

Data Quality, AI Effectiveness, and Food Supply Chain Traceability: A Theory-Driven Framework for Resilience

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Abstract:

AI is becoming more used to improve the traceability and transparency of Moroccan food supply chains. Still, the efficiency of AI-powered traceability systems is strongly based on the quality of the data used. While research has flourished in the fields of AI, digital traceability, and supply chain resilience, the importance of data quality as an eminent antecedent of AI efficiency has not been adequately studied.

This paper adopts a model-focused conceptual design, based on an integrative synthesis of complementary theoretical perspectives to reveal the varieties of ways through which the technical, semantic, and governance dimensions of a high-quality data contribute to improve AI analytical ability and the eventual realization of transparency, traceability, and resilience of the Moroccan food supply chain. Based on the theoretical lenses of Information Quality theory, the Resource-Based View, Dynamic Capabilities Theory, and Socio-Technical Systems theory, the setup regards AI effectiveness as a mediating factor and supply chain complexity and digital maturity as contextual factors which may impact the relationships. A set of research propositions specifies the proposed direct, mediating, and moderating relationships. The proposed framework is conceptual and has not yet been empirically validated; therefore, the proposed relationships should be interpreted as theoretically derived rather than empirically established.

The paper contributes to the literature by integrating data quality, AI effectiveness, transparency, traceability, and resilience within a unified theoretical model and by positioning data quality as a strategic foundation for AI-enabled supply chain capabilities. The framework provides a basis for future empirical validation in Moroccan food supply chain contexts.

Keywords: Data quality; Artificial intelligence; AI effectiveness; Food supply chain; Traceability; Transparency; Supply chain resilience.

Classification JEL : Q13, O33, L23, L15

Paper type: Theoretical Research

1. Introduction

Currently, food supply chains are subject to unpredictable and intricate disruptions like those caused by climate change, food safety recalls, global and political demand fluctuations, and ever increasing regulatory constraints (Aung & Chang, 2014; Olsen & Borit, 2018). In such a scenario, the need for supply chain resilience stands out (Ben-Daya et al., 2019; Toorajipour et al., 2021). Resilience, as generally perceived, is the ability of supply chains to identify, deal effectively with, bounce back, and eventually be more robust after a setback (Christopher & Peck, 2004; Ponomarov & Holcomb, 2009; Wieland & Wallenburg, 2013). In food supply chains, resilience depends partly on the ability to obtain accurate and timely information. Such information concerns food products, production processes, suppliers, and the movement of raw materials. Transparency and traceability are therefore fundamental to risk management, food safety, and effective decision-making among supply chain stakeholder (Aung & Chang, 2014; Olsen & Borit, 2018).

With the rapid growth of digital technologies, many potential avenues have been created for the enhancement and development of these features through different ways and means. One example is the application of artificial intelligence, IoT devices for connectivity and monitoring of physical objects, blockchain for record-keeping and transaction verification and numerous other technologies that will without a doubt be of great assistance in, for example, the monitoring, detection of abnormal situations, and the information sharing as well as the decision-making processes happening in real-time for various levels and different types of players in the supply network (Ben-Daya et al., 2019; Toorajipour et al., 2021). In particular, AI-based applications have been demonstrated to be able to support a great extent of predictive analytics, detection of unforeseen event disruption, and real-time monitoring that will definitely lead towards more adaptable and transparent food supply chains. Despite the potential of advanced AI technologies, their adoption alone is not sufficient to ensure robust traceability and transparency. A key determinant of their effectiveness is the quality of underlying data.

AI algorithms are highly dependent on the characteristics of their input data, including accuracy, completeness, consistency, timeliness, relevance, and reliability (Batini et al., 2009; Wang & Strong, 1996).

In food supply chains, many different types of data come from various actors who use heterogeneous technological systems like sensors, enterprise information systems, certification platforms, blockchain applications, as well as manual processes, etc. So, because of fragmented information systems, inconsistent data definitions, missing observations, delayed updates, and weak governance mechanisms, the quality of supply chain data could be greatly reduced (Hazen et al., 2014; Kache & Seuring, 2017; Queiroz et al., 2021). When low-quality data are used to train or operate AI systems, the resulting outputs may become less accurate, less interpretable, and less useful for traceability and decision-making.

Although data quality, AI, digital traceability, and supply chain resilience have each received increasing scholarly attention, these research streams remain insufficiently integrated. Existing studies have examined the role of data quality in analytics and supply chain management (Cai & Zhu, 2015; Hazen et al., 2014), the contribution of AI and digital technologies to supply chain performance (Dwivedi et al., 2021; Toorajipour et al., 2021), and the role of digital technologies in food traceability (Aung & Chang, 2014; Behnke & Janssen, 2020; Olsen & Borit, 2018). However, less attention has been given to the mechanisms through which distinct dimensions of data quality influence AI effectiveness and, in turn, contribute to transparency, traceability, and resilience. This fragmentation limits a comprehensive understanding of how organizations can convert data resources into AI-enabled supply chain capabilities.

This gap raises the following research question: How can data quality influence food supply chain resilience through AI analytical effectiveness, transparency, and traceability, and how

may digital maturity shape these relationships? This question guides the development of the proposed conceptual framework and its direct, mediating, and moderating relationships.

In an effort to fill the existing void, and following (Jaakkola, 2020), this study adopts a model-oriented conceptual design, supported by an integrative synthesis of complementary theoretical perspectives. Rather than empirically testing an established theoretical model, the study develops an explanatory and empirically testable framework that integrates previously fragmented relationships among data quality, AI analytical effectiveness, transparency, traceability, and food supply chain resilience. The model specifies direct, mediating, and moderating relationships and identifies the contextual conditions under which these relationships may vary.

From the article's scenario, better AI effectiveness helps increase transparency and traceability, thereby enabling food supply chains to be more resilient. We also realize that the links above may depend on two factors of the situation: the level of intricacies in the supply chaining and the level of digitalization. This structure was mainly developed based on the concept of Information Quality Theory which states that high-quality information is the key driver to effective AI analytics. The idea of Dynamic Capabilities helps explain the way that AI-generated transparency together with traceability can allow enterprises to discover, to react, or even to change the way of how they use limited resources. Besides, the Resource-Based View and Socio-Technical Systems Theory highlight how organizational and technological conditions should be met for data and AI to create value. The overall purpose of this article is, that means, to come up with a theoretical basis that incorporates how data quality determines AI outcome and how transparency and traceability that are enabled by AI can make food supply chain more resilient especially in the Moroccan context. A total of fifteen research hypotheses have been identified to describe the direct, mediating, and moderating associations predicted by this theoretical setup.

The paper makes three main contributions:

- First, it extends research on AI-based supply chain traceability by positioning data quality as a central antecedent of AI analytical effectiveness, rather than treating data-related issues primarily as operational or technical problems.
- Second, it develops an integrated framework linking data quality, AI analytical effectiveness, transparency, traceability, and supply chain resilience, thereby connecting research streams that have largely been examined separately.
- Third, it incorporates digital maturity as contextual condition, highlighting how the organizational environment may shape the relationships between data quality, AI effectiveness, transparency, traceability, and resilience.

The proposed framework will work as the theoretical foundation for future empirical studies in the areas of food supply chains and other area with traceability-demanding actors. The rest of the paper is structured below. It begins with the theoretical foundations of this study, and then proceeds with the dimensions of data quality in food supply chain traceability and measures of AI effectiveness in traceability systems. It then outlines the conceptual framework and the research propositions, and then discusses the theoretical and practical implications of the system, and the limitation of this research. The paper ends with the conclusion, which summarizes the main research results, limitations, and directions for future research.

2. Theoretical Foundations

The paper is written under three constructive disciplines: information systems, strategic management, and organizational theory. It is a synthesis of four theories namely Information Quality Theory (IQT), resource-based view (RBV), dynamic capabilities theory (DCT), and

socio-technical systems (STS) perspective, to account for how data quality and AI capabilities can provide transparency, traceability, and resilience for food supply chains.

It includes IQT as its core foundation, treating data quality as an information-processing resource that affects the effectiveness of an AI analysis. RBV theory regards data and capabilities of AI as valuable resources; DCT attributes AI-enabled transparency and traceability with sensing, responding, and resource reconfiguring. The STC perspective emphasizes the link between technological potential with organizational and human factors org. Both lenses justify the hypothesized relationships between data quality, AI analytical capabilities transparency traceability, and food supply chain resilience, and underpin the consideration of contextual roles of digital maturity.

2.1. Information Quality Theory: The Foundation of Data Quality

Information Quality Theory is mainly connected to this research due to the relevance of high-quality information in data processing. Based on (Wang & Strong, 1996), data quality covers the ability of the data to serve its purpose from a user's perspective. This perspective is particularly relevant to AI-driven supply chains, where AI systems depend on data to identify patterns, generate forecasts, classify events, and support decisions. Inaccurate, incomplete, inconsistent, or outdated data can therefore compromise the reliability of AI outputs. Recent research further emphasizes that information quality remains critical in the AI era, while highlighting emerging concerns such as data provenance, volatility, and trustworthiness (Jabbar et al., 2025).

Drawing from this perspective, the present study views data quality as technical quality, semantic quality and governance-related quality. Technical quality of data involves accuracy, completeness, consistency, timeliness, and interoperability. Semantic quality is the degree to which data is understood in a uniform way by the various actors along the supply chains and information systems. Governance-related quality concerns how data validation, security controls, maintenance, and responsibility are managed. This latter view is consistent with the literature on AI-enabled supply chains, which ranks cross-organizational mix, semantic variation, temporal inconsistency, and source ambiguity as the primary data-quality issues of concern.

The heterogeneous and distributed nature of food supply chain data further supports this multidimensional conceptualization. Recent evidence shows that data sparsity, noise, bias, and missing values can substantially reduce supply chain visibility, highlighting the importance of data quality for reliable information flows.

As a foundational classification, (Wang & Strong, 1996) distinguish information quality into four categories: intrinsic, contextual, representational, and accessibility quality. Table 1 summarizes these categories and their key dimensions.

Accordingly, Information Quality Theory provides the basis for proposing that improvements in technical, semantic, and governance-related data quality enhance AI analytical effectiveness. In the proposed framework, data quality represents a foundational condition for effective AI systems.

Essentially, Information Quality Theory emphasizes that high-quality data are fundamental to effective AI analytics. Machine learning algorithms can generate accurate predictions, detect anomalies, and provide real-time insights only when they rely on well-structured, consistent, and reliable datasets. Poor data quality can therefore reduce AI performance, reliability, and transparency while increasing the risk of biased outputs.

Accordingly, this study considers data quality as a critical condition for AI analytical effectiveness in food supply chain traceability systems.

Table 1: the attributes used to measure and define quality

Category	Key Dimensions	Description
Intrinsic IQ	Accuracy, Objectivity, Believability, Reputation	The degree to which information is correct and trustworthy in itself.
Contextual IQ	Relevancy, Value-Added, Timeliness, Completeness, Appropriate Amount	The degree to which information is applicable and useful for the task at hand.
Representational IQ	Interpretability, Ease of Understanding, Concise Representation, Consistent Representation	The degree to which information is presented in a clear, unambiguous format.
Accessibility IQ	Accessibility, Access Security	The degree to which information is available and obtainable when needed.

Note: Frameworks vary. Other key dimensions include Consistency, Precision, and Usability.

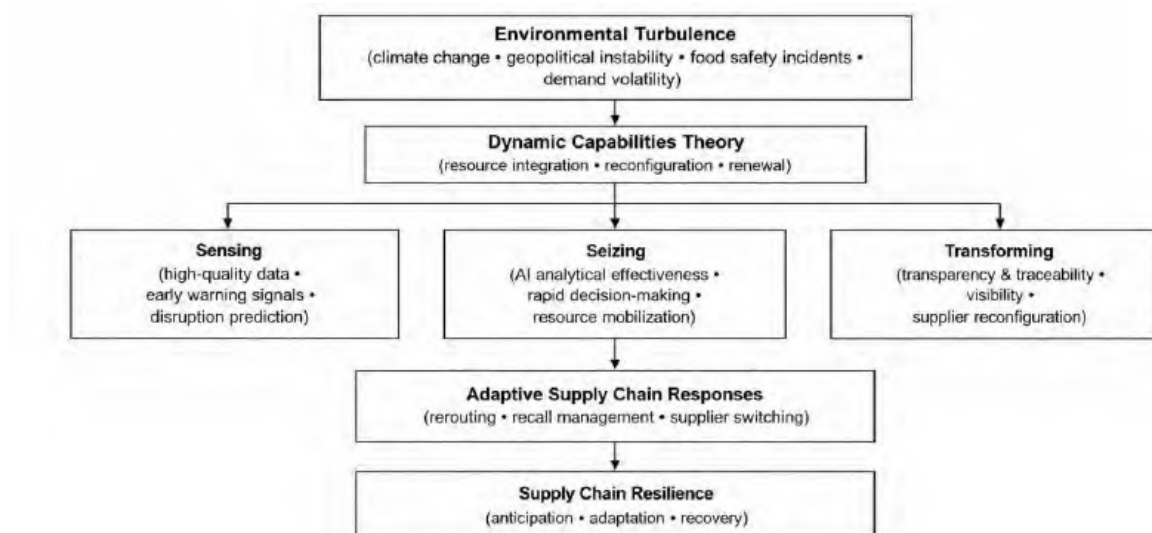
Source: Adapted from Wang and Strong (1996)

2.2. Dynamic Capabilities Theory: From AI-Enabled Information to Supply Chain Resilience

Another related view on how the use of AI-enabled information capabilities can contribute to supply chain resilience is the dynamic capabilities theory. Dynamic capabilities are an organization's ability to sense, seize, and reconfigure its resource endowments (Teece, 2007; Teece et al., 1997). A recent study adopts this view to digital supply chains and reports that Industry 4.0, AI, and blockchain are sources of digital supply chain resilience, through their contribution to sensing agility visibility, and resource reconfiguration capabilities (Dubey et al., 2023; Huang et al., 2023; Longo et al., 2024; Zhao et al., 2023).

The proposal suggests that AI efficacy could reinforce these abilities to analyze substantial quantity of supply chain information, discover patterns, identify abnormalities, produce forecasts, and make timely decisions. When AI-generated insights improve transparency and traceability, supply chain actors gain greater visibility into product flows, operations, and emerging disruptions. This enhanced visibility can support sensing, responding, and resource reconfiguration, which are central to dynamic capabilities and resilience (Huang et al., 2023; Longo et al., 2024).

Figure 1: AI-Enabled Traceability as a Dynamic Capability for Supply Chain Resilience



Source: By the Authors.

Accordingly, Dynamic Capabilities Theory helps explain the proposed relationship between AI-enabled transparency and traceability and supply chain resilience. Rather than assuming that AI automatically generates resilience, the framework views AI-enabled information capabilities

as mechanisms through which organizations strengthen their ability to sense disruptions, respond effectively, and adapt their resources. Recent empirical evidence further supports this perspective by linking AI use and digital capabilities to supply chain resilience through learning, innovation, agility, and adaptation (Ahmed et al., 2025; Pu et al., 2026).

Food supply chains are increasingly exposed to disruptions including climate change, geopolitical chaos, food safety scares, and uneven consumption behaviors (Hobbs, 2020; Ivanov, 2021; Ivanov & Dolgui, 2020). In such contexts, merely possessing static resources is not sufficient to ensure resilience (Christopher & Peck, 2004; Dubey et al., 2021). Dynamic Capabilities Theory therefore provides a useful framework for understanding the role of AI-enabled traceability systems in supporting supply chain activities related to sensing, seizing, and transforming (Bag et al., 2023; Teece et al., 1997; Wamba et al., 2020). AI's ability to detect early warning signals, forecast disruptions, and facilitate swift decision-making is significantly strengthened by high-quality data (Dwivedi et al., 2021; Hazen et al., 2014; Toorajipour et al., 2021). In addition, transparency and traceability enable firms to implement adaptive responses such as rerouting flows, managing recalls, and reconfiguring supplier networks, thereby enhancing supply chain responsiveness and resilience (Behnke & Janssen, 2020; Galvez et al., 2018; Ivanov & Dolgui, 2020; Rejeb et al., 2022).

2.3. Socio-technical Systems Theory: the organizational conditions of AI Effectiveness

Socio-Technical Systems (STS) Theory originates from the foundational work of (Trist & Bamforth, 1951) and was further developed through the contributions of (Emery, F. E., & Trist, E. L., 1960). The theory emphasizes that organizational performance relies on the joint improvement and interdependence of social and technical systems. Rather than viewing technology as the sole determinant, the STS perspective highlights the interaction between technological infrastructure, organizational structures, human actors, work processes, and broader contextual conditions.

This perspective applies mostly well to AI-enabled food supply chain traceability, where information is generated, communicated, and transferred across organizational- and system-outer boundaries. Without the essential processes, skills, governance, interoperability, and digital capabilities, sophisticated AI systems are unlikely to achieve effective transparency or traceability (Gillani et al., 2024; Mwangakala et al., 2024; Zhang, 2024).

In the proposed framework, STS Theory supports the role of digital maturity as a contextual condition. Higher digital maturity reflects stronger technological infrastructure, data-management capabilities, organizational routines, and employee competencies, which can facilitate the translation of AI capabilities into effective transparency and traceability outcomes (Gillani et al., 2024).

2.4. Resource-Based View: Data Quality as a Strategic Resource

The Resource-Based View (RBV) explains the strategic value of data quality by considering resources that are valuable, rare, difficult to imitate, and well supported (Barney, 1991). In digital supply chains, data availability alone does not create competitive advantage; its value depends on quality, accessibility, governance, and the organization's ability to exploit it. Recent research confirms that data-related resource quality is important for developing analytics capabilities and improving organizational performance.

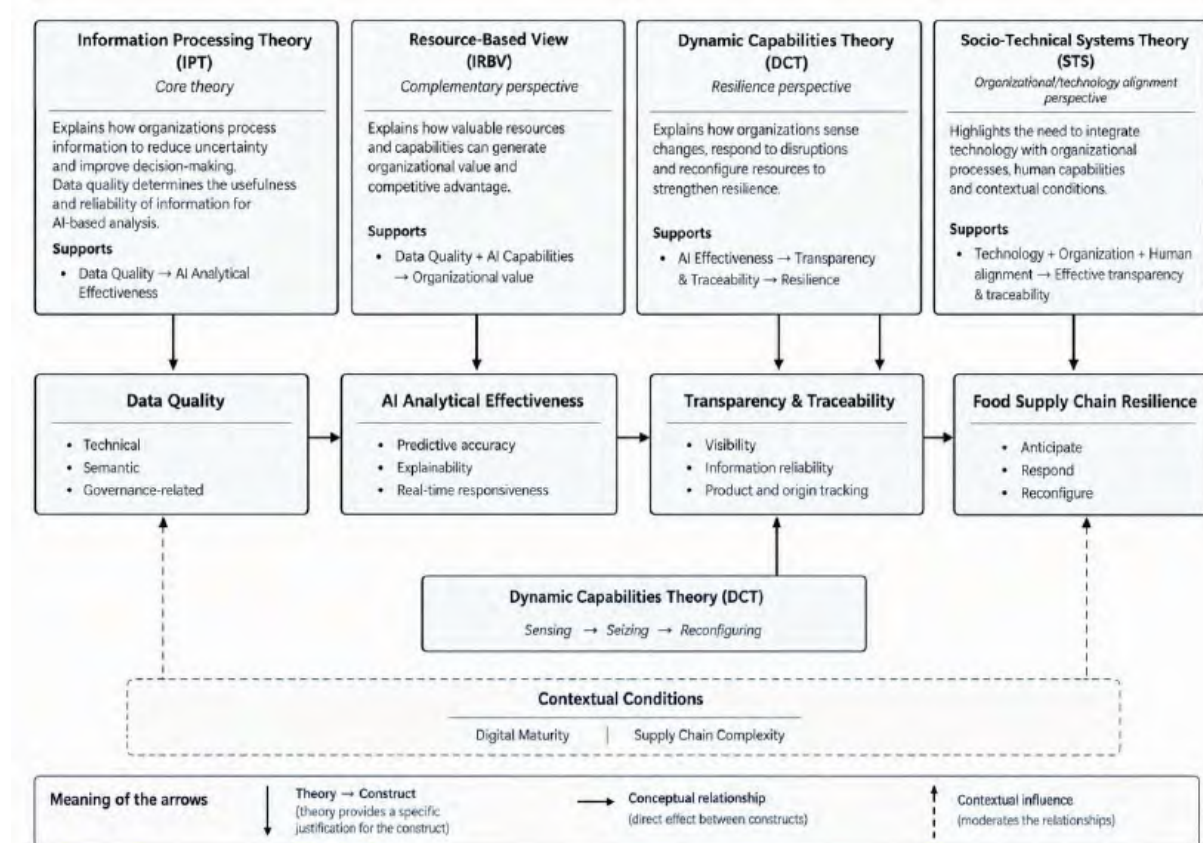
High-quality supply chain data can therefore become a strategic resource when organizations can effectively manage, integrate, and exploit it. AI strengthens this capability by transforming data into predictions, decision support, and recommendations. Recent studies applying RBV show that AI capabilities can enhance supply chain decision-making and process performance (Jackson et al., 2024), while data-driven analytics can strengthen innovation and competitive advantage in food supply chains (Kumar et al., 2024).

Thus, RBV complements Information Quality Theory by extending the role of data quality beyond technical performance to its strategic value. It helps explain how high-quality data, combined with AI and organizational capabilities, can generate valuable supply chain outcomes.

2.5. Theoretical Integration

The four theories provide complementary perspectives for explaining the relationships proposed in the conceptual model. Information Quality Theory provides the primary foundation by explaining how data quality influences the reliability and effectiveness of AI-driven analytics (Jabbar et al., 2025; Wang & Strong, 1996), while the Resource-Based View gives an extension by representing how value can be gained from high quality data when accompanied by resources and capabilities (Barney, 1991; Kumar et al., 2024). Dynamic Capabilities Theory explains how AI-enabled analytical capabilities can help organizations sense changes, respond to disruptions, and reconfigure resources to strengthen supply chain resilience (Pu et al., 2026; Teece, 2007). Socio-Technical Systems Theory further highlights the importance of integrating technology with organizational processes, human capabilities, and contextual conditions to achieve effective transparency and traceability (Gillani et al., 2024).

Figure 2: Theoretical Integration of the Conceptual Model

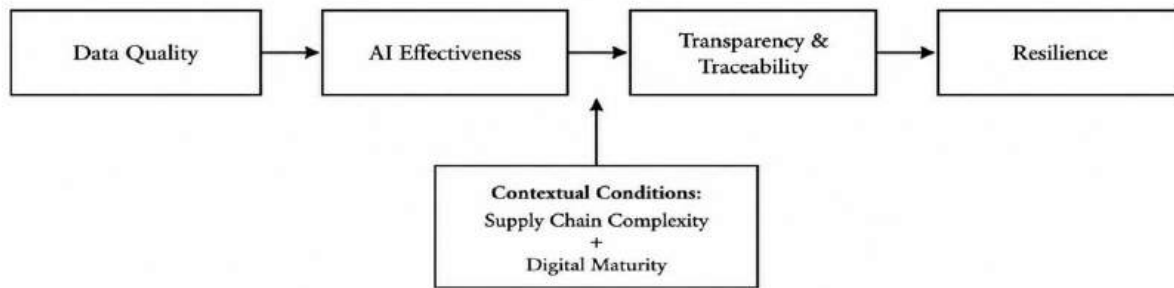


Source: By the Authors.

Basically, these perspectives suggest a stepwise theoretical logic: first, the quality of supply chain data forms the foundation for improved AI analytics; second, effective AI converts supply chain data into valuable information and greater visibility; third, increased transparency and traceability support the identification, diagnosis, and management of disruptions. Yet, achieving these advantages may be limited by factors like digital maturity and the complexity of the supply chain.

The resulting theoretical logic can be therefore stated like this:

Figure 3: conceptual framework of the study



Source: By the Authors.

3. Data Quality Dimensions in Food Supply Chain Traceability

Data quality is a critical foundation for effective traceability in food supply chains, where accurate and reliable information is required to monitor products, processes, and transactions across multiple stages. This section examines the main dimensions of data quality and their relevance to ensuring reliable and effective food supply chain traceability.

3.1. Defining Data Quality

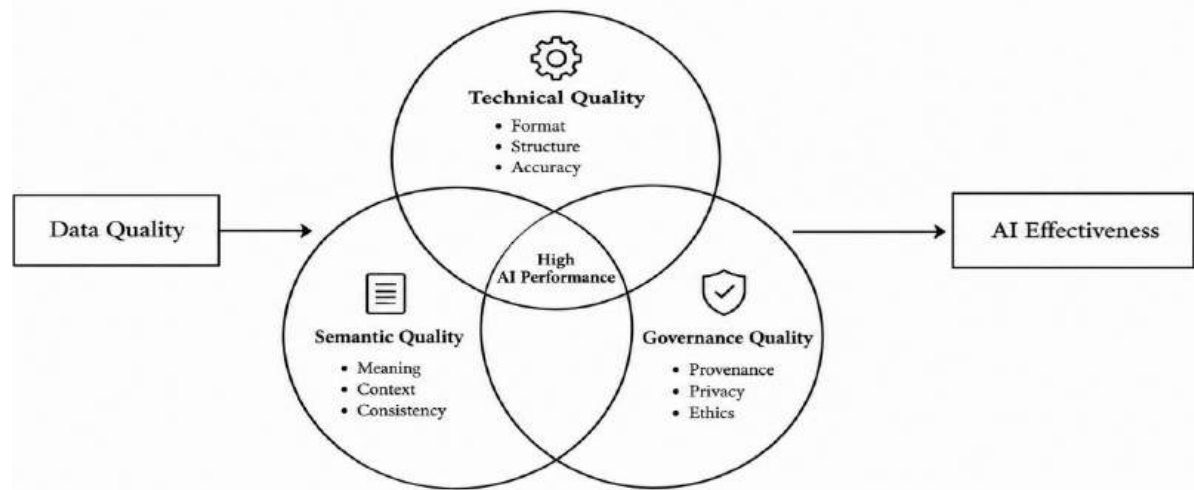
Data quality refers to the extent to which data are fit for their intended use. It is a multidimensional and context-dependent concept, as its relevance depends on how information is collected, managed, and used (Batini & Scannapieco, 2016; Y. W. Lee et al., 2002; Wang & Strong, 1996). This perspective becomes even more relevant in supply chains, in which several actors depend on shared data flows for their value chain operations, performance monitoring, prediction, and decision making. More recently, cross-organizational variety, semantic inconsistencies, and data-origin issues have been identified as potentially the greatest challenges for AI-enabled supply chains (X. Zhu et al., 2025).

Within food supply chains, data quality is critical for traceability as product flows and processes need to be captured correctly and transmitted between multiple stakeholders. Data flows can be connected through IoT, enterprise systems, certification systems, blockchain implementations, manual data entry, and many other sources of data, leading to challenges with data accuracy, quality, validity, interoperability, and standardization. Recent researches point to the importance of systems interoperability and harmonized data for digital food traceability (Gottschald, 2024).

From an AI perspective, data quality is a foundation for analytical effectiveness. Missing, inconsistent, delayed, or ambiguous data can reduce the reliability of AI-generated predictions and decisions. Recent supply chain research similarly identifies data quality, governance, and integration as key conditions for effective AI implementation (Cohen et al., 2026; X. Zhu et al., 2025).

Accordingly, this study conceptualizes data quality as a multidimensional construct comprising technical, semantic, and governance-related data quality. This approach reflects the need for technically reliable data, shared meanings across supply chain actors, and governance mechanisms that support data integrity, accountability, and trustworthiness.

Figure 4: From Data Quality to AI Effectiveness: A Three-Dimensional Framework



Source: By the Authors.

Figure 4 shows data quality across three related dimensions: technical, semantic, and governance quality. Technical quality supports data processing by providing suitable formats and structures. Semantic quality maintains consistent understanding of meaning and context. Governance quality builds trust through controls on origin, privacy, and ethics. These dimensions together expand on the GIGO principle, illustrating how gaps in data quality can result in AI outputs that are inaccurate, unclear, or not trusted. For effective AI in supply chains, all three dimensions must be addressed, positioning data quality as a key thing in AI performance.

Table 2: Distinctive Criteria of Data Quality Dimensions

Dimension	Core question	Main focus	Examples of indicators	Role in interoperability
Technical	Can the data be processed and exchanged?	Data structure, format, accuracy, completeness, timeliness	Format compatibility, data completeness, error rate, processing time	Technical interoperability: enables systems to exchange and process data
Semantic	Do actors interpret the data in the same way?	Meaning, definitions, classifications, context	Common vocabulary, standardized definitions, unit consistency, classification consistency	Semantic interoperability: enables consistent interpretation of data
Governance-related	Can the data be trusted and properly controlled?	Ownership, provenance, access, accountability, compliance	Data ownership, access controls, audit trails, provenance, validation rules	Supports trustworthy data exchange but is not itself interoperability

Source: Authors' conceptualization based on Batini and Scannapieco (2016), Wang and Strong (1996), and relevant supply chain traceability literature.

To clarify the conceptual boundaries between the three dimensions, this study distinguishes the type of data quality problem addressed by each dimension. Technical data quality concerns whether data can be processed and exchanged across systems; semantic data quality concerns whether the meaning of data is consistently understood across actors; and governance-related data quality concerns whether data are properly controlled, documented, authorized, and trusted. Accordingly, interoperability is considered primarily a technical and semantic issue, but with different meanings: technical interoperability enables system-to-system exchange, whereas semantic interoperability enables consistent interpretation. Governance quality does

not refer to interoperability itself, but to the rules and mechanisms that ensure data ownership, provenance, access, accountability, and compliance.

3.2. Technical data quality

Technical data quality refers to the structural and operational characteristics that enable data to be accurately processed, exchanged, and integrated across digital systems. Key attributes include accuracy, completeness, consistency, timeliness, format compatibility, and system-level interoperability (Batini & Scannapieco, 2016; Y. W. Lee et al., 2002; Wang & Strong, 1996). In this study, technical interoperability specifically refers to the ability of heterogeneous systems to exchange and process data through compatible formats, interfaces, and structures. Recent research shows that data sparseness can also reduce supply chain visibility (van Schilt et al., 2024). In this study, technical interoperability specifically refers to the ability of heterogeneous systems to exchange and process data through compatible formats, interfaces, and structures.

In food supply chains, traceability data come from IoT sensors, enterprise systems, certification records, blockchain platforms, and manual inputs. Such heterogeneity can create technical problems, including incompatible formats, missing or delayed data, inconsistencies, and limited interoperability. These issues can restrict information availability and hinder end-to-end traceability (Farina et al., 2025; Powell et al., 2022).

Technical data quality is therefore essential to AI effectiveness. Complete, accurate, consistent, and timely data enable AI systems to identify patterns, detect anomalies, generate predictions, and support timely decisions. Missing or delayed data may reduce analytical reliability, while poor interoperability can limit data integration for traceability (Farina et al., 2025).

Accordingly, technical data quality provides a computational foundation for effective AI processing. Higher technical data quality should therefore enhance AI analytical effectiveness in food supply chain traceability.

3.3. Semantic data quality

Semantic data quality is concerned with the data's fitness for interpretation, meaning, and usage by different interested parties and systems. Technical interoperability is simply the ability of two or more systems to transfer and receive data, while semantic interoperability refers to the synchronized interpretation of data. This way two systems may be technically interoperable and interpret a product, unit, classification, or event in a different manner, leading to semantic misinterpretation. This aspect of semantic interoperability is key in inter-organizational supply chains, where data may be technically accurate and still be misinterpreted due to differences in the definition, classification, or situation (Batini & Scannapieco, 2016; Wang & Strong, 1996). Various actors and systems across food supply chains produce data about products origins quality classes certifications measurement units, and regulatory requirements. Differences in terminology and classification can create semantic inconsistencies and hinder information sharing. Recent research highlights the importance of harmonized data and semantic interoperability for effective food traceability (Gottschald, 2024).

These issues can be addressed through sectoral traceability standards, which specify how the data are to be captured, maintained, and shared between organizations. The GS1 Global Traceability Standard uses Critical Tracking Events (CTEs) and Key Data Elements (KDEs) to structure the traceability information between supply-chain actors. GS1 EPCIS and the Core Business Vocabulary (CBV) represent the formalizing of this information exchange and a standardized 'language' for sharing event data and the business context from the different actors. The Global Dialogue on Seafood Traceability (GDST) builds on this architecture by defining the set of standardized KDEs and CTEs in seafood and the required formats for encoding and

sharing these data electronically. These standards illustrate how shared identifiers, vocabularies, and data definitions can reduce semantic ambiguity across organizations.

Semantic consistency is also essential for AI effectiveness because AI systems must correctly interpret relationships and patterns across heterogeneous data. Inconsistent meanings may lead to incorrect associations, classification errors, or unreliable predictions. Shared vocabularies, standardized classifications, and ontologies can therefore support semantic interoperability and improve AI-enabled traceability and decision-making (Xhani et al., 2025).

Accordingly, semantic data quality provides an interpretive foundation for AI analytical effectiveness by enabling consistent integration and interpretation of supply chain information.

3.4. Governance-related data quality

Governance-related data quality concerns the organizational conditions that ensure data are properly created, validated, controlled, shared, and maintained. While technical quality concerns whether data can be processed and semantic quality whether they are consistently interpreted, governance quality focuses on their provenance, accountability, access, and responsible management (Abraham et al., 2019; Khatri & Brown, 2010).

Data sharing in the food supply chain involves the producers, logistics providers, certification bodies, wholesalers, and the retailers, which raises issues of ownership access validation accountability auditability, and compliance with regulations. Because of this, governance in the form of ownership rules, validation procedures, access rules, audit mechanisms, and accountability structures could improve the reliability of the data for the purposes of supply chain traceability. Recent evidence showed that a digital food traceability system needs proper governance, data sharing arrangements, interoperability, and trusted data management across organizational boundaries (Farina et al., 2025).

Governance-related data quality also influences AI effectiveness because AI systems depend on data that are reliable, traceable, and appropriately managed. Weak provenance or validation can reduce confidence in AI outputs, whereas strong governance can facilitate trustworthy data sharing and support more reliable AI-based analysis (Charlebois et al., 2024; Dwivedi et al., 2021).

Accordingly, governance-related data quality provides the organizational and institutional foundation for reliable AI-enabled traceability. Together, technical, semantic, and governance dimensions ensure that data are processable, interpretable, and trustworthy, providing a comprehensive foundation for AI analytical effectiveness.

4. Artificial Intelligence Effectiveness in Traceability Systems

AI analytical effectiveness refers to AI's ability to transform data into accurate, interpretable, and timely insights that support decision-making. It differs from AI adoption, which concerns implementation rather than the quality and usefulness of AI outputs (Culot et al., 2024; Min, 2010; Toorajipour et al., 2021).

In food supply chains, AI supports forecasting, anomaly detection, quality monitoring, risk assessment, and disruption prediction through machine learning, predictive analytics, and real-time processing (Baryannis et al., 2019; Culot et al., 2024; Teixeira et al., 2025). Its effectiveness, however, depends strongly on data quality, as inaccurate, incomplete, inconsistent, or outdated data can reduce analytical reliability (Hazen et al., 2014; Kache & Seuring, 2017).

Accordingly, this study conceptualizes AI analytical effectiveness through predictive accuracy, interpretability, and real-time responsiveness, reflecting AI's ability to generate reliable, understandable, and timely outputs (Samuels, 2025; Teixeira et al., 2025).

4.1. Predictive accuracy

Predictive accuracy refers to the ability of an artificial intelligence system to generate predictions that closely correspond to observed conditions or future outcomes. In supply chain management, predictive analytics is increasingly used to anticipate fluctuations in demand, operational disruptions, product quality issues, and supplier-related risks. Machine learning and predictive models therefore support risk identification, forecasting, and data-driven decision-making by enabling organizations to detect potential problems and respond proactively. (Baryannis et al., 2019; Toorajipour et al., 2021), with recent research confirming their growing role in supply chain applications (Culot et al., 2024).

In the food supply chains, predictive accuracy makes a difference in demand forecasting, disruption prediction, quality monitoring, contamination-risk detection, and inventory planning. Recent studies demonstrate an increasing reliance on AI-based analytics to support improvements in decision-making, risk management, and resilience (Samuels, 2025; Teixeira et al., 2025). Yet, a reliable prediction is largely determined by the data quality, because data that is incomplete inaccurate inconsistent, or biased may undermine the model accuracy and reliability of a decision (Hazen et al., 2014; Sivarajah et al., 2017).

Thus, in the proposed framework, predictive accuracy represents the analytical dimension of AI effectiveness, reflecting the ability of AI to transform supply chain data into reliable predictions for operational decision-making and risk management.

4.2. Explainability

Explainability is how far a user can comprehend, interpret, and justify an AI system's outputs. Previous work in the field of explainable AI has focused on making algorithms interpretable, providing transparency, and showing human users complex algorithmic decisions (Adadi & Berrada, 2018; Barredo Arrieta et al., 2020). More recently, studies on AI in supply chain management suggest that explainable AI is becoming more important and relevant with the broader use of AI in decision support and the demand from organizations for transparency and accountability in AI support operations (Teixeira et al., 2025).

Explainability matters a lot in food supply chains since AI systems support decision-making related to food safety, quality assurance, supplier evaluation, risk identification, and compliance with rules and regulations. If those making the decisions can't get a clear answer as to why AI made a decision that has an impact on them they could end up not trusting it at all. Explainable AI is an approach which allows AI decisions to be explained and so the decision-making process to be understood and controlled so we know who is responsible for the outcome (Barredo Arrieta et al., 2020). This is increasingly becoming more important as supply chains adopt AI solutions, in particular in the more integrated or human-centric ways of AI adoption that keep people in the loop for interpreting and acting on decisions coming from the AI (Samuels, 2025).

Within the proposed framework, explainability represents the interpretive and accountability dimension of AI effectiveness. It should not be equated with supply chain transparency itself. Rather, explainable AI may facilitate the interpretation and communication of AI-generated information and thereby create conditions that support transparency and traceability.

4.3. Real-time responsiveness

Real-time responsiveness refers to the ability of AI-enabled systems to process continuously changing information and generate outputs quickly enough to support effective supply chain responses. This capability is particularly important in food supply chains, where perishability, transportation conditions, quality deviations, and food safety incidents require rapid intervention.

The growing use of IoT devices, connected systems, and real-time data streams enables AI to continuously monitor supply chain conditions and detect anomalies or emerging risks (Ben-Daya et al., 2019; Kache & Seuring, 2017). Recent studies confirm the increasing use of real-time data processing and predictive capabilities to improve supply chain decision-making and responsiveness (Culot et al., 2024; Samuels, 2025).

In food supply chains, real-time responsiveness supports monitoring temperature, shipment status, inventory, quality deviations, and potential disruptions. However, its effectiveness depends not only on computational capabilities but also on the timeliness, accessibility, interoperability, and completeness of data, creating a direct link between data quality and AI effectiveness.

Effective AI outputs can enhance monitoring, anomaly detection, risk identification, and decision-making across supply chain stages, thereby improving information visibility and product traceability (Culot et al., 2024; Samuels, 2025; Teixeira et al., 2025). Thus, AI effectiveness is conceptualized as a mediating mechanism between data quality and supply chain transparency and traceability.

Table 3: Indicative Measurement Dimensions and Items for AI Analytical Effectiveness

Dimension	Quantitative indicators	Measurement	Perceptuel indicators	Likert scale
Predictive Accuracy	Prediction accuracy	% correct predictions	AI provides accurate predictions.	1–5
	Forecast error	Mean Absolute Error / Root Mean Square Error (%)	AI predictions are consistent with actual outcomes.	1–5
	—	—	AI forecasts support reliable decisions.	1–5
Explainability	Explainable outputs	% of outputs with explanations	AI outputs are understandable to decision-makers.	1–5
	Explanation time	Average time to interpret an output	The reasons behind AI recommendations can be understood.	1–5
	—	—	AI outputs provide sufficient information to justify decisions.	1–5
Real-Time Responsiveness	Processing time	Average seconds/minutes	AI processes supply chain data promptly.	1–5
	Detection latency	Average time between event and detection	AI rapidly detects emerging events and anomalies.	1–5
	Data-to-decision time	Average time from data capture to actionable output	AI provides information quickly enough for operational decisions.	1–5

Note: Quantitative indicators can be obtained from AI, ERP, IoT, or traceability-system records. Perceptuel indicators can be measured using a five-point Likert scale (1 = strongly disagree; 5 = strongly agree). The proposed indicators are indicative and should be refined and validated empirically.

Source: By the Authors.

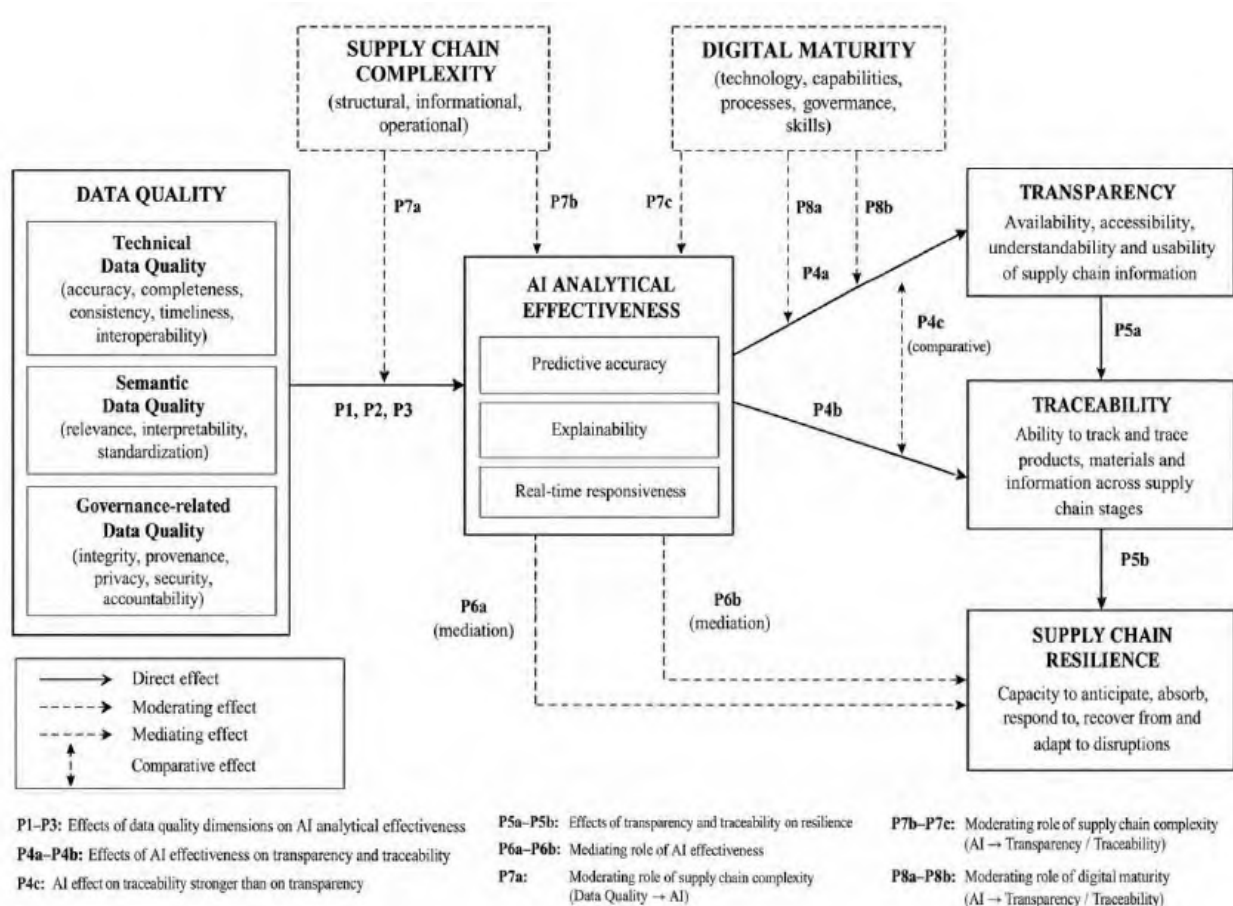
To facilitate the empirical operationalization of AI analytical effectiveness, the three dimensions identified above: predictive accuracy, explainability, and real-time responsiveness can be assessed using both objective and perceptual indicators. Objective measures capture the observable performance of AI systems, whereas perceptual measures reflect users' assessments of their effectiveness in practice. Table X summarizes the proposed indicators and measurement approaches, providing a basis for their future empirical testing and validation.

5. Conceptual framework and Research Propositions

Building on the theoretical constructs and relationships established in the sections above, the

paper proposes a conceptual model that presents the relationship between data quality, AI-based analytical effectiveness, transparency, traceability, and food supply chain resilience. The conceptual model also presents the moderating effect of supply chain complexity and digital maturity. The overall research structure is summarized in Figure 3 to support the formulation of research propositions.

Figure 5: Conceptual frame work proposition



Source: By the authors

Figure 5 summarizes the conceptual framework developed in this study. It proposes that technical, semantic, and governance-related data quality influence AI analytical effectiveness, which in turn enhances supply chain transparency and traceability. These outcomes are expected to strengthen supply chain resilience, while supply chain complexity and digital maturity act as contextual moderators.

5.1. Data Quality and AI Effectiveness

The proposed framework assumes that the effectiveness of AI in food supply chain traceability depends on the quality of the data processed by AI systems. Technical, semantic, and governance-related issues of data quality so form the basis of getting AI to deliver outputs that are not only accurate and interpretable, but also timely and fit for purposes like decision making (Culot et al., 2024; Mikalef & Gupta, 2021). New studies show that data and technology requirements will still remain the main criteria that determine the successful deployment of AI in supply chains (Culot et al., 2024; Mikalef & Gupta, 2021).

In food supply chains, this relationship is particularly important because data are generated by multiple actors, systems, and technologies. Recent reviews highlight that interoperability, data

integration, technological readiness, and data reliability remain major challenges for digital traceability systems (Bekkouche & de-Magistris, 2025; Vasileiou et al., 2026).

P1: *Technical data quality positively influences AI analytical effectiveness.*

P2: *Semantic data quality positively influences AI analytical effectiveness.*

P3: *Governance-related data quality positively influences AI analytical effectiveness.*

5.2. AI Effectiveness and Transparency

One of the ways AI helps increase supply chain transparency is by converting heterogeneous supply chain data into an accessible, timely, and interpretable form. For instance, for food supply chains, AI-powered insights can aid in surveillance, flagging irregularities, identifying risks, and providing updates to various participants across the supply chain. Some recent papers indicate that AI and related digital technologies are playing a significant role in increasing information visibility and transparency on food production and supply lines (Bekkouche & de-Magistris, 2025; Culot et al., 2024).

Even with these benefits, the fact is that AI doesn't lead to transparency automatically. What it can bring about will, in part, depend on the quality of data that goes in the AI processing and the level of interpretation and utilization skills possessed by the various stakeholders. So, the recent scholarly works underline the importance of technical integration, interoperability, and organizational capabilities as key prerequisites to fully realize the benefits of transparency offered by digitally transparent supply chains (Vasileiou et al., 2026).

P4a: *AI analytical effectiveness positively influences food supply chain transparency.*

5.3. AI Effectiveness and Traceability

AI can strengthen food supply chain traceability by supporting the identification, monitoring, and analysis of products and related information across supply chain stages. Recent research highlights the growing integration of AI with IoT, blockchain, and other digital technologies to support end-to-end traceability, food safety, and quality monitoring (Rossi et al., 2025; Vasileiou et al., 2026).

AI enabled systems can also enable anomaly detection, predictive monitoring and real-time analysis of information related to supply chains. A recent review on the application of machine learning in food industry indicates that the most prominent applications are traceability transparency quality control and real-time monitoring, while identifying data availability and system integration as challenges.

P4b: *AI analytical effectiveness positively influences food supply chain traceability.*

5.4. Comparative Effect of AI Analytical Effectiveness on Transparency and Traceability

Although AI analytical effectiveness is expected to enhance both transparency and traceability, the strength of these effects may differ because the two constructs represent distinct outcomes. AI can directly support traceability by processing identification, movement, transaction, and event-related data, detecting anomalies, and linking information across supply chain stages. Transparency, in contrast, depends not only on the generation and processing of information but also on its accessibility, disclosure, and sharing among relevant stakeholders. Consequently, the effect of AI analytical effectiveness may be more direct and pronounced for traceability than for transparency.

P4c: *The effect of AI analytical effectiveness on supply chain traceability is stronger than its effect on supply chain transparency.*

5.5. Transparency and Traceability as Distinct Outcomes

Despite in reality transparency and traceability are highly interrelated, they can be considered as different supply chain functionalities. Traceability is mainly about the capability to trace

products with relevant information to supply chain tiers whereas transparency refers mainly to whether this information is available, understandable and accessible to key stakeholders. Recent reviews related to food supply chains show that traceability and transparency continue to be portrayed as related but separable features of digitalization (Bekkouche & de-Magistris, 2025; Vasileiou et al., 2026).

In line with that, this study sees transparency and traceability as two AI-derived analytical effectiveness outcomes that are complementary yet distinct, instead of combining them into a unified construct.

5.6. Transparency, Traceability and Resilience

Transparency and traceability can contribute to food supply chain resilience by improving visibility, reducing information asymmetry, and enabling earlier detection of disruptions. Better access to information can facilitate coordination and support faster responses to food safety incidents, quality problems, supply disruptions, and recall situations. Recent studies associate digital traceability with improved food safety, information flows, and supply chain coordination (Bekkouche & de-Magistris, 2025; Vasileiou et al., 2026).

These features can make a real difference when it comes to large, complicated food supply chains where the disruptions can spread quickly across a group of different actors. AI-driven monitoring and predictive analytics may help reinforce this capability (Culot et al., 2024; Rossi et al., 2025). Using them as a tool, organizations can pinpoint the risks as they arise, and react faster.

P5a: *Food supply chain transparency positively influences supply chain resilience.*

P5b: *Food supply chain traceability positively influences supply chain resilience.*

5.7. Mediating Role of AI Effectiveness

Data quality is not expected to improve transparency and traceability automatically. Rather, AI analytical effectiveness provides a mechanism through which high-quality data can be transformed into useful analytical outputs. Recent research on AI in supply chain management emphasizes that the value of AI depends on the quality of underlying data, technological integration, and organizational capabilities (Culot et al., 2024).

Thus, accurate, consistent, meaningful, and well-governed data can enhance the ability of AI systems to generate reliable predictions, interpretable outputs, and timely responses. These outputs can subsequently improve supply chain visibility and traceability. AI effectiveness is therefore proposed as a mediator between data quality and transparency and traceability.

P6a: *AI analytical effectiveness mediates the relationship between data quality and transparency.*

P6b: *AI analytical effectiveness mediates the relationship between data quality and traceability.*

5.8. Moderating Role of Supply Chain Complexity

Complexity of the supply chain may impact AI effectiveness and the capacity of AI systems to deliver transparency and traceability outcomes. Food supply chains involve multiple stakeholders, products, geographical locations, information systems, and organizational processes, which increase the volume, diversity, and interdependence of data that must be processed and integrated. Recent studies identify multi-party structures, information diversity, and interoperability challenges as important obstacles to effective digital traceability (Bekkouche & de-Magistris, 2025; Vasileiou et al., 2026). From the Socio-Technical Systems perspective, a more complex supply chain has a higher interdependence among technological systems, organizational procedures, and actors. As a result, the quality of data might become more relevant as more information comes from diverse and integrated sources that a system

would need to work with. Higher complexity may therefore strengthen the importance of data quality for AI analytical effectiveness.

P7a: *Supply chain complexity moderates the relationship between data quality and AI analytical effectiveness, such that the relationship is stronger under higher levels of supply chain complexity.*

However, complexity may also affect how effectively AI-generated insights are translated into transparency and traceability. In highly complex supply chains, information must pass through more organizational boundaries, systems, processes, and stakeholders. Although effective AI can produce relevant and timely information, turning these outputs into transparent information flows and reliable traceability can become more difficult as coordination and interoperability requirements increase. Thus, supply chain complexity may condition the extent to which AI analytical effectiveness translates into transparency and traceability outcomes.

P7b: *Supply chain complexity moderates the relationship between AI analytical effectiveness and supply chain transparency, such that the relationship varies with the level of supply chain complexity.*

P7c: *Supply chain complexity moderates the relationship between AI analytical effectiveness and supply chain traceability, such that the relationship varies with the level of supply chain complexity.*

5.9. Moderating Role of Digital Maturity

Digital maturity represents an organization's ability to integrate digital technologies, data, skills, processes, and governance mechanisms into its operations. The latest research on AI in supply chain management demonstrates that effective AI use is contingent upon technological, organizational, environmental, and human factors not just technology.

Organizations with higher levels of digital maturity will presumably be more capable of incorporating AI outputs into making decisions and passing information to other parts of the supply chain. Digital maturity may therefore strengthen the contribution of AI effectiveness to supply chain transparency and traceability.

Consistent with a Resource-Based View perspective, digital maturity levels also reveal the extent to which an organization is capable of using and integrating technological and organizational resources. Existing research shows that digital infrastructure, data-management abilities, human skills, and digital routines could enable firms' ability to achieve operational capabilities and value creation from AI-generated outputs (Barney, 1991; Teece et al., 1997). Accordingly, organizations with higher levels of digital maturity may be better positioned to convert AI analytical effectiveness into effective transparency and traceability. The Socio-Technical Systems perspective complements this view by emphasizing the alignment of digital technologies with organizational processes, skills, and human actors. Digital maturity therefore provides both a resource-based and socio-technical foundation for the proposed moderating relationships.

P8a: *Digital maturity positively moderates the relationship between AI analytical effectiveness and transparency.*

P8b: *Digital maturity positively moderates the relationship between AI analytical effectiveness and traceability.*

The preceding discussion led to research propositions addressing data quality, AI analytical effectiveness, transparency and traceability, and supply chain resilience. Together, these propositions provide the theoretical foundation for the conceptual model and explain how AI-enabled capabilities can create value in food supply chains. The model also considers contextual factors that may influence the strength of these relationships. Table 4 summarizes the research propositions, while Table 5 presents their theoretical foundations and main explanatory mechanisms.

Table 4: Summary of Research Propositions

Proposition	Proposed Relationship
P1	Technical Data Quality → AI Analytical Effectiveness
P2	Semantic Data Quality → AI Analytical Effectiveness
P3	Governance-related Data Quality → AI Analytical Effectiveness
P4a	AI Analytical Effectiveness → Food Supply Chain Transparency
P4b	AI Analytical Effectiveness → Food Supply Chain Traceability
P4c	AI Analytical Effectiveness → Traceability stronger than → Transparency
P5a	Food Supply Chain Transparency → Supply Chain Resilience
P5b	Food Supply Chain Traceability → Supply Chain Resilience
P6a	Data Quality → AI Analytical Effectiveness → Transparency
P6b	Data Quality → AI Analytical Effectiveness → Traceability
P7a	Supply Chain Complexity moderates Data Quality → AI Analytical Effectiveness
P7b	Supply Chain Complexity moderates AI Analytical Effectiveness → Transparency
P7c	Supply Chain Complexity moderates AI Analytical Effectiveness → Traceability
P8a	Digital Maturity moderates AI Analytical Effectiveness → Transparency
P8b	Digital Maturity moderates AI Analytical Effectiveness → Traceability

Source: Author's conceptualization.

Table 5: Theoretical Bases of the Research Propositions

Proposition	Proposed Relationship	Theoretical basis
P1	Technical Data Quality → AI Analytical Effectiveness	Information Quality Theory
P2	Semantic Data Quality → AI Analytical Effectiveness	Information Quality Theory; Socio-Technical Systems Theory
P3	Governance-related Data Quality → AI Analytical Effectiveness	Information Quality Theory; Socio-Technical Systems Theory
P4a	AI Analytical Effectiveness → Food Supply Chain Transparency	Dynamic Capabilities Theory
P4b	AI Analytical Effectiveness → Food Supply Chain Traceability	Dynamic Capabilities Theory
P4c	AI Analytical Effectiveness → Traceability stronger than → Transparency	Dynamic Capabilities Theory
P5a	Food Supply Chain Transparency → Supply Chain Resilience	Dynamic Capabilities Theory
P5b	Food Supply Chain Traceability → Supply Chain Resilience	Dynamic Capabilities Theory
P6a	Data Quality → AI Analytical Effectiveness → Transparency	Information Quality Theory; Dynamic Capabilities Theory
P6b	Data Quality → AI Analytical Effectiveness → Traceability	Information Quality Theory; Dynamic Capabilities Theory
P7a	Supply Chain Complexity moderates Data Quality → AI Analytical Effectiveness	Socio-Technical Systems Theory
P7b	Supply Chain Complexity moderates AI Analytical Effectiveness → Transparency	Socio-Technical Systems Theory
P7c	Supply Chain Complexity moderates AI Analytical Effectiveness → Traceability	Socio-Technical Systems Theory
P8a	Digital Maturity moderates AI Analytical Effectiveness → Transparency	Resource-Based View; Socio-Technical Systems Theory
P8b	Digital Maturity moderates AI Analytical Effectiveness → Traceability	Resource-Based View; Socio-Technical Systems Theory

Source: Author's conceptualization.

In table 4, we have gathered all the research proposals mentioned in this paper and identified the logical relationships among them. These research proposals, in a way, outline the complex chain of different data quality dimensions which most of the time work as the indicator that AI analytics are more efficient, Because of this leading to better transparency and traceability performance, and finally supply chains with enhanced resilience. Besides, the paper has also

considered the influence of environmental factors by including supply chain complexity and digital maturity as the two moderating variables. Ultimately, the chain of propositions suggested here lays down a solid ground for understanding how data capabilities empowered by AI can contribute to the enhancement of transparency, traceability, and resilience in the food supply chains.

Table 5 simultaneously reveals the theoretical bases of the research propositions and illustrates the ways the proposed relationships operate. The table indicates that the research structure is based on many different yet complementary theories which collectively depict the relationships among data quality, artificial intelligence transparency traceability, and resilience in food supply chains.

6. Discussion and Contributions

The research proposes an integrative model outlining how technical, semantic, and governance aspects of data quality influence the effectiveness of AI analytical capabilities and how capabilities generated by AI may support transparency, traceability, and food supply chain resilience. The framework further recognizes that these relationships are context-dependent by incorporating supply chain complexity and digital maturity as moderating conditions. The proposed relationships are summarized in 15 propositions covering direct, comparative, mediating, and moderating effects. Recent research similarly highlights the growing role of AI, digital traceability, and integrated data technologies in strengthening food safety, traceability, and supply chain capabilities (Rossi et al., 2025; D. Xie et al., 2023).

6.1. Theoretical Contributions

This paper improves the knowledge of data quality in the Information Quality Theory literature. It moves from a single, overall information attribute to three distinct dimensions for AI-enabled food supply chains: technical quality, semantic quality, and governance-related quality. In theory, P1-P3 describe the three dimensions separately to lay the foundation of the theoretical model that P1-P3 contribute to AI analytical effectiveness: technical quality describes the processing and exchanging capabilities of data; semantic quality reflects the interpretation of data; the governance-related quality assures the trustworthiness and manageable access to data. That means, the setup illustrates that the value of data to AI is driven by its technical features, as well as its meaning and management. Such multidimensional data quality is mainly crucial in the food traceability when dealing with the mix of sources and the disconnection of sources of information (Rossi et al., 2025; Xie et al., 2025).

The study adds to the Dynamic Capabilities perspective by identifying AI analytical effectiveness as a mechanism thorough which data resources are converted into supply chain capabilities. Propositions P4a and P4b suggest that effective AI improves transparency and traceability, while P5a and P5b connect these information-based capabilities to supply chain resilience. Recent research also finds that AI and digital technologies can boost predictive abilities monitoring traceability, and responsiveness in food supply chains (Rossi et al., 2025; D. Xie et al., 2023). P6a and P6b further specify AI analytical effectiveness as a mediating mechanism through which data quality may contribute to transparency and traceability. P4c extends this reasoning by proposing a comparative difference between the effects of AI analytical effectiveness on traceability and transparency, providing a basis for examining whether these outcomes respond differently to AI capabilities.

The RBV and the STS perspective further include in the framework to explain the contextual differences in AI-enabled outcome. From the RBV perspective, digital maturity is an organizational capacity to synergize and use their technological, data, and people resources. The latest empirical study also considers digital maturity as a resource-based capability that enables the supply chain resilience by creating value with visibility flexibility risk mitigation,

and collaboration (e. g. research evidence from emerging-market supply chains). This evidence substantiates the hypotheses P8a and P8b, indicating that the digital maturity moderates the direct effects of the AI analytic effectiveness and its transparency and traceability. The Socio-Technical Systems (STS) perspective supports this hypothesis as it focuses on the co-evolution of technological system, work system, and people. The latest research combining the RBV and the STS perspective in supply chain literature highlighted the importance of applying AI capability to the human and organizational resources rather than deploying AI as an autonomous technological resource (Vann Yaroson et al., 2025).

Taken together, these theoretical contributions provide an integrated explanation of how data quality, AI capabilities, organizational resources, and supply chain conditions interact to support transparency, traceability, and resilience.

6.2. Methodological Contributions

The methodological contribution of the framework lies in specifying a testable structure that combines direct, mediating, comparative, and moderating relationships. P1- P3 establish the direct effects of the three data quality dimensions on AI analytical effectiveness. P4a- P4b and P5a-P5b specify the main structural relationships leading from AI effectiveness to transparency, traceability, and resilience, while P6a- P6b identify the proposed mediating role of AI analytical effectiveness. P4c introduces a comparative test between the effects of AI analytical effectiveness on transparency and traceability. Finally, P7a- P7c and P8a- P8b specify the moderating roles of supply chain complexity and digital maturity.

For future empirical validation, PLS-SEM is proposed as the primary analytical approach because the framework is relatively complex, includes mediation and moderation effects, and is intended to explain and predict endogenous constructs. PLS-SEM is particularly appropriate when the research model includes composite or formative specifications and has a prediction-oriented objective (Hair & Alamer, 2022). Recent supply chain research also demonstrates the use of PLS-SEM to empirically examine complex relationships involving AI, digital capabilities, and supply chain outcomes (Vann Yaroson et al., 2025).

However, the final choice of measurement specification should be determined empirically rather than assumed in advance. If the constructs are operationalized predominantly as reflective common factors and the main objective becomes theory confirmation and assessment of global model fit, covariance-based SEM (CB-SEM) may provide an appropriate alternative (Dash & Paul, 2021). Similarly, fuzzy-set qualitative comparative analysis (fsQCA) could (Vann Yaroson et al., 2025), SEM by examining asymmetric and configurational relationships, particularly where different combinations of data quality, AI effectiveness, complexity, and digital maturity may lead to similar resilience outcomes. The combined use of PLS-SEM and fsQCA has been proposed as a way of capturing both symmetric net effects and asymmetric configurations in management research.

The future sample size should also not be determined solely by the traditional “10-times rule.” Instead, an a priori power analysis should be conducted based on the most complex structural relationship, the expected effect size, significance level, statistical power, and number of predictors. This approach would provide a more rigorous basis for determining the minimum sample required for empirical testing. Thus, PLS-SEM is proposed as the primary method, while CB-SEM and fsQCA are recognized as alternative or complementary approaches depending on the final measurement model, research objective, and available sample.

6.3. Managerial Contributions

The proposed framework provides differentiated implications for actors according to their position in the food supply chain and their level of digital maturity. For producers, particularly organizations with lower digital maturity, priority should be given to establishing reliable data-

capture processes, standardized product and event information, basic interoperability, and data-governance mechanisms before expanding advanced AI applications. These recommendations directly relate to P1- P3 and P7a and are consistent with recent reviews showing that fragmented data, interoperability problems, and uneven technological readiness remain important challenges for digital food traceability (Rossi et al., 2025).

For logistics actors and distributors working at various steps of the supply chain, the key focus is to enable integration of heterogeneous information sources and to boost real-time exchange of information related to traceability. AI-enabled systems need to rest on common data architectures, defined information ownership, and infrastructure to interpret information across organizational borders. Recent research on AI-enabled food traceability similarly emphasizes the integration of AI with IoT, blockchain, and other digital technologies to improve monitoring, information integration, and traceability across the farm-to-table chain (M. Xie et al., 2025).

For organizations with higher digital maturity, managerial attention can shift toward advanced AI capabilities, including predictive analytics, explainable AI, and real-time responsiveness. Higher digital maturity may facilitate the combination of technological infrastructure, data capabilities, organizational processes, and employee skills required to transform AI outputs into transparency and traceability outcomes, as proposed in P8a and P8b. Recent research on AI-enabled supply chains also emphasizes that technological capabilities need to be combined with organizational and human capabilities to achieve effective outcomes (Vann Yaroson et al., 2025).

For regulatory and sectoral authorities, the framework highlights the importance of common traceability standards, interoperable data requirements, data-access rules, and auditable information practices. Such measures can reduce fragmentation between supply chain actors and facilitate more consistent information exchange. New research in agri-food traceability emphasizes the need for harmonized traceability mechanisms and data structures for enabling end-to-end visibility and accountability (Rossi et al., 2025).

Across all actor groups, the appropriate priorities may differ according to digital maturity and supply chain complexity. Less digitally mature organizations may need to concentrate on building out data infrastructure and governance, for example. More digitally mature organizations may need to concentrate on advanced analytics, real-time integration and explainability. And organizations with highly complex supply chains may need to concentrate on interoperability, coordination, and data standardization.

6.4. Critical Limitations of the Conceptual Framework

Notwithstanding its integrative value, the structure has some inherent theoretical weaknesses. First, the model necessarily abstracts from relationships that could be much more complicated in the real world. Our linear conceptual ordering from data quality, to AI analytical effectiveness and then to transparency, traceability, and resilience does not include all potential feedbacks or contingencies between these concepts. For instance, greater traceability could themselves lead to further data, which then influence AI analytical effectiveness. Research on AI-enabled food systems also highlight that digital traceability is not a strictly linear techno-organizational process, but rather comprises dynamic interplay between technological and organizational mechanisms of design and governance (Rossi et al., 2025).

Second, the framework does not explicitly incorporate competing organizational and economic conditions that may influence AI outcomes. Factors such as implementation costs, financial resources, organizational resistance to change, employee skills, leadership support, cybersecurity risks, and organizational culture may affect the ability to convert data and AI capabilities into operational value. Recent research on human–AI collaboration in supply chains identifies technological, ethical, and organizational barriers that can influence the effectiveness

of AI implementation (Vann Yaroson et al., 2025). Their omission should therefore be considered a boundary of the proposed model rather than evidence that they are irrelevant. Third, the framework treats supply chain complexity and digital maturity as contextual moderators, but their effects may vary across organizations, products, and supply chain configurations. The model does not try to represent all dimensions of complexity or digital transformation. Recent evidence also highlights that digital maturity may be enabled via different individual supply chain capabilities, not only a single route to resilience. Next, empirical research should investigate whether other contextual factors strengthen the model. Finally, the framework remains conceptual and has not been empirically tested. All the propositions, like the comparative proposition (P4c), and the moderating propositions (P7a- P7c and P8a- P8b) should be perceived as expectations based on the theory, and not as empirical relationships established in the existing literature.

7. Conclusion and future research

This study addresses the question of how data quality may influence food supply chain resilience through AI analytical effectiveness, transparency, and traceability, while considering the contextual roles of supply chain complexity and digital maturity. The proposed framework integrates three dimensions of data quality: technical, semantic, and governance-related with three dimensions of AI analytical effectiveness: predictive accuracy, explainability, and real-time responsiveness. It further proposes that AI analytical effectiveness contributes to transparency and traceability, which are subsequently associated with food supply chain resilience. Supply chain complexity and digital maturity are incorporated as contextual conditions that may influence these relationships. The framework is not presented as an established causal structure but as a set of theoretically grounded propositions requiring empirical validation.

Conceptually, our proposed system has some limitations. First, it has not yet been empirically tested, so the measurements and relationships among dimensions are theoretical predictions. Future testing is expected that might show that technical, semantic, and governance-related data quality are separate but complementary dimensions, and that predictive accuracy, explainability, and real-time responsiveness are the most salient and independent ways of measuring AI analytical effectiveness. Second, the broad sectoral scope does not empirically identify a specific food product, supply chain layout, geographic region, or organization type. In doing so, issues around perishability or processing level, regulatory environment, information sharing requirements may affect the strength and direction of any of the shown relationships. Third, the system diagrams many relationships as ordered, sequential ties, but the reality may involve counteracting or feedback relationships, like advances in traceability providing more data that then influences data quality and AI analytical effectiveness. Finally, the setup does not explicitly include factors like AI implementation costs, organizational resistance, employee capabilities, leadership support cybersecurity organizational culture, or AI readiness. These exclusions outline the scope of the model, not the insignificance of the factors. Future research should empirically test the 15 propositions developed in the final framework. P1- P3 examine the relationships between technical, semantic, and governance-related data quality and AI analytical effectiveness. P4a- P4b examine the effects of AI analytical effectiveness on transparency and traceability, while P4c proposes that this effect may differ in strength between traceability and transparency. P5a- P5b examine the relationships between transparency, traceability, and supply chain resilience. P6a- P6b propose the mediating role of AI analytical effectiveness between data quality and transparency and between data quality and traceability. P7a- P7c examine the moderating role of supply chain complexity, while P8a- P8b

examine the moderating role of digital maturity. This harmonized numbering provides a clear reference structure for subsequent empirical studies.

Future studies should first validate the proposed measurement structure using primary or secondary organizational data. Structural equation modeling could be used to assess the measurement and structural models and to examine the proposed direct, mediating, comparative, and moderating relationships. PLS-SEM may be appropriate where the final model involves complex relationships, composite or formative specifications, and a prediction-oriented objective (Hair & Alamer, 2022). CB-SEM could provide an alternative where the constructs are primarily modeled as reflective common factors and the research objective emphasizes theory confirmation and global model fit (Dash & Paul, 2021). Multi-group analysis could also be used to compare organizations according to digital maturity, technological integration, or supply chain configuration. Longitudinal studies would further help determine whether improvements in data quality and AI capabilities are followed by measurable changes in transparency, traceability, and resilience over time. Case studies and mixed-method designs could complement quantitative approaches by examining how organizations implement data governance, integrate heterogeneous data sources, and translate AI-generated information into operational decisions.

Future research should investigate differences across types of foods and supply-chain arrangements. Perishables, such as fresh fruits and lettuce, could be optimized for rapid data acquisition and monitoring; product shelf life and contamination risks could reinforce the benefit of real-time traceability. New research on fruit supply chains emphasizes the design of flexible applications, whereas new research on lettuce suggests that the value of traceability depends on food types and hazards (Cader et al., 2025; Y. G. Lee et al., 2025). Agricultural commodities like grains may pose distinct issues, since blending aggregation standardization, and regulatory compliance may give rise to traceability discontinuities; recent research on agricultural traceability offers a relevant starting point for further investigation (Pang et al., 2024).

The supply chains for processed foods involve many more stages and actors, probably making the flows of information and the potential need for coordination more difficult; a recent study on the food-processing supply chain illustrates how digital technologies can create opportunities for improved traceability in these supply chains (Rahaman et al., 2024). Cross-category comparisons would help determine whether the associations tested here hold across product categories or depend on the degree of perishability of the factor profile, the degree of processing, the need for traceability, or the supply chain structure.

To sum up, future work could add other organizational and technological conditions to the framework, such as AI readiness, data-sharing capability, organizational learning, implementation costs, organizational resistance, cybersecurity, or trust in AI-generated information. Such extensions should remain theoretically justified and empirically tested rather than being introduced solely to increase model complexity. Overall, the proposed framework provides a structured starting point for a cumulative research agenda on AI-enabled food supply chain traceability. Future empirical research can validate, refine, compare, or challenge the 15 propositions across different food sectors, organizational contexts, levels of digital maturity, supply chain configurations, and methodological approaches.

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