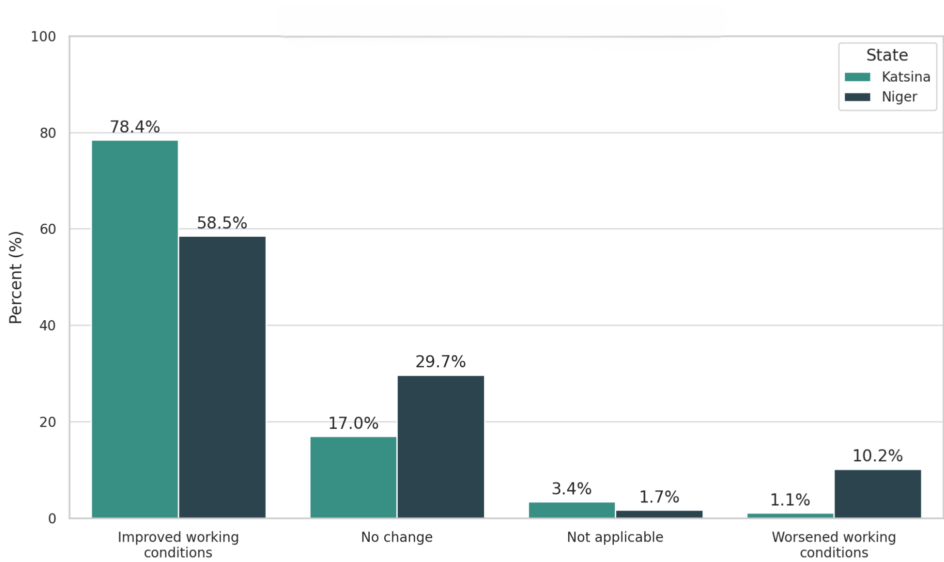


**Figure 2.8:** Labor Practices Impact by State

### Interpretation of RQ1 Findings

The descriptive analysis reveals that farmers involved in the AgriFi project report substantial perceived economic benefits, particularly in areas such as market access, profitability, and financial services. These results align with AgriFi's stated goals of improving agricultural value chains through blockchain-enabled transparency, credit access, and digital profiling.

**Economic Benefits:** Perceptions of market-related improvements are widespread: 59.2% of farmers report better access to buyers or markets, with consistent responses across both Niger and Katsina. This is a key indicator that AgriFi's digital structuring and aggregation of farm clusters may be supporting market engagement—even in regions like Katsina, where infrastructural limitations persist. Notably, this pattern corresponds with later regression results (Section 2.5.2), which demonstrate that training quality and access (Training Index) significantly increase the likelihood of reporting market access gains.

Profitability perceptions are also high, with over 61% of farmers reporting increased farm income. However, our econometric analysis suggests caution in interpreting this result. Regression models show no strong association with profitability, indicating that farmers' responses may reflect general optimism or anticipated benefits, rather than tangible financial outcomes attributable to the platform at this stage. This emphasizes the need for longitudinal tracking to determine whether perceived profit gains are sustained or realized over time.

Access to financial services stands out as a widely perceived gain, with 82% of farmers reporting better access to credit or insurance. The consistency of this pattern across states supports the argument that blockchain's transparency may enhance farmers' confidence in institutional finance. However, later models show this perception is also influenced by contextual factors: for instance, being located in Niger—where the model is investor-driven—significantly increases the odds of reporting financial access improvements. In contrast, a lack of extension support (particularly "no extension") markedly reduces these odds, highlighting that supportive ecosystem services still matter even in tech-mediated trust systems.

Perceptions of economic stability and resilience against shocks are more nuanced. While 54.4% of farmers report greater economic stability and 56.8% feel more resilient, nearly a third to a half see no meaningful improvement. Qualitative responses suggest that while inputs and insurance contribute to perceived resilience, farmers with longer experience tend to express greater confidence in managing volatility—an observation later reinforced in regression models, where farm experience ($>$10 years) is a strong predictor of perceived resilience. Conversely, training and extension—so influential in market access—have limited impact on perceived resilience, suggesting that structural resilience may require more than informational or input support.

**Social Benefits:** In contrast to the clearer economic signals, social impacts remain more context-dependent and uneven. Roughly 58.7% of farmers report improved community dynamics, but these are not uniformly distributed: trust-building appears stronger in Niger, where cooperative clustering is more embedded in the implementation strategy. In Katsina, where AgriFi's rollout emphasizes subsidy delivery, the platform may not yet foster the kind of group-level organization necessary for broader social transformation.

Moreover, only 36% of farmers report new interactions with local actors (e.g., traders or buyers). This indicates that AgriFi's promise of value chain integration is still in its early stages and may require more deliberate facilitation. In Katsina, the relatively higher rate (52.3%) suggests stronger logistical engagement with local networks, though this may be driven by state coordination rather than systemic market development.

On labor practices, 67% of respondents report improved coordination and work conditions, with particularly strong responses in Katsina (78.4%). These patterns suggest that AgriFi's role in streamlining operations and inputs may indirectly foster labor organization. However, some farmers in Niger report increased work burdens (10.2%), particularly those operating outside cooperative clusters or managing larger plots. This hints at a need for better alignment between resource delivery and labor planning, especially for more isolated producers.

To summarize, the analysis of RQ1 shows that:

- Perceived economic gains dominate, particularly in market access, credit inclusion, and profitability expectations.
- Training and farm experience emerge as key correlates of these perceptions, foreshadowing their confirmed importance in the regression results.
- Social benefits are present but more variable and appear highly dependent on local implementation strategies and cooperative structures.
- Perceived improvements in profitability and resilience are evident but not uniformly associated with AgriFi's direct interventions, suggesting areas for future refinement and study.

These findings highlight the promise of blockchain-enabled agriculture in improving perceptions of opportunity and inclusion, while also underlining the importance of complementary mechanisms—like extension, experience, and training—in realizing AgriFi's full potential. The next section 2.5.2 builds on these insights by quantifying the socio-economic predictors of these perceived benefits through econometric modeling.

### 2.5.2 Socio-Economic Predictors of Perceived Benefits (RQ2)

#### Model Specification and Rationale

To explore which socio-economic characteristics most significantly influence smallholder farmers' perceptions of AgriFi's benefits, we estimated six models (*Table 2.5*), each targeting a specific perceived outcome: market access, profitability, economic stability, access to financial services, resilience to shocks, and a composite Perceived Economic Benefit Index (PEBI).

All models were estimated on complete-case samples, thus observations with no missing values on the predictors or the outcome. To assess relative fit, we report **Akaike Information Criterion (AIC)** and **McFadden's pseudo-$R^2$** for each discrete-outcome model; for the OLS regression, we report the standard **$R^2$**. Full regression tables are presented below; coefficients are displayed alongside standard errors, with significance markers denoted as * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$.

**Table 2.5:** Predictors of Perceived Benefits from AgriFi: Regression Coefficients and Significance Across Six Outcome Models

| **Predictor** | **Market Access** | **Profitability** | **Economic Stability** | **Financial Services** | **Resilience** | **PEBI** |
|---|---|---|---|---|---|---|
| Training Index | +0.59*** | +0.04 | +0.45 . | +0.37 . | –0.04 | +0.06* |
| Farm Exp 5–10y | +0.31 | +0.33 | –1.53 . | –0.01 | +0.13 | +0.07 |
| Farm Exp >10y | +0.97 . | +1.48 . | –1.38 | +0.31 | +0.99** | +0.23** |
| Education2 (Primary) | –1.10* | –0.30 | –0.97 | +0.51 | –0.23 | –0.17 . |
| Education3 (Secondary) | –1.46** | +0.47 | –0.85 | +0.93 | –0.52 . | –0.23** |
| Education4 (Higher) | –0.69 | +0.71 | –0.34 | –0.44 | –0.60 . | –0.13 |
| Age2 (26–40) | –0.92 | +0.12 | +0.35 | –1.80 | –0.63 . | –0.15 |
| Age3 (41–55) | –0.66 | +0.01 | +0.11 | –1.21 | –0.63 | –0.11 |
| Age4 (>55) | –0.63 | –0.67 | +0.21 | –2.01 | –0.84 . | –0.28* |
| Gender (Female) | +0.54 | –0.43 | –0.63 | –0.44 | –0.10 | –0.02 |
| Farm Size2 | –0.81* | –0.68 | +0.63 | –0.01 | –0.19 | –0.10 |
| Farm Size3 | +0.13 | –0.54 | +1.21 | +0.20 | +0.28 | +0.00 |
| Ext_Acc2 (Irregular) | +0.46 | –1.08 | –1.15 | –1.50 . | +0.03 | –0.11 |
| Ext_Acc3 (None) | +0.07 | +0.05 | –0.29 | –1.78* | –0.74* | –0.12 |
| State (Niger) | +0.27 | +0.91 | +1.01 | +1.54** | –0.21 | +0.13 . |

*Note*: Standard errors omitted for brevity. Significance levels: . $p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. Reference categories: Age 18–25, Gender (Male), Education (None), FarmExp (<5y), Farm Size (<1 ha), Extension Access (Regular), State (Katsina).

**Market Access (Ordinal Logistic Regression):** The results of the ordinal logistic regression reveal that Training Index is the strongest and most consistent predictor of perceived improvements in market access (+0.59, $p < 0.001$). This confirms that higher-quality and more frequent training is central to unlocking the market-related benefits of AgriFi. Training empowers farmers to better understand and use the digital platform, especially for finding and transacting with new buyers, and also strengthens trust in the technology's value.

The analysis also highlights significant negative associations for education at the primary (–1.10, $p < 0.05$) and secondary (–1.46, $p < 0.01$) levels**.** That is, farmers with some formal education are *less* likely to report market access improvements compared to those with no education. This may reflect higher expectations or a more critical attitude among educated farmers, who might benchmark AgriFi against more advanced or established market solutions, while uneducated farmers see clear relative progress..

A negative effect for medium farm size (1–5 ha, –0.81, $p < 0.05$) was also observed. These mid-sized farmers appear less able to benefit from AgriFi's current operational focus, possibly because the platform's cooperative aggregation model better fits very smallholders or clustered producers. This suggests a need for tailored strategies to ensure mid-sized operators are not left behind.

There is a borderline positive effect for long-term farming experience (>10 years, +0.97, $p < 0.1$), indicating that highly experienced farmers are more likely to perceive market access gains—likely due to their greater familiarity with the sector, social capital, and adaptive capacity to leverage new platforms.

Other demographic and structural variables, including gender, age, state, and extension access, were not significant predictors in this model.

**Economic Stability (Binary Logistic Regression):** The model exploring perceived improvements in economic stability yields two main findings. Training Index shows a positive association with perceived economic stability (+0.45, $p < 0.1$), suggesting that higher-quality or more frequent training may begin to foster a greater sense of income security among farmers. Although this effect is only marginally significant, it highlights the potential of capacity-building efforts to influence broader perceptions of economic well-being.

In contrast, there is a borderline significant negative association for farmers with 5–10 years of experience (–1.53, $p < 0.1$). This intermediate group is less likely to perceive stability gains than those with less experience. This "missing middle" effect may arise because newer farmers receive more project support and long-term farmers have more adaptive strategies, leaving those in the middle less able to fully benefit from AgriFi at this stage.

No other predictors—including gender, age, education, state, farm size, or extension access—emerge as significant in the model. This indicates that, in the current phase of project implementation, the effects of training and experience outweigh those of fixed demographic factors for perceived economic stability.

**Profitability (Binary Logistic Regression):** The model for perceived profitability shows limited explanatory power, with few significant predictors. The only notable association is a borderline positive effect for long-term farm experience (>10 years, +1.48, $p < 0.1$). This suggests that seasoned farmers—who have greater familiarity with agricultural cycles and risk—may be better able to convert AgriFi's digital tools into measurable profit gains, even in the early stages of platform rollout.

Training Index (+0.04) and extension access do not significantly predict perceived profitability in this model, a finding that contrasts with their prominent roles in market access and overall perceived benefits. This result may reflect the time it takes for structural improvements—such as training and support—to translate into concrete income gains, which often lag behind improvements in knowledge or market opportunity.

Other factors—including age, gender, education, farm size, and state—do not emerge as significant predictors. This suggests that, in the current phase, profitability perceptions are shaped more by accumulated farming experience than by demographic or engagement factors.

In sum, the model points to farm experience as a potential enabler of profitability, but otherwise underscores that perceived income gains may lag behind other types of benefits like stability or access, particularly in a project still in its early deployment stage.

**Resilience to Economic Shocks (Probit Model):** The resilience model highlights two main findings. First, long-term farming experience ($>$10 years, $+$0.99, p $<$ 0.01) is a strong, positive, and statistically significant predictor of perceived resilience. This underscores the value of accumulated skills and adaptive capacity for managing shocks.

Second, the absence of extension support (Ext_Acc3, –0.74, p $<$ 0.05) is a significant negative predictor. Farmers without regular extension contact are much less likely to feel resilient, demonstrating the continued importance of institutional support and advisory services in preparing for economic volatility.

Several other variables approach significance at the 10% level, including:

- Older age (Age2: –0.63, Age4: –0.84, $p \approx 0.08$)
- Secondary (–0.52, $p \approx 0.08$) and higher education (–0.60, $p \approx 0.06$)

These trends suggest that older and more educated farmers may be more skeptical or cautious in evaluating their own resilience, perhaps due to higher expectations or greater risk awareness. Training Index does not show any effect on resilience in this model.

Taken together, the model indicates that experience and institutional support (through extension) are pivotal for farmers to feel more resilient, while formal training alone may not yet suffice to shift resilience perceptions during the early stages of platform implementation.

**Access to Financial Services (Binary Logistic Regression):**

Perceived improvements in financial service access are most strongly predicted by project context and institutional support. Farmers in Niger State are much more likely to report better access to credit and insurance ($+$1.54, $p < 0.01$), reflecting the impact of the private investment and financial integration model in that state. Extension access is also critical: the absence of extension contact (–1.78, $p < 0.05$) is a significant negative predictor, and irregular contact (–1.50, $p < 0.1$) has a borderline negative effect. Training Index shows a borderline positive association ($+$0.37, $p < 0.1$), but appears most influential when combined with regular extension and a supportive implementation context. Other individual characteristics (age, gender, education, farm size) are not significant predictors in this model.

**Composite Outcome: Perceived Economic Benefit Index (OLS Regression)**

The OLS regression on the Perceived Economic Benefit Index (PEBI) highlights several important predictors of farmers' overall perceived benefit from AgriFi.

**Positive predictors** are led by long-term farming experience. Farmers with more than 10 years of experience ( $+0.23$, $p < 0.01$ ) are significantly more likely to report higher perceived benefits. This suggests that experienced farmers are particularly adept at leveraging AgriFi's digital tools, financial products, and new market opportunities, translating them into tangible gains. Their accumulated skills, stronger social networks, and adaptive capacity allow them to benefit from innovation more rapidly and fully than less experienced peers. Training Index ( $+0.06$, $p < 0.05$ ) is also a significant positive predictor: every incremental improvement in training quality or access directly increases PEBI scores, confirming the fundamental role of capacity building not only for technical onboarding, but also as a driver of confidence, trust, and sustained digital engagement.

In contrast, **negative predictors** include both educational attainment and age. Secondary education ( –0.23, $p < 0.01$ ) and, to a lesser extent, primary education ( –0.17, $p < 0.1$ ) are associated with lower perceived benefit relative to no formal education. This unexpected finding, also observed in other models, likely reflects an "expectation gap": farmers with some schooling may have higher standards or a more critical view of new platforms, making them less easily satisfied by incremental improvements. Older age ( $> 55$; –0.28, $p < 0.05$ ) is another significant negative predictor, perhaps indicating persistent digital exclusion among older farmers, skepticism toward technology, or a lower perceived return on new investments later in a farming career.

Contextual and project-specific factors also play a role. Being located in Niger State ( $+0.13$, $p < 0.1$ ) is marginally associated with higher perceived benefit, suggesting that the more finance-oriented, private investment model implemented there is starting to yield greater perceived gains, even if this effect remains moderate. By contrast, neither extension access nor farm size shows significant associations with the composite benefit index, indicating that their impact may be nuanced or outcome-specific rather than general.

Summary of significant predictors for PEBI:

- **Positive:** Long-term farm experience ( $> 10$ years), higher Training Index, Niger State context.
- **Negative:** Secondary (and primary) education, older age ( $> 55$ ).
- **Non-significant:** Extension access, farm size.

## Cross-Model Synthesis

The regression results across all six outcome models highlight a clear and consistent pattern. Dynamic, engagement-related factors—especially training quality and long-term farming experience—emerge as the primary drivers of positive perceptions of AgriFi's economic impact. In contrast, fixed demographic traits such as age, gender, and farm size play a much less prominent or inconsistent role.

Training Index is the most robust and recurrent enabler, showing high significance for perceived market access and for the Perceived Economic Benefit Index (PEBI), as well as marginal significance for financial access and economic stability. High-quality, accessible training is thus confirmed as not merely a technical support, but also a key trust-building mechanism and gateway to digital platform adoption. Similarly, long-term farm experience (over ten years) is a crucial positive predictor, supporting the idea that experienced farmers are better positioned to translate AgriFi's innovations into measurable economic gains by leveraging their greater knowledge, networks, and adaptive skills.

Education—particularly at the secondary level—consistently shows a negative association with perceived benefits, suggesting the presence of an "expectation gap" among more educated farmers. This highlights the importance of targeted or advanced engagement strategies for this subgroup. Extension access also proves critical: while not significant for market access or profitability, the absence of extension support is a strong negative predictor for both resilience and financial access, reinforcing the continued importance of advisory and institutional support for the most vulnerable or least-connected farmers. Finally, geographic context matters: the implementation model in Niger increases the likelihood of reporting better financial access, likely due to the stronger integration of digital finance there. However, for market access and resilience, state-level effects are less pronounced, implying that how a program is delivered and how farmers are engaged may be more important than location alone.

*In summary:*

- "Soft" factors—training, experience, and targeted support—are central to perceived value from digital platforms.
- Static traits (age, gender, farm size) have limited or inconsistent effects.
- Sustained investment in engagement and delivery strategies will determine the inclusivity and success of such programs.

## 2.6 Conclusions

This study provides the first quantitative assessment of smallholder farmers' early perceptions of AgriFi, a blockchain-enabled agricultural platform piloted in Niger and Katsina States, Nigeria. By combining domain-specific regression models and a multidimensional Perceived Economic Benefit Index (PEBI), the analysis offers new insight into which features and implementation strategies are most likely to deliver meaningful value for different groups of farmers.

The results indicate that AgriFi is already associated with a range of positively perceived economic outcomes. Most farmers report improvements in market access, financial inclusion, and profitability, and these gains are well summarized by the PEBI composite index. Social benefits—such as enhanced community dynamics or improved labor practices—are less pronounced at this early stage and appear to require more time and targeted facilitation to fully materialize.

The analysis identifies several key factors driving positive perceptions. High-quality training and sustained extension access are especially important for increasing farmers' sense of benefit from the platform, particularly regarding market access, finance, and resilience. Longer-term farming experience also consistently predicts higher perceived profitability and resilience, likely reflecting greater adaptive capacity. In contrast, medium-scale farmers and those with secondary education are often more critical, pointing to possible expectation gaps or structural barriers that may require further attention. While demographic characteristics like age and gender have limited influence, the absence of regular extension support clearly reduces perceived benefits in domains such as resilience and financial access.

Comparative analysis between Niger and Katsina reveals that differences in project design and service integration shape outcomes. Niger's private investment model, with its stronger focus on training, extension, and integrated financial services, produces higher engagement and greater perceived benefits across domains and in the PEBI. By contrast, the input-oriented, state-led approach in Katsina delivers more modest economic gains and appears to limit broader perceptions of value, suggesting that input-only models may be insufficient to unlock the full potential of digital agriculture platforms.

These findings have several clear implications for scaling AgriFi and similar initiatives. Investment in training and extension should remain a priority to ensure inclusive engagement and long-term impact. Platform design must be tailored to local needs, combining logistical and financial innovation with robust farmer support. As AgriFi matures, future research should track farmers longitudinally—including non-participants—to establish whether early perceived benefits translate into sustained economic or social improvements and to identify evolving trust dynamics and usage patterns. Further research should also address slower-moving social and behavioral dimensions of platform adoption—especially for women, cooperative members, and remote farmers—and integrate participatory feedback to adapt tools to real-world needs.

Given the early-stage nature of AgriFi, several directions for further investigation are particularly warranted:

- **Longitudinal studies** are needed to determine whether the perceived gains identified here translate into lasting economic and social improvements over multiple seasons.
- Including **non-participant control groups** in future data collection will strengthen causal inference and enable more robust impact attribution.
- **Disaggregated analyses**—especially focused on gender, cooperative engagement, and remote-area inclusion—can reveal social effects and barriers that may emerge

more slowly or require tailored metrics.

- A deeper understanding of **behavioral dimensions**—how initial perceptions evolve into sustained usage and trust in the platform—will benefit from mixed-method research designs.

- Ongoing attention to **platform co-design and iterative user feedback** will be essential for optimizing platform functionality, user satisfaction, and equitable access as AgriFi scales and adapts.

Methodologically, this study demonstrates the value of embedding early-stage perception data within a rigorous, multi-model quantitative framework. While causal inference is limited by the lack of a counterfactual and the cross-sectional design, this approach has generated actionable insights into which factors matter most for perceived benefit and where the greatest opportunities for program refinement lie.

Nevertheless, limitations persist. Self-reported perceptions may not always reflect actual gains, and the non-random sample of enrolled farmers constrains the generalizability of findings. Regional implementation differences—especially the lack of integrated finance in Katsina—also shape both the strengths and the interpretability of results. There is also the possibility that more motivated or capable farmers both engage more and receive better training, potentially inflating measured effects.

In summary, AgriFi's early promise rests not simply on its technical infrastructure, but on the enabling conditions that make it meaningful for farmers: comprehensive training, accumulated experience, responsive extension, and adaptive, participatory design. Under these conditions, blockchain-enabled platforms can help overcome persistent barriers such as limited credit access and market fragmentation. As AgriFi and similar platforms evolve, future work must continue to evaluate not just economic returns, but also their capacity to build trust, enhance agency, and drive systemic transformation in rural value chains.

# References

Aker, J. C., and I. M. Mbiti (2010). "Mobile phones and economic development in Africa." *Journal of Economic Perspectives*, 24(3), 207–232. doi:10.1257/jep.24.3.207. url: https://doi.org/10.1257/jep.24.3.207.

Aker, J. C., I. Ghosh, and J. Burrell (2016). "The promise (and pitfalls) of ICT for agriculture initiatives." *Agricultural Economics*, 47(S1), 35–48. doi:10.1111/agec.12301. url: https://doi.org/10.1111/agec.12301.

Alkire, S., and J. Foster (2011). "Counting and multidimensional poverty measurement." *Journal of Public Economics*, 95(7–8), 476–487. doi:10.1016/j.jpubeco.2010.11.006. url: https://doi.org/10.1016/j.jpubeco.2010.11.006.

Banerjee, A. V., and E. Duflo (2009). "The experimental approach to development economics." *Annual Review of Economics*, 1, 151–178. doi:10.1146/annurev.economics.050708.143235. url: https://doi.org/10.1146/annurev.economics.050708.143235.

Barrett, C. B. (2010). "Measuring food insecurity." *Science*, 327(5967), 825–828. doi:10.1126/science.1182768. url: https://doi.org/10.1126/science.1182768.

Barrett, C. B., M. E. Bachke, M. F. Bellemare, H. C. Michelson, S. Narayanan, and T. F. Walker (2012). "Smallholder participation in contract farming: Comparative evidence from five countries." *World Development*, 40(4), 715–730. doi:10.1016/j.worlddev.2011.09.006. url: https://doi.org/10.1016/j.worlddev.2011.09.006.

Barrett, C. B., L. Christiaensen, M. Sheahan, and A. Shimeles (2017). "On the structural transformation of rural Africa." *Journal of African Economies*, 26(Suppl. 1), i11–i35. doi:10.1093/jae/ejx009. url: https://doi.org/10.1093/jae/ejx009.

Barrett, C. B., C. M. Moser, O. V. McHugh, and J. Barison (2004). "Better technology, better plots, or better farmers? Identifying changes in productivity and risk among Malagasy rice farmers." *American Journal of Agricultural Economics*, 86(4), 869–888. doi:10.1111/j.0002-9092.2004.00640.x. url: https://doi.org/10.1111/j.0002-9092.2004.00640.x.

Beaman, L., D. Karlan, B. Thuysbaert, and C. Udry (2014). "Self-selection into credit markets: Evidence from agriculture in Mali (NBER Working Paper No. 20387)." National Bureau of Economic Research. doi:10.3386/w20387. url: https://doi.org/10.3386/w20387.

Bernard, T., M. H. Collion, A. de Janvry, P. Rondot, and E. Sadoulet (2008). "Do village organizations make a difference in African rural development? A study for Senegal and Burkina Faso." *World Development*, 36(11), 2188–2204. doi:10.1016/j.worlddev.2007.10.010. url: https://doi.org/10.1016/j.worlddev.2007.10.010.

Bijman, J., R. Muradian, and A. D. Cechin (2012). "Agricultural cooperatives and value chain coordination". In A. H. J. Helmsing and S. Vellema (Eds.), *Value chains, inclusion and endogenous development*, pp. 82–101. Routledge.

Casino, F., T. K. Dasaklis, and C. Patsakis (2019). "A systematic literature review of blockchain-based applications: Current status, classification and open issues." *Telecommunications Systems*, 71(1), 1–32. doi:10.1016/j.tele.2018.11.006. url:

https://doi.org/10.1016/j.tele.2018.11.006.

Conley, T. G., and C. R. Udry (2010). "Learning about a new technology: Pineapple in Ghana." *American Economic Review*, 100(1), 35–69. doi:10.1257/aer.100.1.35. url: https://doi.org/10.1257/aer.100.1.35.

Deaton, A. (2010). "Instruments, randomization, and learning about development." *Journal of Economic Literature*, 48(2), 424–455. doi:10.1257/jel.48.2.424. url: https://doi.org/10.1257/jel.48.2.424.

Di Falco, S., and M. Veronesi (2013). "How can African agriculture adapt to climate change? A counterfactual analysis from Ethiopia." *Land Economics*, 89(4), 743–766. doi:10.3368/le.89.4.743. url: https://doi.org/10.3368/le.89.4.743.

Feder, G., R. E. Just, and D. Zilberman (1985). "Adoption of agricultural innovations in developing countries: A survey." *Economic Development and Cultural Change*, 33(2), 255–298. doi:10.1086/451461. url: https://doi.org/10.1086/451461.

Feder, G., and R. Slade (1984). "The acquisition of information and the adoption of new technology." *American Journal of Agricultural Economics*, 66(3), 312–320. doi:10.2307/1240798. url: https://doi.org/10.2307/1240798.

Fafchamps, M. (2004). *Market institutions in sub-Saharan Africa: Theory and evidence*. MIT Press.

Giné, X., and D. Yang (2009). "Insurance, credit, and technology adoption: Field experimental evidence from Malawi." *Journal of Development Economics*, 89(1), 1–11. doi:10.1016/j.jdeveco.2008.09.007. url: https://doi.org/10.1016/j.jdeveco.2008.09.007.

Global Findex Database. (2022). *Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19*. World Bank. url: https://globalfindex.worldbank.org/.

Imbens, G. W., and J. M. Wooldridge (2009). "Recent developments in the econometrics of program evaluation." *Journal of Economic Literature*, 47(1), 5–86. doi:10.1257/jel.47.1.5. url: https://doi.org/10.1257/jel.47.1.5.

Kamilaris, A., Fonts, A., and Prenafeta-Boldú, F. X. (2019). The rise of blockchain technology in agriculture and food supply chains. *Trends in Food Science & Technology*, 91, 640–652. https://doi.org/10.1016/j.tifs.2019.07.034

Jack, W., and T. Suri (2014). "Risk sharing and transactions costs: Evidence from Kenya's mobile money revolution." *American Economic Review*, 104(1), 183–223. doi:10.1257/aer.104.1.183. url: https://doi.org/10.1257/aer.104.1.183.

Jayne, T. S. and D. Ameyaw (2016). "Africa's evolving food systems: Drivers of change and the scope for influencing them." In 2016 Global Food Policy Report (pp. 2–11), IFPRI. doi:10.2499/9780896295827_01. url: https://doi.org/10.2499/9780896295827_01.

Lawal, A. I., Adeola, O., Adedoyin, F. F., Ajide, K. B., Bekun, F. V., and Kirikkaleli, D. (2025). Blockchain technology for agriculture in Africa: Opportunities, challenges, and policy directions. Discover Sustainability, 6(1), 111.https://doi.org/10.1007/s43621-025-01125-9

Lee, J., G. Gereffi, and J. Beauvais (2022). "Global value chains and agrifood standards: Challenges and possibilities for smallholders in developing countries." *World Development*, 139, 105306. doi:10.1016/j.worlddev.2020.105306. url: https://doi.org/10.1016/j.worlddev.2020.105306.

Lybbert, T. J., and D. A. Sumner (2012). "Agricultural technologies for climate change in developing countries: Policy options for innovation and technology diffusion." *Food Policy*, 37(1), 114–123. doi:10.1016/j.foodpol.2011.11.001. url: https://doi.org/10.1016/j.foodpol.2011.11.001.

Lybbert, T. J., and B. Wydick (2018). "Hope as aspirations, agency, and pathways: Poverty dynamics and micro-interventions." *World Development*, 105, 271–285. doi:10.1016/j.worlddev.2017.12.005. url: https://doi.org/10.1016/j.worlddev.2017.12.005.

Mohammed, A., Potdar, V., Quaddus, M., and Hui, W. (2023). Blockchain adoption in food supply chains: A systematic literature review on enablers, benefits, and barriers. *IEEE Access*, 11, 18165–18184. https://doi.org/10.1109/ACCESS.2023.3246411

Nakamoto, S. (2008). "Bitcoin: A peer-to-peer electronic cash system." url: https://bitcoin.org/bitcoin.pdf.

Ostrom, E. (1990). *Governing the commons: The evolution of institutions for collective action*. Cambridge University Press. https://doi.org/10.1017/CBO9780511807763

Ravallion, M. (2001). "The mystery of the vanishing benefits: An introduction to impact evaluation." *World Bank Economic Review*, 15(1), 115–140. doi:10.1093/wber/15.1.115. url: https://doi.org/10.1093/wber/15.1.115.

Sen, A. (1999). *Development as freedom*. Oxford University Press.

Suri, T., and W. Jack (2016). "The long-run poverty and gender impacts of mobile money." *Science*, 354(6317), 1288–1292. doi:10.1126/science.aah5309. url: https://doi.org/10.1126/science.aah5309.

Treiblmaier, H., and R. Beck (Eds.). (2019). *Business transformation through blockchain: Volume I*. Palgrave Macmillan. url: https://doi.org/10.1007/978-3-319-98911-2.

Van den Broeck, K., and S. Dercon (2011). "Information flows and social externalities in a model of technology adoption." *Journal of Development Economics*, 95(2), 231–239. doi:10.1016/j.jdeveco.2010.05.008. url: https://doi.org/10.1016/j.jdeveco.2010.05.008.

Venkatesh, V., M. G. Morris, G. B. Davis, and F. D. Davis (2003). "User acceptance of information technology: Toward a unified view." *MIS Quarterly*, 27(3), 425–478. doi:10.2307/30036540. url: https://doi.org/10.2307/30036540.

Wossen, T., T. Abdoulaye, A. Alene, M. G. Haile, S. Feleke, A. Olanrewaju, and V. Manyong (2017). "Impacts of extension access and cooperative membership on technology adoption and household welfare." *Journal of Rural Studies*, 54, 223–233. doi:10.1016/j.jrurstud.2017.06.022. url: https://doi.org/10.1016/j.jrurstud.2017.06.022.

World Bank. (2019). *Enabling the business of agriculture 2019*. url: https://eba.worldbank.org/.

# Appendix

This appendix reports the complete estimation results for the six regression models described in Section 2.5.2. All models include the following covariates:

- **Age:** 26–40, 41–55, 56+ (reference: 18–25)
- **Gender:** Male (reference: Female)
- **Education:** Primary, Secondary, Higher (reference: No formal education)
- **Farm Experience:** 5–10 yrs, >10 yrs (reference: <5 yrs)
- **Farm Size:** 1–5 ha, >5 ha (reference: <1 ha)
- **Training Index:** Continuous
- **Extension Access:** Occasional, Regular (reference: None/Infrequent)
- **State:** Niger (reference: Katsina)

**Estimation methods:**

- Table A1: Ordered logistic (thresholds reported)
- Tables A2–A4: Binary logistic
- Table A5: Probit
- Table A6: OLS

Sample size: $n = 206$ in all models.

Significance codes: $\cdot$ $0.05 \leq p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.

**Table A1:** Ordered logistic regression: Perceived Market Access ($n = 206$)

| **Predictor** | **Estimate** | **Std. Error** | **t-value** | **p-value** |
|---|---|---|---|---|
| 26–40 (Age2) | $-0.923^{\cdot}$ | 0.601 | -1.54 | 0.125 |
| 41–55 (Age3) | -0.657 | 0.653 | -1.01 | 0.314 |
| 56+ (Age4) | -0.629 | 0.775 | -0.81 | 0.417 |
| Female | 0.545 | 0.409 | 1.33 | 0.183 |
| Primary (Edu2) | $-1.105^{*}$ | 0.533 | -2.07 | 0.039 |
| Secondary (Edu3) | $-1.458^{**}$ | 0.490 | -2.98 | 0.003 |
| Higher (Edu4) | -0.691 | 0.498 | -1.39 | 0.166 |
| 5–10 yrs (FarmExp2) | 0.308 | 0.437 | 0.71 | 0.484 |
| >10 yrs (FarmExp3) | $0.969^{\cdot}$ | 0.503 | 1.93 | 0.054 |
| 1–5 ha (Size2) | $-0.806^{*}$ | 0.398 | -2.03 | 0.043 |
| >5 ha (Size3) | 0.131 | 0.567 | 0.23 | 0.818 |
| TrainingIndex | $0.586^{***}$ | 0.158 | 3.72 | <0.001 |
| Occasional (Ext_Acc2) | 0.457 | 0.504 | 0.91 | 0.362 |
| Regular (Ext_Acc3) | 0.066 | 0.441 | 0.15 | 0.881 |
| Niger (State) | 0.273 | 0.385 | 0.71 | 0.479 |
| Thresholds | | | | |
| No \| Uncertain | -1.274 | 0.889 | -1.43 | 0.153 |
| Uncertain \| Yes | -0.604 | 0.885 | -0.68 | 0.495 |
| Log-Likelihood | -171.1 | | | |
| McFadden $R^2$ | 0.082 | | | |
| AIC | 376.22 | | | |
| LR $\chi^2$ | 56.32 | | | <0.001 |

**Table A2:** Binary logistic regression: Profitability ($n = 206$)

| **Predictor** | **Estimate** | **Std. Error** | **z-value** | **p-value** |
|---|---|---|---|---|
| (Intercept) | 1.524 | 1.312 | 1.16 | 0.245 |
| 26–40 (Age2) | 0.123 | 0.790 | 0.16 | 0.876 |
| 41–55 (Age3) | 0.011 | 0.872 | 0.01 | 0.990 |
| 56+ (Age4) | -0.667 | 1.031 | -0.65 | 0.517 |
| Female | -0.434 | 0.574 | -0.76 | 0.449 |
| Primary (Edu2) | -0.300 | 0.792 | -0.38 | 0.705 |
| Secondary (Edu3) | 0.471 | 0.803 | 0.59 | 0.558 |
| Higher (Edu4) | 0.708 | 0.824 | 0.86 | 0.390 |
| 5–10 yrs (FarmExp2) | 0.331 | 0.607 | 0.55 | 0.586 |
| >10 yrs (FarmExp3) | 1.478$^{\cdot}$ | 0.827 | 1.79 | 0.074 |
| 1–5 ha (Size2) | -0.680 | 0.597 | -1.14 | 0.255 |
| >5 ha (Size3) | -0.538 | 0.901 | -0.60 | 0.550 |
| TrainingIndex | 0.042 | 0.228 | 0.18 | 0.855 |
| Occasional (Ext_Acc2) | -1.082 | 0.751 | -1.44 | 0.150 |
| Regular (Ext_Acc3) | 0.048 | 0.787 | 0.06 | 0.952 |
| Niger (State) | 0.906 | 0.634 | 1.43 | 0.153 |
| Log-Likelihood | -80.48 | | | |
| McFadden $R^2$ | 0.129 | | | |
| AIC | 160.95 | | | |
| LR $\chi^2$ | 19.33 | | | 0.196 |

**Table A3:** Binary logistic regression: Economic Stability ($n = 206$)

| Predictor | Estimate | Std. Error | z-value | p-value |
|---|---|---|---|---|
| (Intercept) | 2.817$^{\cdot}$ | 1.592 | 1.77 | 0.077 |
| 26–40 (Age2) | 0.353 | 1.022 | 0.35 | 0.730 |
| 41–55 (Age3) | 0.107 | 1.063 | 0.10 | 0.920 |
| 56+ (Age4) | 0.212 | 1.237 | 0.17 | 0.864 |
| Female | -0.631 | 0.665 | -0.95 | 0.343 |
| Primary (Edu2) | -0.970 | 0.997 | -0.97 | 0.330 |
| Secondary (Edu3) | -0.849 | 0.921 | -0.92 | 0.357 |
| Higher (Edu4) | -0.344 | 0.987 | -0.35 | 0.727 |
| 5–10 yrs (FarmExp2) | $-1.535^{\cdot}$ | 0.887 | -1.73 | 0.084 |
| >10 yrs (FarmExp3) | -1.380 | 1.026 | -1.35 | 0.179 |
| 1–5 ha (Size2) | 0.630 | 0.658 | 0.96 | 0.339 |
| >5 ha (Size3) | 1.207 | 0.974 | 1.24 | 0.215 |
| TrainingIndex | 0.451$^{\cdot}$ | 0.259 | 1.74 | 0.081 |
| Occasional (Ext_Acc2) | -1.152 | 0.883 | -1.31 | 0.192 |
| Regular (Ext_Acc3) | -0.289 | 0.883 | -0.33 | 0.743 |
| Niger (State) | 1.014 | 0.706 | 1.44 | 0.151 |
| Log-Likelihood | -55.15 | | | |
| McFadden $R^2$ | 0.130 | | | |
| AIC | 142.30 | | | |
| LR $\chi^2$ | 16.46 | | | 0.346 |

**Table A4:** Binary logistic regression: Financial Services Access ($n = 206$)

| Predictor | Estimate | Std. Error | z-value | p-value |
|---|---|---|---|---|
| (Intercept) | $3.223^{*}$ | 1.531 | 2.11 | 0.035 |
| 26–40 (Age2) | -1.802 | 1.137 | -1.59 | 0.113 |
| 41–55 (Age3) | -1.212 | 1.181 | -1.03 | 0.305 |
| 56+ (Age4) | -2.015 | 1.245 | -1.62 | 0.106 |
| Female | -0.439 | 0.572 | -0.77 | 0.442 |
| Primary (Edu2) | 0.505 | 0.803 | 0.63 | 0.530 |
| Secondary (Edu3) | 0.932 | 0.735 | 1.27 | 0.205 |
| Higher (Edu4) | -0.440 | 0.642 | -0.69 | 0.493 |
| 5–10 yrs (FarmExp2) | -0.009 | 0.579 | -0.02 | 0.987 |
| >10 yrs (FarmExp3) | 0.310 | 0.656 | 0.47 | 0.637 |
| 1–5 ha (Size2) | -0.012 | 0.530 | -0.02 | 0.981 |
| >5 ha (Size3) | 0.203 | 0.708 | 0.29 | 0.774 |
| TrainingIndex | $0.374^{\cdot}$ | 0.213 | 1.76 | 0.079 |
| Occasional (Ext_Acc2) | $-1.503^{\cdot}$ | 0.867 | -1.73 | 0.083 |
| Regular (Ext_Acc3) | $-1.776^{*}$ | 0.860 | -2.07 | 0.039 |
| Niger (State) | $1.535^{**}$ | 0.584 | 2.63 | 0.009 |
| Log-Likelihood | -78.70 | | | |
| McFadden $R^2$ | 0.188 | | | |
| AIC | 189.40 | | | |
| LR $\chi^2$ | 36.57 | | | 0.002 |

**Table A5:** Probit regression: Resilience Against Shocks ($n = 206$)

| **Predictor** | **Estimate** | **Std. Error** | **z-value** | **p-value** |
|---|---|---|---|---|
| (Intercept) | $1.435^{**}$ | 0.554 | 2.59 | 0.010 |
| 26–40 (Age2) | $-0.633^{\cdot}$ | 0.364 | -1.74 | 0.082 |
| 41–55 (Age3) | -0.626 | 0.396 | -1.58 | 0.114 |
| 56+ (Age4) | $-0.839^{\cdot}$ | 0.475 | -1.77 | 0.077 |
| Female | -0.104 | 0.259 | -0.40 | 0.687 |
| Primary (Edu2) | -0.228 | 0.335 | -0.68 | 0.496 |
| Secondary (Edu3) | $-0.525^{\cdot}$ | 0.297 | -1.77 | 0.077 |
| Higher (Edu4) | $-0.603^{\cdot}$ | 0.320 | -1.89 | 0.059 |
| 5–10 yrs (FarmExp2) | 0.128 | 0.278 | 0.46 | 0.645 |
| >10 yrs (FarmExp3) | $0.986^{**}$ | 0.321 | 3.07 | 0.002 |
| 1–5 ha (Size2) | -0.193 | 0.245 | -0.79 | 0.431 |
| >5 ha (Size3) | 0.279 | 0.353 | 0.79 | 0.429 |
| TrainingIndex | -0.039 | 0.094 | -0.41 | 0.680 |
| Occasional (Ext_Acc2) | 0.033 | 0.316 | 0.11 | 0.916 |
| Regular (Ext_Acc3) | $-0.738^{*}$ | 0.290 | -2.55 | 0.011 |
| Niger (State) | -0.207 | 0.255 | -0.81 | 0.417 |
| Log-Likelihood | -119.76 | | | |
| McFadden $R^2$ | 0.150 | | | |
| AIC | 271.53 | | | |
| LR $\chi^2$ | 42.23 | | | <0.001 |

**Table A6:** OLS regression: Perceived Economic Benefit Index (PEBI) ($n = 206$)

| Predictor | Estimate | Std. Error | t-value | p-value |
|---|---|---|---|---|
| (Intercept) | $3.193^{***}$ | 0.143 | 22.37 | $< 2\times10^{-16}$ |
| 26–40 (Age2) | -0.150 | 0.096 | -1.56 | 0.121 |
| 41–55 (Age3) | -0.114 | 0.104 | -1.10 | 0.274 |
| 56+ (Age4) | $-0.281^{*}$ | 0.122 | -2.30 | 0.023 |
| Female | -0.021 | 0.067 | -0.32 | 0.751 |
| Primary (Edu2) | $-0.169^{\cdot}$ | 0.086 | -1.97 | 0.050 |
| Secondary (Edu3) | $-0.229^{**}$ | 0.077 | -2.98 | 0.003 |
| Higher (Edu4) | -0.130 | 0.081 | -1.60 | 0.112 |
| 5–10 yrs (FarmExp2) | 0.071 | 0.073 | 0.97 | 0.334 |
| >10 yrs (FarmExp3) | $0.232^{**}$ | 0.083 | 2.79 | 0.006 |
| 1–5 ha (Size2) | -0.099 | 0.064 | -1.55 | 0.123 |
| >5 ha (Size3) | 0.001 | 0.089 | 0.01 | 0.995 |
| TrainingIndex | $0.058^{*}$ | 0.024 | 2.41 | 0.017 |
| Occasional (Ext_Acc2) | -0.114 | 0.081 | -1.41 | 0.159 |
| Regular (Ext_Acc3) | -0.116 | 0.073 | -1.58 | 0.116 |
| Niger (State) | $0.128^{\cdot}$ | 0.066 | 1.94 | 0.054 |
| Residual SE | 0.3493 | (190 df) | | |
| $R^2$ | 0.1987 | | | |
| Adj. $R^2$ | 0.1354 | | | |
| F-statistic | $3.14^{***}$ | (15,190) | | 0.00013 |

**Notes:**

- All models were estimated on complete-case data ($n = 206$).
- All categorical variables are dummy-coded; reference category noted in parentheses.
- Ordered logits use `polr` (MASS); binary logits and probits use `glm`; OLS uses `lm`.
- Thresholds reported only for the ordered-logit model.
- Significance: $\cdot$ $0.05 \le p < 0.10$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$.
- Standard errors in parentheses; t-values (for ordered logits and OLS) or z-values (for logit/probit) in brackets where shown.

# Chapter 3

# Identifying Opportunities for Blockchain in African Agriculture: A Readiness Index and Cluster Analysis

## Abstract

This paper develops and validates a comprehensive, data-driven Readiness Index to assess the potential of blockchain-enabled agrifood platforms across Sub-Saharan Africa (SSA). Leveraging an extensive set of open-access secondary indicators across multiple domains—including digital connectivity, institutional capacity, farmer readiness, infrastructure quality, gender inclusion, and policy environment—we construct and test four objective weighting schemes: equal weights, Principal Component Analysis (PCA)-based weights, entropy-derived weights, and institutional surrogate weights. Employing robust Monte Carlo simulations and sensitivity analyses, our findings indicate strong structural stability of the index, confirming that country rankings remain resilient across varied weighting methodologies. A k-means clustering analysis identifies distinct readiness profiles among SSA countries—categorized as Leaders, Emerging, Transitional, and At-Risk. Each cluster exhibits unique strengths and limitations in terms of digital connectivity, institutional trust, infrastructure, and inclusivity, providing tailored policy implications for blockchain-driven agrifood interventions. The study underscores the importance of strategic investments in infrastructure, training, and governance structures to realize blockchain's full potential in enhancing agricultural sustainability, market access, and financial inclusion. By offering a transparent, reproducible, and systematically robust analytical tool, this research not only fills a critical gap in the existing literature but also equips policymakers, development agencies, and investors with actionable insights for targeted, context-specific deployments of blockchain technologies in agrifood systems across SSA.

## 3.1 Introduction

Across sub-Saharan Africa (SSA), the promise of blockchain-enabled agricultural platforms rests on the region's readiness to adopt and sustain digital agri-solutions. Extending the farmer-level findings from the Nigerian case study in Chapter 2, pilot projects in East Africa have demonstrated that distributed-ledger technologies can improve produce traceability (Tian, 2016), reduce transaction costs through smart contracts (Kamilaris & Prenafeta-Boldú, 2019), and extend smallholder access to finance via tokenized incentives. However, scaling these innovations beyond isolated case studies requires more than technical feasibility: it demands a macro-level readiness lens that pinpoints which countries possess the requisite digital connectivity, institutional capacity, and infrastructure (World Bank, 2024; GSMA, 2023).

Zotti (2025) provided micro-evidence on farmers' perceived economic and social benefits of participating in a blockchain-enabled marketplace. However, these insights—rooted in a single-country context—cannot substitute for a comprehensive, region-wide assessment of structural enablers and barriers. To date, no existing framework systematically integrates public secondary data across SSA to rank countries by their digital-agrifood "readiness," leaving policymakers without the decision-support tools needed for strategic deployment (OECD, 2008; Nardo et al., 2005).

To fill this gap, this paper constructs a 2025 SSA Readiness Index by harnessing open-access secondary indicators—ranging from mobile-money penetration to corruption perception, rural 4G coverage, and gender-disaggregated connectivity—and applying four objective weighting schemes. Our approach is fully transparent, reproducible, and grounded in established composite-index methodologies (Shannon, 1948; Jolliffe, 2002).

Specifically, we:

1. Compute four index variants: (i) equal weights, (ii) PCA-based weights (first principal component, 62.5% variance explained), (iii) entropy-derived weights, and (iv) institutional surrogate weights drawn from global sub-pillar assignments (GSMA, 2023; TI, 2024).

2. Assess robustness via 10,000 Dirichlet-Monte Carlo draws and a "tornado" sensitivity analysis, summarizing that >90% of random weight perturbations produce Spearman correlations $\geq 0.94$ with the equal-weight baseline (Saltelli et al., 2008; Nardo et al., 2005).

3. Segment SSA economies through k-means clustering ($k = 4$, average silhouette $=$ 0.59), mapping geographic patterns and illustrating stability of country groupings across equal-weight and PCA-weight schemes via alluvial flows (Rousseeuw, 1987).

In what follows, Section 3.2 details our data sources, preprocessing pipeline, and the four weighting algorithms. Section 3.3 presents the robustness envelope and sensitivity diagnostics. Section 3.4 describes the clustering strategy and its validation (elbow and silhouette plots), before profiling the four readiness clusters. Section 3.5 discusses policy implications for targeting blockchain-enabled agri-platforms in SSA, and Section 3.6 concludes with recommendations for longitudinal validation and future index updates.

## 3.2 Methods

### 3.2.1 Data and Preprocessing

To build a transparent, reproducible Readiness Index for 48 SSA countries, we assembled and cleaned a core set of 11 country-level indicators. Our preprocessing comprised four key steps: indicator selection, retrieval, normalization, and imputation.

#### Indicator selection

Indicators were selected based on their demonstrated relevance as structural enablers or barriers to the adoption and effective utilization of blockchain-enabled agrifood solutions. We classified these indicators across five key domains, each justified by existing literature:

- **Digital Connectivity:**
  - Internet Users (% of population using the Internet): Internet penetration directly influences farmers' ability to access digital platforms, interact with market stakeholders, and leverage blockchain technology effectively (Queiroz & Wamba, 2019; Kamilaris & Prenafeta-Boldú, 2019).
  - Mobile Money (% of adults with a mobile-money account): Mobile money infrastructure enables financial inclusion, reduces transaction costs, and supports seamless integration of digital payments and blockchain-based smart contracts, especially in agricultural contexts (Aker & Mbiti, 2010; Jack & Suri, 2014).
  - Rural 4G (% of rural population covered by 4G): Reliable rural connectivity is fundamental for real-time data sharing, remote sensing, and IoT integration, all critical for blockchain operational effectiveness in agriculture (Deichmann et al., 2016; Ayim et al., 2022).
- **Institutional Trust:**
  - Corruption Perceptions Index (CPI, 0–100): Blockchain's value is maximized in contexts with high trust deficits. Countries with lower perceived corruption provide more favorable environments for blockchain adoption due to higher institutional reliability and transparency (Casino et al., 2019).
  - Regulatory Quality (score, –2.5 to +2.5): Effective regulatory frameworks significantly influence technology adoption by ensuring predictability, safeguarding rights, and supporting innovation ecosystems essential for blockchain deployment (Tripathi et al., 2022; Christensen et al., 2006).

  - E-signature Law (binary existence indicator): Legal frameworks for electronic signatures underpin trust, legitimacy, and enforceability of smart contracts, which are critical for blockchain-based agricultural platforms (Treiblmaier & Beck, 2019; Casino et al., 2019).

- **Farmer Share:**
  - Agricultural Employment (% of total employment): High agricultural employment indicates significant stakeholder engagement in agriculture, reflecting potential demand and transformative scope for blockchain-based solutions on rural livelihoods (Wossen et al., 2017).

- **Infrastructure and Cost:**
  - Electricity Access (% of population with electricity access): Reliable electricity access is essential for powering devices, servers, and blockchain networks, critical to the implementation and sustainability of agritech platforms.
  - Logistics Performance Index (scale 1–5): Efficient logistics systems facilitate goods movement, data synchronization, and integration into blockchain platforms, enhancing overall agricultural supply chain efficiency.
  - Handset Affordability (smartphone cost as % of GDP per capita): Affordable smartphones improve accessibility and adoption rates among smallholder farmers, ensuring equitable participation in blockchain-driven agritech ecosystems.

- **Gender and Inclusion:**
  - Gender Gap (percentage-point gap in mobile ownership between genders): A narrower gender gap in mobile ownership ensures inclusive digital participation, maximizing the reach and equitable impact of blockchain technologies across diverse farmer groups (Ayim et al., 2022; Asongu & Nwachukwu, 2018).

Each indicator aligns with critical determinants of successful blockchain integration into agrifood systems, supported by academic literature, enabling a comprehensive readiness assessment across Sub-Saharan Africa.

All raw indicator files were harmonized and processed via min-max normalization. We transformed every indicator $x_{c,j}$ onto a common $[0,1]$ scale via the formula:

$$x'_{c,j} = \frac{x_{c,j} - \min_c x_{c,j}}{\max_c x_{c,j} - \min_c x_{c,j}}$$

following standard practices in composite-indicator construction (OECD 2008).

For variables representing costs or barriers—specifically handset affordability (cost as a share of GDP per capita) and farmgate logistics cost—we first applied an inversion

$x^*_{c,j} = \frac{1}{x_{c,j}}$ so that higher scaled values unambiguously indicate greater readiness. This harmonization ensures that all eleven indicators contribute positively to the composite metrics. Upon completion, the cleaned, $48 \times 11$ matrix was set up for subsequent weighting.

To maintain the full sample of 48 countries for principal-component and entropy-based weighting, we addressed missingness and infinite values through a transparent mean-based imputation. Specifically, any infinite results—arising, for example, from division by zero during inversion—were first recast as NA. We then computed the arithmetic mean for each indicator column, excluding NA entries, and substituted all remaining NA values with these column means. Overall, imputed entries represented fewer than 10% of the dataset, a level low enough that any associated reduction in within-indicator variance is negligible. By avoiding list-wise deletion, this method preserves the overall distributional integrity of each indicator and ensures a complete and consistent data matrix for the four weighting schemes that follow.

### 3.2.2 Weighting Schemes

To mitigate the arbitrariness inherent in any single weighting rule and to assess the structural stability of country rankings, we constructed four distinct composite-index variants. Each variant yields a score $I_c$ for country $c$ via:

$$I_c = \sum_{j=1}^{m} \omega_j x_{c,j} \qquad \sum_{j=1}^{m} \omega_j = 1$$

where $x_{c,j}$ is the normalized value of indicator $j$ for country $c$, $m = 11$, and $\omega_j$ is the indicator weight.

Below, we summarize each weighting scheme and the rationale behind it:

1. **Equal-weight baseline.**
   Every indicator is treated with identical importance, so that

   $$I_{eq,c} = \frac{1}{m} \sum_{j=1}^{m} x_{c,j}$$

   This neutral arithmetic-mean approach serves as an intuitive reference benchmark and is widely used in sustainability indices (OECD, 2008; Nardo et al., 2005).

2. **PCA-based weights.**
   Following Jolliffe (2002), we performed a principal-component analysis (PCA) on the centered (but not variance-scaled) indicator matrix. We extracted the first

principal component (PC1), which captures the greatest share of variance (62.5% in our data), and took the absolute loadings $\ell_j$ on PC1 as raw weights. After normalizing $\ell_j$ to sum to one, the PCA index is:

$$I_{pca,c} = \sum_{j=1}^{m} \frac{|\ell_j|}{\sum_{k=1}^{m} |\ell_k|} x_{c,j}$$

This variance-driven scheme automatically up-weights indicators that most differentiate country performance.

3. **Entropy-based weights.**
Drawing on Shannon's (1948) information-theoretic framework, for each indicator $j$ we computed the normalized distribution across countries as $p_{c,j} = \frac{x_{c,j}}{\sum_{i=1}^{n} x_{i,j}}$, then calculated its entropy

$$e_j = -\frac{1}{\ln n} \sum_{c=1}^{n} p_{c,j} \ln p_{c,j}$$

where $n$ is the number of countries. Values near 0 indicate highly concentrated distributions; values near 1 indicate uniform distributions. We then define the degree of diversification $d_j = 1 - e_j$, capturing each indicator's information richness—higher $d_j$ means greater dispersion and thus greater weight. We then set

$$\omega_j^{(ent)} = \frac{d_j}{\sum_{k=1}^{m} d_k} \qquad I_{ent,c} = \sum_{j=1}^{m} \omega_j^{(ent)} x_{c,j}$$

so that indicators with more dispersed (information-rich) distributions receive greater weight (Zeleny, 1998).

4. **Institutional surrogate weights.**
To align with established expert consensus, we adopted sub-pillar weights published by GSMA in its Mobile Connectivity Index and by Transparency International for the CPI (GSMA, 2023; TI, 2024). After mapping each of our 11 indicators to its corresponding sub-pillar and normalizing, the index becomes

$$I_{inst,c} = \sum_{j=1}^{m} \omega_j^{(inst)} x_{c,j}$$

where $\omega_j^{(inst)}$ reflects the external institution's assigned importance.

All four index variants were computed in R and combined into a long-form table to facilitate direct comparison across schemes.

### 3.2.3 Robustness and Sensitivity

Composite indices can be sensitive to the choice of weights. To demonstrate the structural stability of our SSA Readiness Index, we performed two complementary analyses.

#### Dirichlet Monte Carlo

We generated 10,000 random weight vectors:

$$\mathbf{w}_i \sim \mathrm{Dirichlet}(1, \ldots, 1)$$

For each draw $i$, we computed the corresponding index:

$$I_{i,c} = \sum_j \omega_{i,j} x_{c,j}$$

and its Spearman rank correlation $\rho_i$ with the equal-weight baseline (Nardo et al., 2005). The resulting distribution $\{\rho_i\}$ had a median of 0.872 and a 90th percentile of 0.937. These high correlations confirm that country rankings are robust to large, random re-weightings of the indicators.

#### Tornado Sensitivity

Building on sensitivity-analysis best practice (Saltelli et al., 2008), we perturbed each indicator's weight by $\pm 25\%$ around the equal-weight vector. For indicator $j$, we set:

$$\omega_j = \frac{\frac{1}{m}(1 \pm 0.25)}{\sum_k \omega_k}$$

and recomputed Spearman $\rho$. The resulting tornado plot shows that, for almost every indicator, $\rho$ remains above 0.99. In other words, no single weight adjustment can materially alter the overall ranking, underscoring the index's structural stability.

### 3.2.4 Clustering and Validation

To translate our continuous readiness scores into actionable groupings, we segmented SSA countries using a k-means clustering approach, complemented by diagnostic checks to ensure robust, well-separated clusters.

#### Overall Index and K-Means:

We first distilled each country's readiness into a single overall score, computed as the arithmetic mean of the four variant indices (equal-weight, PCA-based, entropy-based, institutional). This composite measure captures the central tendency of multiple weighting philosophies and smooths idiosyncratic fluctuations. Applying k-means clustering to the standardized overall scores, we evaluated solutions from $k = 2$ up to $k = 6$.

An elbow plot of the total within-cluster sum of squares (WSS) revealed a pronounced inflection point at $k = 4$, beyond which additional clusters yielded only marginal reductions in compactness. We then calculated the average silhouette width for each $k$; at $k = 4$, the mean silhouette score reached $0.589$, comfortably within the range interpreted as "good" separation (Rousseeuw, 1987). Taken together, these diagnostics guided our selection of four clusters as the optimal partition—balancing parsimony with meaningful differentiation among country groups.

#### Geographic Mapping and Alluvial Flows:

To visualize the spatial distribution of these readiness clusters, we joined each country's cluster label to a shapefile of Sub-Saharan Africa boundaries and rendered the results using `tmap`. The resulting map highlights contiguous regions sharing similar readiness profiles, revealing geographic corridors of high or low digital-agrifood readiness.

Recognizing that cluster membership at the extremes may vary with weighting choice, we further employed an alluvial diagram to compare the bottom and top readiness quintiles under the equal-weight and PCA-based indices. Each "stream" traces a country's movement (or stability) across quintile boundaries when transitioning from a neutral to a variance-driven weighting scheme. This flow chart not only underscores the resilience of the core cluster structure but also pinpoints economies whose relative ranking is most sensitive to methodological assumptions.

## 3.3 Results

### 3.3.1 Index Rankings

Table 3.1 presents the ten highest- and lowest-scoring SSA countries under our equal-weight index (the full ranking is reported in Appendix A). The readiness scores span a broad range—from 49.22 points in the case of Seychelles to just 16.69 points for

South Sudan—underscoring substantial disparities in the structural conditions required for blockchain-enabled agrifood platforms to thrive.

Countries at the top of the distribution share a combination of strong digital connectivity, reliable infrastructure, and favorable institutional environments. For example, Seychelles (49.22), Ghana (46.42), and Botswana (43.28) benefit from high internet penetration, widespread mobile-money adoption, and low perceived corruption, enabling them to leverage distributed-ledger solutions more readily. In contrast, the bottom decile—headed by South Sudan (16.69), Chad (21.77), and Burundi (21.79)—faces severe deficits in both physical and digital infrastructure, as well as governance challenges that impede technology adoption.

Across the full sample of 48 countries, the mean readiness score is 35.4 (SD = 8.7), with the interquartile range (IQR) stretching from 28.0 to 42.5 points.

**Table 3.1:** Top & Bottom Ten SSA Countries by Equal-Weight Readiness Score

| Top 10 Rank | Country | Score | Bottom 10 Rank | Country | Score |
|---|---|---|---|---|---|
| 1 | Seychelles | 49.22 | 39 | Sierra Leone | 29.27 |
| 2 | Ghana | 46.42 | 40 | Burkina Faso | 28.76 |
| 3 | Botswana | 43.28 | 41 | Guinea-Bissau | 28.25 |
| 4 | Cape Verde | 42.93 | 42 | Niger | 27.97 |
| 5 | Mauritius | 42.62 | 43 | CAR | 27.96 |
| 6 | Kenya | 42.37 | 44 | Ethiopia | 26.54 |
| 7 | South Africa | 42.34 | 45 | Congo (DRC) | 22.45 |
| 8 | Lesotho | 41.25 | 46 | Burundi | 21.79 |
| 9 | Gabon | 41.12 | 47 | Chad | 21.77 |
| 10 | Senegal | 38.57 | 48 | South Sudan | 16.69 |

*Notes:* Readiness scores are on a 0–100 scale, computed as the simple average of 11 min–max–scaled indicators. The equal-weight index provides a neutral benchmark; alternative weighting schemes (PCA, entropy, institutional) yield highly correlated rankings (Spearman $\rho > 0.87$ for all pairwise comparisons).

These rankings set the stage for deeper robustness checks (Section 3.3.2) and clustering analyses (Section 3.4), demonstrating that the broad patterns of relative readiness are consistent across weighting methodologies and resilient to both random and targeted weight perturbations.

### 3.3.2 Robustness

To ensure that our country rankings are not an artifact of any single weighting rule, we carried out two complementary robustness checks.

Figure 3.1 shows graphically the results of the Dirichlet Monte Carlo test. The distribution of $\{\rho_i\}$ has:

- **Median** $\rho = 0.872$

- **90th percentile** $\rho = 0.937$

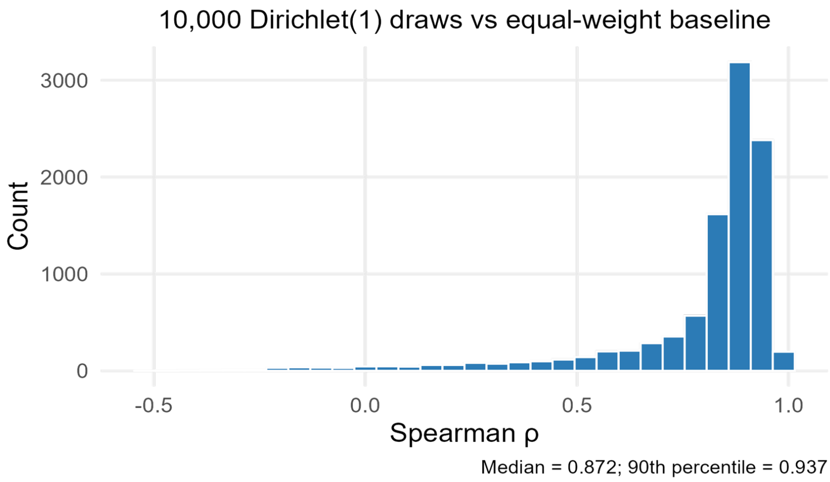


**Figure 3.1:** Distribution of Spearman correlations ($\rho_i$) between random Dirichlet-weighted indices and the equal-weight baseline across 10,000 simulations.

These high correlations confirm that random re-weightings do not alter the overall ranking in any substantive way.

We then perturbed each indicator's weight by $\pm 25\%$ around the uniform vector (with renormalization) and recomputed Spearman $\rho$. In every case, $\rho$ remained above 0.99 (see Figure 3.2), demonstrating that no single indicator can overturn the ranking.

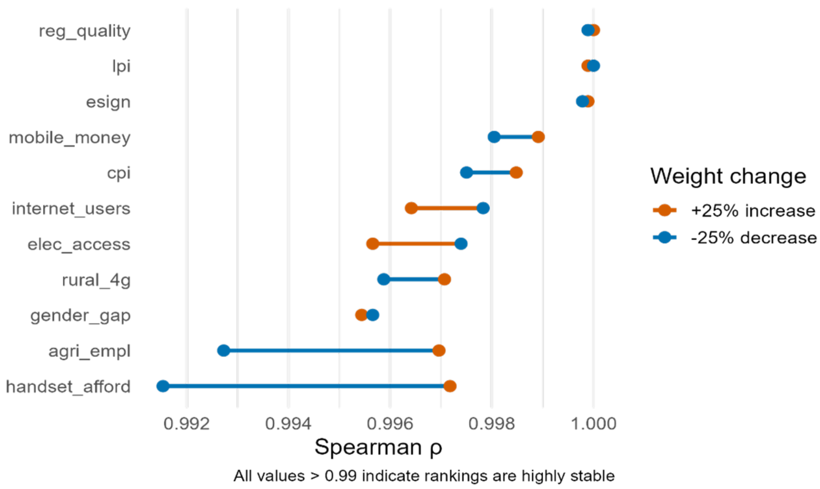


**Figure 3.2:** Tornado sensitivity analysis: Minimum and maximum Spearman correlation ($\rho$) resulting from perturbing each indicator's weight by $\pm 25\%$.

## 3.4 Clusters' analysis

Having established a robust set of country-level readiness scores, we next sought to identify natural groupings that could inform regionally tailored policy interventions. We defined each country's overall readiness as the simple mean of the four index variants, and then applied k-means clustering with rigorous validation at each step.

First, we needed an objective basis for selecting the number of clusters. As shown in Figure 3.3, the elbow plot of total within-cluster sum of squares (WSS) bends sharply at $k = 4$, indicating that adding more than four clusters yields only marginal improvements in compactness. To confirm, we computed the average silhouette width for $k = 2 \ldots 6$; at $k = 4$ the mean silhouette score reaches 0.589, squarely within the "good" range for cluster separation. Together, these diagnostics give us confidence that a four-cluster solution balances parsimony and distinctiveness.

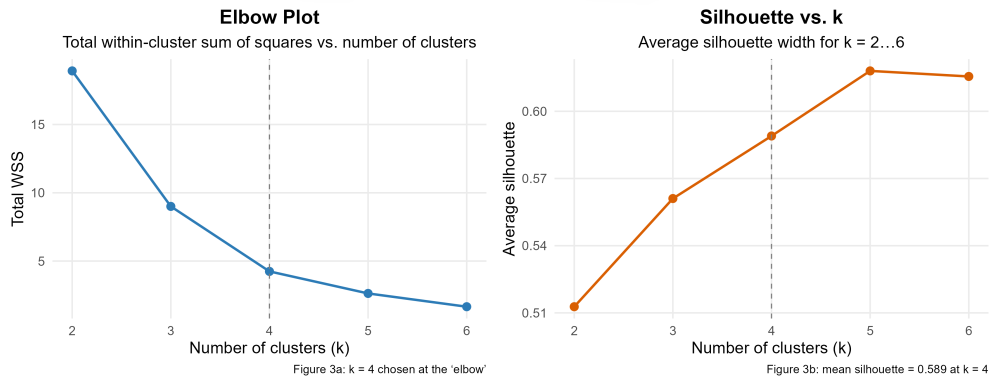


**Figure 3.3:** Left: Elbow plot of total within-cluster sum of squares (WSS) as a function of $k$. Right: Average silhouette width for $k = 2$ to $k = 6$; mean silhouette score at $k = 4$ is 0.589.

When we overlay our four clusters onto the SSA boundary map (Figure 3.4), clear geographic "zones of readiness" emerge:

- **Cluster 1 (Leaders):** Spans both island and coastal economies with top-tier readiness. This group includes Seychelles, Cape Verde, Ghana, Kenya, and Gabon, while in Southern Africa it covers Botswana, South Africa, Lesotho, and Mauritius. These countries combine digital connectivity (>70% Internet use, >45% mobile-money), reliable infrastructure (>85% electrification, >95% rural 4G), and strong institutional scores (CPI $\approx$ 47/100, e-sign law present), forming a contiguous corridor of high blockchain readiness.

- **Cluster 4 (At-Risk):** Sits squarely in the hinterlands. It comprises countries such as Chad, Congo (DRC), Burundi, and South Sudan, where fundamental deficits persist: electricity access <20%, Internet use <20%, rural 4G <60%, low CPI (<20/100), and weak regulatory quality. These structural failures create a belt of low readiness extending from central to eastern SSA.

- **Cluster 2 (Emerging):** Appears in coastal-inland transition zones—e.g., Côte d'Ivoire, Cameroon, Uganda, Tanzania, Sudan, Mali, Nigeria—where physical infrastructure (electricity $\approx$60%, rural 4G $\approx$80%) is solid but institutional trust remains moderate (CPI $\approx$34/100).

- **Cluster 3 (Transitional):** Includes countries in West Africa like Niger, Burkina Faso, Benin, Guinea, and Southern Africa like Angola, Zambia, Mozambique, plus the entire Horn of Africa—characterized by strong farmer share (agri-employment ≈49%) and logistics performance (LPI ≈2.4/5) but marked gender and governance gaps (Internet <30%, mobile-money <20%, CPI ≈28/100).

Together, these clusterings highlight where digital-agrifood platforms can be scaled immediately (Leaders), where governance and interoperability measures must come first (Emerging), where inclusion and trust campaigns are crucial (Transitional), and where foundational investments in power, broadband, and regulation are prerequisites (At-Risk).

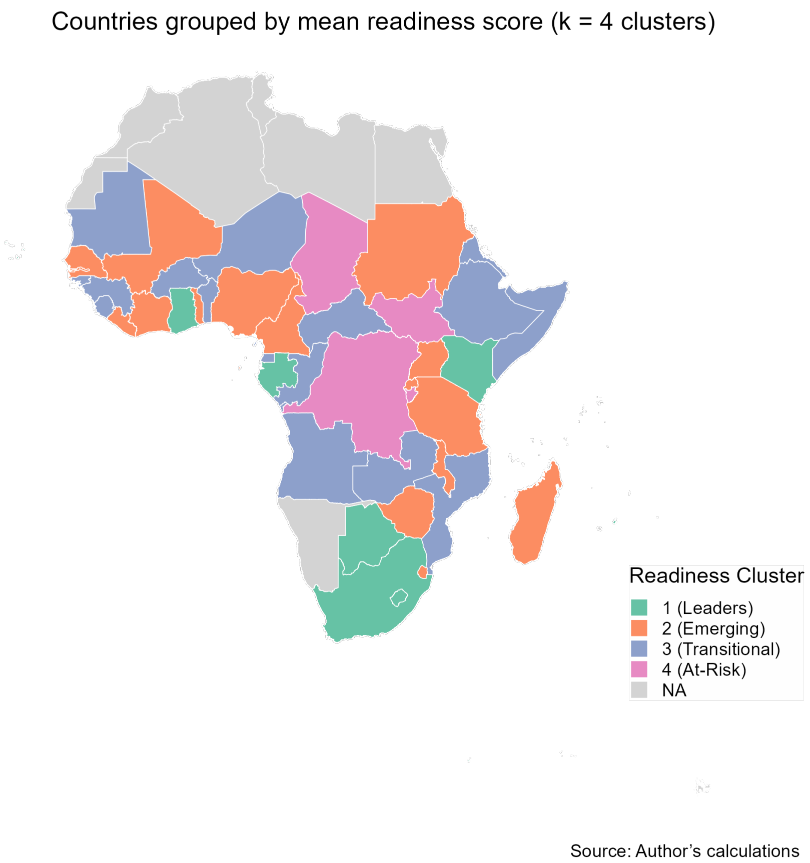


**Figure 3.4:** Geographic distribution of SSA countries by readiness cluster: 1 (Leaders), 2 (Emerging), 3 (Transitional), 4 (At-Risk).

Figure 3.5 provides a comprehensive view of how countries move across all five quintiles when comparing the equal-weight and PCA-based indices. The alluvial diagram shows each country's position in the full distribution, making it possible to track transitions not only at the extremes but also among intermediate quintiles.

The results reveal strong overall stability: while some countries shift between adjacent quintiles depending on the weighting scheme, the vast majority remain within the same or a neighboring group. Notably, 85% of countries classified in the lowest (Q1) or highest (Q5) quintile under the equal-weight index remain in the same extreme group under

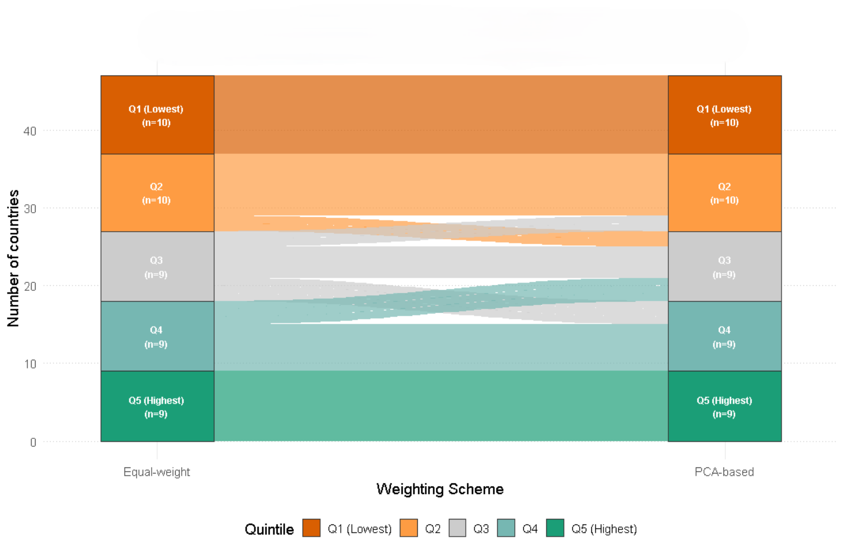


**Figure 3.5:** Alluvial diagram: Country movement across all quintiles under equal-weight vs. PCA-based indices. 85% of countries remain in the same extreme quintile (Q1/Q5) under both schemes.

the PCA-based index. This confirms that the identification of "Leaders" and "At-Risk" countries is robust to changes in index construction, and that intermediate shifts primarily affect countries closer to the center of the distribution.

This visualization underscores the reliability of the index in ranking both top and bottom performers, while also providing transparency about the sensitivity of intermediate classifications to methodological choices.

Finally, Figure 3.6 presents a heatmap of normalized indicator values by cluster, visually summarizing relative strengths and weaknesses across key readiness domains.

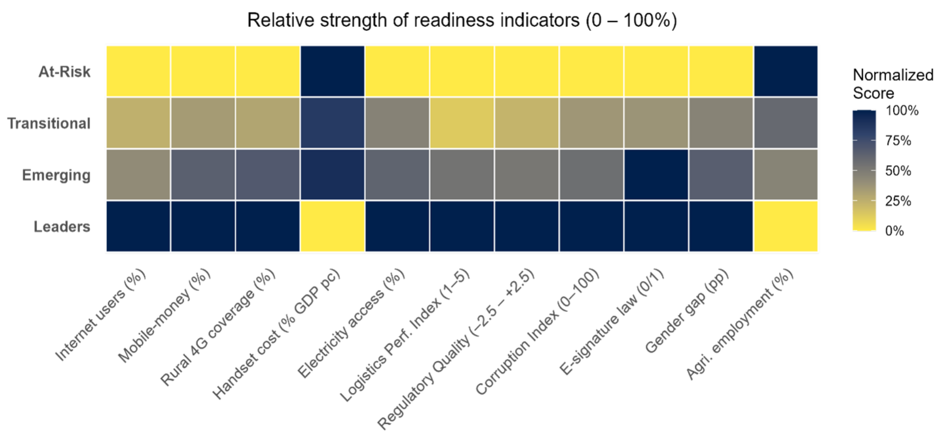


**Figure 3.6:** Cluster "fingerprints": Heatmap of normalized indicator values for each readiness cluster. Darker cells indicate stronger performance on the respective dimension.

The **Leaders** cluster is distinguished by dark shades across almost all indicators. These countries also display notably light cells for handset affordability and agricultural employment, signaling both greater device accessibility and a less agriculture-dependent economic structure.

**At-Risk** countries, in contrast, are marked by light shading on most indicators—indicating systemic deficits—yet show dark cells for both handset affordability (less affordable devices) and agricultural employment (greater reliance on farming).

**Emerging** and **Transitional** clusters display intermediate shading throughout. Emerging countries demonstrate relative strengths in infrastructure and governance (e-sign), while Transitional clusters are characterized by higher agricultural employment and moderate performance in other domains.

Overall, Figure 3.6 offers an immediate, intuitive visualization of each cluster's readiness profile. The case of handset affordability underscores the importance of device accessibility alongside improvements in digital, institutional, and infrastructural capacities, along with economic diversification.

## 3.5 Discussion

This study set out to assess where blockchain-enabled agrifood platforms can most effectively scale across Sub-Saharan Africa. By constructing a data-driven readiness index based on eleven open-access indicators—ranging from digital infrastructure and financial access to institutional trust and gender inclusion—we derived a robust ranking of 48 countries and identified four distinct clusters. These clusters not only represent varying degrees of preparedness but also reveal clear spatial patterns, pointing to regionally grounded pathways for digital agriculture.

### 3.5.1 Zones of Readiness: Four Clusters, Four Narratives

The first and most advanced cluster, which we label **Leaders**, includes countries such as Seychelles, Ghana, Botswana, Cape Verde, Mauritius, Kenya, South Africa, Lesotho, Gabon, and Senegal. Nine of these ten nations appear in the top 10 of our readiness ranking (see Table 3.1), underscoring their strong digital infrastructure, regulatory maturity, and financial inclusion. These countries score exceptionally well across several key indicators: internet usage rates hover around 70%, rural 4G coverage exceeds 95%, mobile money use approaches 45%, and e-signature frameworks are already in place. Gender gaps are relatively narrow, handset costs are low, and logistics systems are functioning.

Together, these features form a powerful enabling environment. Spatially, this cluster traces a corridor stretching across Southern and coastal West Africa, encompassing both island economies and urbanized mainland hubs. These countries are not just ready for pilots—they are ready for scaled, integrated blockchain ecosystems. Smart contracts, decentralized input distribution, digital credit scoring, and farm-to-market traceability systems can be implemented with minimal friction.

Moving to the second cluster—**Emerging** countries—we find a group that sits at the edge of readiness. Countries such as Côte d'Ivoire, Cameroon, Uganda, Tanzania, Sudan, Mali, and Nigeria combine decent rural 4G coverage (approximately 80%) and moderate logistics scores with growing digital access and mobile money adoption. However, institutional variables still present headwinds. The average Corruption Perception Index (CPI) remains low (approximately 34/100), regulatory quality is uneven, and digital trust frameworks—such as e-signature laws and interoperable identity systems—are often incomplete or underutilized.

These countries tend to occupy coastal–inland transition zones—geographically and politically situated between more advanced economies and fragile hinterlands. The strategic approach here must prioritize institutional and regulatory groundwork: creating space for public–private experimentation, establishing governance sandboxes, and ensuring that the digital rails of identity and data-sharing are in place before platforms are scaled to millions of farmers.

The third group—**Transitional** countries—presents a more complex story. This cluster includes Niger, Burkina Faso, Benin, Guinea, Angola, Zambia, Mozambique, and most of the Horn of Africa. These countries typically perform well in certain dimensions while lagging in others. For instance, many boast high levels of agricultural employment (approximately 49%) and improving logistics networks, suggesting strong underlying farmer engagement and supply chain potential. Yet digital inclusion remains limited. Internet usage and mobile money penetration are below regional averages, handset affordability is a constraint, and institutional scores remain middling. Gender disparities are particularly notable in access to mobile technology.

These nations are not digitally barren, but they are socially uneven, requiring tailored interventions that go beyond infrastructure. This is where blockchain's potential as a trust-building tool is most powerful—to bring transparency to cooperative structures, streamline aggregation logistics, and empower smallholders through collective data ownership and visibility. Here, blockchain should be introduced through community-based approaches that center around women's digital literacy, farmer-led onboarding, and culturally sensitive training.

Lastly, we turn to the **At-Risk** cluster—a belt of countries in the hinterlands of central and eastern Sub-Saharan Africa, including Chad, the Democratic Republic of Congo, Burundi, and South Sudan. All of these countries rank in the bottom 10 of the index. They face compounding constraints across every readiness dimension: internet usage and mobile money adoption fall below 20%, rural 4G coverage remains patchy, and regulatory environments are weak or nonexistent. E-signature laws are typically absent. Trust in institutions is extremely low, and infrastructural deficits—electricity, road networks, mobile coverage—are deep and widespread. In these contexts, blockchain is not a viable near-term solution for sectoral transformation. The focus must be on "infrastructure-first" investments: electrification, digital connectivity, and the building blocks of e-governance.

That said, these countries need not be excluded from innovation. Lightweight, low-barrier tools—such as blockchain-based savings groups, SMS-enabled crop registration, or mobile-friendly land tenure records—can plant the seeds of digital trust, building familiarity and institutional learning in anticipation of future readiness.

### 3.5.2 Geographic Anchoring of Readiness

Overlaying these clusters onto the SSA map reveals how structural and spatial patterns reinforce one another. *Leaders* form a digitally connected corridor running through Southern and coastal West Africa, while *At-Risk* countries form a belt of marginalization across central and eastern regions. In between, *Emerging* and *Transitional* countries populate the transitional interior—zones with partial infrastructure but uneven inclusion. These contours suggest not just policy categories but actual zones of opportunity and constraint where geography, governance, and connectivity intersect.

### 3.5.3 Stability of the Index

Importantly, the structure of these clusters is not a product of methodological chance. Across four weighting schemes—equal weighting, PCA-based variance weighting, Shannon entropy, and institutional surrogate weights—the cluster assignment of countries remains consistent. Spearman correlation coefficients exceed 0.87 across all scenarios, and a 10,000-draw Monte Carlo test using random weight permutations confirms the index's structural robustness. Even under wide perturbations, the ranking and clustering remain stable, indicating that the observed readiness patterns reflect real, persistent differences, not analytical artifacts.

### 3.5.4 Implications and Beyond

This clustering framework provides a concrete, evidence-based roadmap for scaling blockchain-based digital platforms:

- In *Leader* countries, the infrastructure and trust environment already exist. The challenge is no longer basic adoption, but integration—how to link traceability, finance, and logistics in one interoperable ecosystem.

- In *Emerging* contexts, governance comes first. Strengthening digital identity, standardizing data protocols, and creating regulatory sandboxes will create fertile ground for such platform expansion.

- In *Transitional* countries, inclusion is the binding constraint. Blockchain can serve as a transparency engine for cooperatives, women's groups, and logistics networks—but only if paired with targeted engagement strategies.

- In *At-Risk* states, ambition must align with reality. Rather than scaling prematurely, it should experiment with low-tech pilots while supporting foundational infrastructure and institutional reforms.

This tiered approach ensures not only that resources are used efficiently, but that blockchain-based platforms can achieve impact with integrity—adapting to local conditions rather than imposing one-size-fits-all solutions.

### 3.5.5 Limitations and Future Research

Despite its analytical power, this index comes with limitations. First, data currency remains a challenge—some indicators rely on 2022–2023 sources and may not fully reflect fast-moving reforms. Second, the index operates at the national level and does not account for within-country variations, which can be especially stark in large federated states. Third, some key variables—such as cooperative density or access to agricultural extension services—could not be included due to data scarcity. Finally, no quantitative index can capture informal trust dynamics, political risk, or cultural readiness for change.

To address these gaps, future research should pursue three directions:

1. Incorporate subnational data to better reflect regional disparities.
2. Develop a longitudinal version of the index to track changes over time.
3. Combine this quantitative foundation with qualitative fieldwork to better understand local attitudes, expectations, and institutional landscapes.

## 3.6 Conclusions

This paper has developed a transparent and analytically robust Readiness Index to assess the potential for scaling blockchain-enabled agrifood platforms across 48 Sub-Saharan African countries. Drawing on eleven openly available indicators—spanning digital access, institutional trust, infrastructure, financial inclusion, and gender equity—we constructed four composite weighting schemes: equal weights, variance-based PCA, Shannon entropy, and institutional surrogates. Despite these methodological differences, the country rankings produced by each scheme were highly correlated. Rigorous stress testing—including 10,000 Monte Carlo simulations with random Dirichlet weights and indicator-specific tornado perturbations—confirmed that the ranking structure and cluster segmentation are stable, even under substantial weight variability.

Through clustering of k-means, we translate these scores into four readiness archetypes: leaders, emerging, transitional, and at risk, each reflecting consistent structural patterns. These clusters also display clear spatial coherence: Leaders form a digital corridor from coastal West Africa to Southern Africa; Emerging and Transitional countries occupy interior transition zones with solid infrastructure but uneven inclusion and trust; At-Risk nations form a belt of foundational deficits across Central and Eastern Africa.

Each cluster carries distinct policy implications:

- **Leaders** (e.g., Seychelles, Ghana, Kenya, Botswana) are ready for *scaled, full-feature blockchain deployments*, including traceability, smart contracts, and digital finance. Their high digital penetration, mobile money use, and strong institutional frameworks provide a fertile environment for platform growth.

- **Emerging countries** (e.g., Côte d'Ivoire, Nigeria, Uganda) require a *phased approach*—prioritizing regulatory sandboxes, e-signature laws, and data-sharing standards before mass integration of farmer networks.

- **Transitional countries** (e.g., Niger, Angola, Ethiopia) face a *social inclusion gap*. Here, blockchain's potential lies in coordination and transparency tools, but success hinges on investment in community engagement, gender-focused training, and cooperative empowerment.

- **At-Risk countries** (e.g., Chad, DRC, South Sudan) are not yet positioned for platform deployment. They first need "infrastructure-first" investments—broadband access, rural electrification, and legal frameworks—before meaningful blockchain integration can occur. Low-tech pilots may nonetheless help build early trust and familiarity.

Importantly, this Readiness Index is not a static diagnostic. It offers a foundation for a dynamic, living decision-support tool. Annual updates can track progress and policy impacts, while future extensions should integrate subnational data to account for rural–urban and regional disparities. Qualitative fieldwork, too, will be essential to capture the informal norms, risk perceptions, and trust dynamics that quantitative indicators cannot reach.

As the digital transformation of agriculture accelerates, tools like this index will help governments, development partners, and platform developers answer a critical question: not just how blockchain can work, but where it can work—and when. By aligning technical ambition with on-the-ground capacity, the index provides a roadmap for responsible, inclusive, and scalable blockchain deployment in African agriculture.

# References


Aker, J. C., & Mbiti, I. M. (2010). “Mobile Phones and Economic Development in Africa.” *Journal of Economic Perspectives*, 24(3), 207–232. doi:10.1257/jep.24.3.207. url: `https://doi.org/10.1257/jep.24.3.207`.

Asongu, S. A., & Nwachukwu, J. C. (2018). “Educational, political and technological factors of mobile phone penetration and inclusive human development in Africa.” *Technological Forecasting and Social Change*, 129, 164–172.

Ayim, G., Dadzie, S. K., & Adams, S. (2022). “Mobile phone penetration, gender gap and inclusive development in sub-Saharan Africa.” *Telecommunications Policy*, 46(1), 102248. doi:10.1016/j.telpol.2021.102248. url: `https://doi.org/10.1016/j.telpol.2021.102248`.

Casino, F., Dasaklis, T. K., & Patsakis, C. (2019). “A systematic literature review of blockchain-based applications: Current status, classification and open issues.” *Telecommunications Systems*, 71, 339–371.

Christensen, C. M., Baumann, H., Ruggles, R., & Sadtler, T. M. (2006). Disruptive innovation for social change. *Harvard Business Review*, 84(12), 94–101.

Deichmann, U., Goyal, A., & Mishra, D. (2016). “Will digital technologies transform agriculture in developing countries?” *Agricultural Economics*, 47(S1), 21–33.

Jack, W., & Suri, T. (2014). “Risk sharing and transactions costs: Evidence from Kenya’s mobile money revolution.” *American Economic Review*, 104(1), 183–223.

Jolliffe, I. T. (2002). *Principal Component Analysis* (2nd ed.). Springer.

Kamilaris, A., & Prenafeta-Boldú, F. X. (2019). “A review on the practice of big data analysis in agriculture.” *Computers and Electronics in Agriculture*, 143, 23–37.

Lawal, A. I., Adeola, O., Adedoyin, F. F., Ajide, K. B., Bekun, F. V., & Kirikkaleli, D. (2025). Blockchain technology for agriculture in Africa: Opportunities, challenges, and policy directions. Discover Sustainability, 6(1), 111.`https://doi.org/10.1007/s43621-025-01125-9`

Lin, Q., Wang, H., Pei, X., & Wang, J. (2020). "Food safety traceability system based on blockchain and EPCIS." IEEE Access, 7, 20698–20707.

Mohammed, A., Potdar, V., Quaddus, M., & Hui, W. (2023). Blockchain adoption in food supply chains: A systematic literature review on enablers, benefits, and barriers. *IEEE Access, 11*, 18165–18184. https://doi.org/10.1109/ACCESS.2023.3246411

Nardo, M., Saisana, M., Saltelli, A., Tarantola, S., Hoffman, A., & Giovannini, E. (2005). *Handbook on Constructing Composite Indicators: Methodology and User Guide*. OECD Publishing.

OECD. (2008). *Handbook on Constructing Composite Indicators: Methodology and User Guide* (2nd ed.). OECD Publishing.

Queiroz, M. M., & Wamba, S. F. (2019). “Blockchain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA.” *International Journal of Information Management*, 46, 70–82.

Rousseeuw, P. J. (1987). “Silhouettes: A graphical aid to the interpretation and validation of cluster analysis.” *Journal of Computational and Applied Mathematics*, 20, 53–65.

Saltelli, A., Chan, K., & Scott, E. M. (Eds.). (2008). *Sensitivity Analysis*. Wiley.

Shannon, C. E. (1948). "A mathematical theory of communication." *Bell System Technical Journal*, 27(3), 379–423.

Treiblmaier, H., & Beck, R. (2019). *Business transformation through blockchain: Volume I*. Palgrave Macmillan.

Wossen, T., Abdoulaye, T., Alene, A., Haile, M. G., Feleke, S., Olanrewaju, A., & Manyong, V. (2017). "Impacts of extension access and cooperative membership on technology adoption and household welfare." *Journal of Rural Studies*, 54, 223–233.

World Bank. (2021). *World Development Report 2021: Data for Better Lives*. World Bank.

World Bank. (2024). *World Development Report 2024: The Middle Income Trap*. World Bank.

Zeleny, M. (1998). *Multiple Criteria Decision Making: eight concepts of optimality*. McGraw-Hill.

Zotti, C. (2025). "Perceived Economic and Social Benefits of AgriFi: Early Evidence from a Blockchain-Enabled Platform in Nigeria." Working Paper.

# Data Sources

World Bank. (2023). *World Development Indicators*.

FAO. (2023). *Agricultural Data Portal*.

ITU. (2022). *ICT Price and Usage Trends*.

GSMA. (2023–2024). *Rural 4G Coverage and Mobile Gender Gap Reports*.

Transparency International. (2024). *Corruption Perceptions Index 2024 Methodology*.

UN Cyberlaw Tracker. (2024). *E-Signature and Digital ID Legislation*.

# Appendix

This appendix provides supplementary material supporting the analysis presented in Paper III. Table A1 reports the full set of readiness scores for all Sub-Saharan African countries included in the study, calculated under four distinct weighting schemes: equal weights, PCA-based variance weights, entropy-based information weights, and institutional surrogate weights. Table A2 presents the normalized indicator values used for cluster analysis, offering a comparative snapshot of readiness across the identified country clusters.

**Table A1:** Full SSA Readiness Scores under Four Weighting Schemes.

| Country | Equal-Weight (%) | PCA-Based (%) | Entropy-Based (%) | Institutional (%) |
|---|---|---|---|---|
| Seychelles | 49.22 | 73.40 | 45.23 | 56.56 |
| Ghana | 46.42 | 69.06 | 43.63 | 53.89 |
| Botswana | 43.28 | 64.53 | 40.02 | 49.80 |
| Cape Verde | 42.93 | 64.57 | 40.44 | 49.36 |
| Mauritius | 42.62 | 64.96 | 39.41 | 49.98 |
| Kenya | 42.37 | 61.12 | 39.66 | 49.39 |
| South Africa | 42.34 | 64.68 | 39.20 | 49.34 |
| Lesotho | 41.25 | 61.32 | 39.00 | 47.54 |
| Gabon | 41.12 | 63.98 | 38.37 | 48.78 |
| Senegal | 38.57 | 55.82 | 35.46 | 45.89 |
| Malawi | 38.52 | 55.08 | 38.03 | 43.61 |
| Cameroon | 38.43 | 58.13 | 35.85 | 45.14 |
| Uganda | 38.23 | 53.74 | 35.99 | 44.89 |
| Côte d'Ivoire | 37.98 | 54.48 | 34.26 | 44.80 |
| Eswatini | 37.93 | 59.83 | 35.63 | 44.19 |
| Zimbabwe | 36.58 | 54.97 | 36.21 | 40.62 |
| Tanzania | 36.47 | 51.63 | 34.94 | 40.96 |
| Rwanda | 36.30 | 48.46 | 31.95 | 44.69 |
| Togo | 36.09 | 53.66 | 33.82 | 42.19 |
| São Tomé & Príncipe | 35.99 | 53.80 | 33.81 | 42.15 |
| Mali | 35.36 | 50.88 | 32.10 | 42.83 |
| Madagascar | 34.44 | 49.78 | 33.31 | 40.90 |
| Gambia | 34.34 | 54.65 | 32.82 | 38.79 |
| Liberia | 33.76 | 48.33 | 32.60 | 39.88 |
| Nigeria | 33.73 | 53.87 | 31.44 | 39.33 |
| Angola | 33.25 | 48.23 | 31.82 | 38.35 |
| Sudan | 33.15 | 50.91 | 31.34 | 39.05 |
| Benin | 32.93 | 45.84 | 29.23 | 39.62 |
| Zambia | 32.91 | 45.86 | 29.50 | 39.22 |
| Guinea | 31.96 | 47.49 | 29.20 | 37.86 |
| Eritrea | 31.92 | 48.30 | 29.80 | 37.86 |
| Mozambique | 31.52 | 44.75 | 28.68 | 37.35 |
| Comoros | 31.49 | 50.03 | 28.95 | 38.37 |
| Somalia | 31.29 | 49.50 | 30.09 | 36.29 |

| Country | Equal-Weight (%) | PCA-Based (%) | Entropy-Based (%) | Institutional (%) |
|---|---|---|---|---|
| Mauritania | 30.67 | 47.47 | 28.62 | 35.86 |
| Congo - Brazzaville | 30.67 | 45.27 | 28.88 | 36.33 |
| Equatorial Guinea | 29.94 | 47.55 | 30.81 | 32.08 |
| Sierra Leone | 29.27 | 42.51 | 27.58 | 34.10 |
| Burkina Faso | 28.76 | 40.92 | 26.66 | 32.97 |
| Guinea-Bissau | 28.25 | 40.00 | 26.19 | 33.93 |
| Niger | 27.97 | 37.57 | 25.91 | 32.43 |
| Central African Republic | 27.96 | 40.20 | 29.99 | 29.28 |
| Ethiopia | 26.54 | 38.27 | 25.38 | 30.99 |
| Congo - Kinshasa (DRC) | 22.45 | 31.67 | 21.41 | 26.53 |
| Burundi | 21.79 | 28.33 | 20.49 | 25.26 |
| Chad | 21.77 | 28.16 | 20.43 | 25.35 |
| South Sudan | 16.69 | 23.60 | 14.64 | 21.01 |

**Table A2:** Normalized indicator values (0–1 scale) by readiness cluster.

| Cluster | Agri empl | CPI | Elec. access | E-sign | Gender gap | Handset afford. | Internet users | LPI | Mobile money | Reg. quality | Rural 4G |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 (Leader) | 0.223 | 0.468 | 0.866 | 0.889 | 0.951 | 0.206 | 0.691 | 0.552 | 0.432 | 0.496 | 0.963 |
| 2 (Emerging) | 0.428 | 0.337 | 0.591 | 0.889 | 0.659 | 0.509 | 0.383 | 0.628 | 0.298 | 0.340 | 0.795 |
| 3 (Transitional) | 0.212 | 0.606 | 0.866 | 0.889 | 0.951 | 0.206 | 0.771 | 0.619 | 0.432 | 0.596 | 0.963 |
| 4 (At-Risk) | 0.491 | 0.275 | 0.471 | 0.647 | 0.489 | 0.487 | 0.290 | 0.458 | 0.182 | 0.257 | 0.589 |

*Note:* **Agri_empl** = Agricultural employment; **CPI** = Corruption Perceptions Index; **Elec_access** = Electricity access; **E-sign** = E-signature law; **Gender_gap** = Gender gap in mobile ownership; **Handset_afford** = Handset affordability; **Internet_users** = Internet users; **LPI** = Logistics Performance Index; **Mobile_money** = Mobile money use; **Reg_quality** = Regulatory quality; **Rural_4G** = Rural 4G coverage.

# General Conclusions

This thesis set out to critically examine the potential and limitations of blockchain-enabled innovation in African agrifood systems through a multidimensional, evidence-based approach. By combining conceptual, micro-empirical, and macro-structural perspectives, the three chapters collectively contribute to a more comprehensive understanding of how digital technologies—particularly blockchain—can support sustainability and inclusion in agricultural development.

**The first chapter** mapped the existing scientific literature on blockchain applications in the agrifood sector. The scoping review demonstrated that scholarly interest in this area is expanding rapidly, with growing attention to sustainability dimensions—especially social and environmental considerations—alongside technical and economic aspects. Nonetheless, the analysis revealed that empirical research remains fragmented, with significant methodological and contextual gaps, particularly concerning real-world implementation and long-term impacts. By applying the Triple Bottom Line framework, the chapter clarified both the current state of knowledge and the areas requiring deeper investigation, providing a conceptual foundation for the following studies.

**The second chapter** offered original field-based evidence from Nigeria, examining how smallholder farmers engaged with the AgriFi blockchain platform perceive its economic and social benefits. The results indicated clear perceived economic advantages—mainly in market access, financial inclusion, and profitability—while social outcomes appeared more heterogeneous and context-dependent. The econometric analysis identified the quality of training, sustained extension support, and accumulated farming experience as significant predictors of positive perceptions. In contrast, medium-scale farmers and those with secondary education were more likely to encounter structural or expectation-related barriers. These findings underscore the need for farmer-centred platform design and highlight that effective adoption depends on both technological provision and the broader institutional and human-capital environment.

**The third chapter** expanded the scope to the regional level by developing and validating a Readiness Index for 48 Sub-Saharan African countries. This composite index revealed substantial heterogeneity in the structural conditions enabling blockchain adoption in agriculture. The multidimensional clustering approach identified four readiness profiles—*Leaders*, *Emerging*, *Transitional*, and *At-Risk*—each characterised by distinct strengths and vulnerabilities in digital connectivity, institutional quality, and inclusiveness. The results provide actionable insights for policy: while a small group of countries is ready for large-scale digital innovation, many others remain constrained by deficits in infrastructure, inclusion, and institutional trust, requiring sequenced investment and reform strategies.

Taken together, these studies demonstrate that the transformative potential of blockchain in African agriculture depends not only on the technology itself but on the alignment of digital infrastructure, institutional context, and inclusive support systems.

Achieving sustainable and equitable digital transformation demands the integration of rigorous research, adaptive policymaking, and continuous engagement with farmers and stakeholders across all levels of the agrifood system.

Across the three chapters, several cross-cutting insights emerge. Blockchain's contribution to sustainability depends fundamentally on the reconfiguration of trust: cryptographic verification and traceability mechanisms can complement but never replace institutional reliability and relational trust. Smallholder adoption dynamics also reflect core principles of technology-adoption theory, where perceived usefulness must be accompanied by effective enabling conditions—training, extension, and institutional support—to translate into meaningful outcomes. At the same time, macro-level readiness determines whether these enablers can scale, reinforcing the importance of sequencing infrastructure, capacity, and governance reforms to achieve systemic transformation.

In addressing the central research questions, the thesis has shown that while the academic literature offers expanding conceptual insights into blockchain's role in agrifood systems, empirical evidence remains uneven. The fieldwork in Nigeria confirms that tangible economic benefits emerge when human and institutional capacities are present, while the readiness analysis demonstrates how structural deficits constrain scalability and inclusion. Together, these results provide a coherent answer to where blockchain innovation can most effectively contribute to sustainable and inclusive agrifood transitions in Africa.

Looking ahead, future research should build on these findings by extending empirical analysis through longitudinal and comparative designs, and by incorporating qualitative perspectives to better capture trust, behavioural dynamics, and local adaptation processes. Strengthening interdisciplinary collaboration between economists, technologists, and development practitioners will be key to understanding how blockchain can interact with social norms and governance structures in diverse agricultural settings.

From a policy standpoint, the evidence points to a sequenced approach to digital transformation: foundational investments in connectivity, training, and extension should precede large-scale blockchain deployments, particularly in contexts where institutional trust remains fragile. Countries that already possess stronger digital ecosystems can focus on integration between traceability, finance, and advisory services, whereas those with weaker infrastructure must first prioritise enabling conditions and inclusion mechanisms.

Methodologically, this thesis demonstrates the value of combining complementary approaches—systematic review, econometric field analysis, and composite-index modelling—to investigate complex development challenges. This integrated design not only ensured coherence across scales of analysis but also reinforced the robustness of the evidence base. The resulting framework can inform future assessments of digital innovation in agriculture, providing both analytical depth and practical orientation.

More broadly, the findings contribute to the wider discourse on digital transformation in development, illustrating how technological innovation must be accompanied by institutional trust-building, capacity investment, and inclusive governance to deliver equitable outcomes.

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