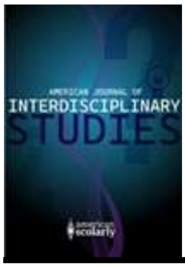

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THE INFLUENCE OF IOT AND DIGITAL TECHNOLOGIES ON FINANCIAL RISK MONITORING AND INVESTMENT EFFICIENCY IN GLOBAL SUPPLY CHAINS

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Abstract

This study addresses the problem that many global supplies chain enterprises still experience delayed, fragmented financial risk monitoring and suboptimal investment efficiency because operational data are not consistently captured and integrated across cloud and enterprise platforms. The purpose was to test whether Internet of Things capability (IoT) and digital technology integration (DTI) improve financial risk monitoring effectiveness (FRM) and, in turn, investment efficiency (IE). Using a quantitative, cross-sectional, case-based design, survey data were collected from enterprise functions (supply chain, logistics, procurement, operations, and finance/risk) in a single organizational case (N = 210), with 62.4% operations-facing and 37.6% finance/risk-facing respondents. Constructs were measured on 5-point Likert scales and showed strong reliability (aIoT = .86, aDTI = .88, aFRM = .90, aIE = .85), with above-neutral mean scores (IoT M = 3.78, DTI M = 3.69, FRM M = 3.73, IE M = 3.61). The analysis plan included descriptive statistics, Pearson correlations, multiple regression with controls (size, supply chain complexity, tenure, digital maturity), and mediation testing using bootstrap resampling (5,000). Headline findings show that IoT and DTI significantly predicted FRM (β = .28, p < .001; β = .41, p < .001; R^2 = .52), FRM predicted IE (β = .43, p < .001; IE model R^2 = .53), and both IoT and DTI retained significant direct effects on IE (β = .12, p = .031; β = .17, p = .004). Mediation results indicate partial mediation via FRM, with significant indirect effects for IoT (0.12, 95% CI [0.07, 0.19]) and DTI (0.18, 95% CI [0.11, 0.27]). The findings imply that enterprises should prioritize end-to-end data integration and finance-ready monitoring routines, because improved FRM is a primary mechanism through which digital capability translates into more disciplined, efficient investment decisions.

Keywords

IOT Capability; Digital Technology Integration; Financial Risk Monitoring; Investment Efficiency; Global Supply Chains

INTRODUCTION

The Internet of Things (IoT) is commonly defined as a networked ecosystem in which physical objects equipped with identifiers, sensors, and connectivity generate, transmit, and exchange data to support monitoring, coordination, and decision-making across organizational boundaries (Atzori et al., 2010). In supply chain contexts, IoT is typically operationalized through technologies such as RFID, wireless sensor networks, edge devices, gateways, and cloud-linked platforms that create persistent digital traces of goods, assets, and processes across upstream and downstream partners (Angeles, 2005). Digital technologies, in a supply chain analytics sense, include the socio-technical stack that captures, integrates, stores, and analyzes these traces—enterprise systems, cloud services, data warehouses, and algorithmic tools used for descriptive and predictive analytics (Nelson et al., 2005).

Financial risk monitoring in global supply chains refers to the continuous identification, measurement, and tracking of exposure that can affect liquidity, working capital, default probabilities, payment delays, and market valuation impacts related to supply disruptions and information asymmetries (Hendricks & Singhal, 2005). Investment efficiency, in corporate finance research, is often framed as the degree to which firms avoid value-destroying over-investment and under-investment, with information quality and transparency acting as central explanatory mechanisms for efficient capital allocation (Biddle et al., 2009). These constructs have international significance because global supply chains operate across heterogeneous regulatory regimes, currency and credit environments, infrastructure conditions, and reporting practices, creating complex real-time risk profiles for multinational buyers, suppliers, and logistics providers (Gunasekaran et al., 2017). As cross-border trade scales and supply networks become more distributed, the informational distance between physical operations and financial decision-making expands, increasing the value of sensor-derived visibility and analytics that can compress uncertainty into measurable indicators suitable for risk dashboards, credit decisions, and investment appraisals (Arfan et al., 2021; Atzori et al., 2010). In this framing, IoT and digital technologies function as measurement infrastructures that translate operational reality into finance-relevant signals—enabling organizations to monitor risk conditions, quantify variability, and evaluate whether investments in supply chain processes and digital assets correspond to measurable efficiency improvements (Jahid, 2021; Lee & Lee, 2015).

A central proposition in the operations and information systems literature is that improved visibility and information quality are prerequisites for reliable monitoring, because measurement systems that are inaccurate, incomplete, or delayed produce distorted interpretations of risk and performance (Trkman et al., 2010). IoT infrastructures advance visibility by capturing granular events—location pings, temperature excursions, production timestamps, and custody transfers—that can be transformed into indicators of shipment reliability, lead-time volatility, inventory accuracy, and disruption probability (Chae, 2015; Akbar & Farzana, 2021). RFID-based traceability, for example, has been widely discussed as a mechanism for closing information gaps across retailing, logistics, and multi-tier supply networks through automatic identification and real-time data capture (Gelsomino et al., 2016; Reza et al., 2021). Research using RFID-enabled production and logistics datasets illustrates how operational traces can be structured for analytic use, including cleansing, warehousing, and pattern extraction that supports planning and control decisions (Saikat, 2021; Zhong et al., 2015). When visibility increases, monitoring becomes less reliant on periodic manual reports and more reliant on continuously updated process states, allowing financial risk monitoring functions—credit control, treasury, or supply chain finance platforms—to align their assessments with live operational conditions (Hofmann, 2005; Shaikh & Aditya, 2021). Supply chain finance literature emphasizes that ICT-enabled trade process visibility supports working-capital optimization and financing solutions that depend on credible information about invoices, deliveries, and counterparties (Gubbi et al., 2013; Kanti & Shaikat, 2021). In parallel, disruption research shows that supply chain disturbances can materially affect long-run stock price performance and equity risk, reinforcing the need for monitoring systems that detect early warning signals tied to operational events (Kache & Seuring, 2017; Zobayer, 2021a). In practice-oriented analytics research, the argument extends further: data streams from IoT devices are valuable only when transformed into structured information that decision-makers can interpret consistently, which foregrounds governance topics such as data quality, reliability, and integration maturity (Kshetri, 2018; Zobayer, 2021b). The risk-monitoring relevance of IoT thus depends on the entire digital pipeline—capture, integration, quality assurance, and analytics—because each stage shapes the accuracy of risk indicators that finance teams use for exposure management and investment evaluation (Mishra et al., 2018).

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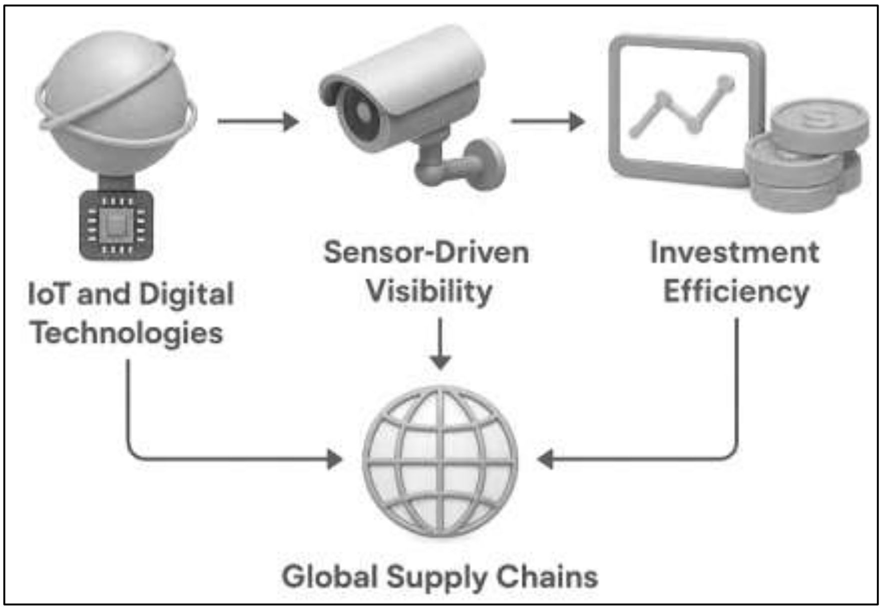
Digital technologies influence monitoring not merely by increasing data volume but by enabling analytical interpretation of operational signals into finance-oriented metrics such as probability of delay, expected cash conversion cycle impacts, and counterparty risk flags (Amin & Praveen, 2023; Hasan & Ashraful, 2023; Waller & Fawcett, 2013). Within business analytics research, supply chain performance improvements are often linked to the ability to combine analytical capabilities with process maturity and information system support, implying that analytics produces value when embedded within coordinated decision routines (Ibne & Kamrul, 2023; Mushfequr & Ashraful, 2023; Tang, 2006). Big data and business analytics scholarship in supply chain settings emphasizes that heterogeneous data—sensor feeds, transactional records, and external signals—can be operationalized through descriptive and predictive analytics to improve planning, responsiveness, and performance measurement (Roy & Kamrul, 2023; Saba et al., 2023; Waller & Fawcett, 2013).

Figure 1: IoT-enabled visibility and investment efficiency in global supply chains



Empirical work on big data analytics in logistics and supply chain management similarly positions analytics as a managerial capability that converts multi-source datasets into actionable insights, supporting more precise control and decision-making under uncertainty (Wang et al., 2016). In international supply chains, uncertainty is intensified by multi-tier supplier dependencies and longer lead times, and risk monitoring requires frequent updates as conditions change across geographies and organizational boundaries (Saba & Kanti, 2023; Wamba et al., 2015). Conceptual and empirical work on disruption management links the value of monitoring to the ability to recognize risk triggers early enough to adjust sourcing, inventory, or transportation decisions, a logic that aligns with analytics-enabled dashboards and exception management (Shaikh & Farabe, 2023; Tan et al., 2015; Haider & Hozyfa, 2023). Within this information-processing view, IoT expands the informational bandwidth and timeliness of signals, while digital analytics expands interpretive power by extracting patterns, correlations, and risk scores that can be integrated into financial controls and governance (Trkman et al., 2010; Zobayer, 2023). Analytics studies also show that data-driven infrastructures can support innovation capabilities by improving how firms derive knowledge and competitiveness from operational data, which has relevance for investment efficiency when digital investments are evaluated based on measurable improvements in process outcomes (Tan et al., 2015). The combination of continuous IoT visibility and analytics-enabled interpretation therefore constitutes a monitoring architecture that can tighten the linkage between operational disturbances and financial exposure, enabling organizations to treat risk monitoring as a data-driven function rather than a periodic reporting exercise (Schoenherr & Speier-Pero, 2015).

Global supply chains create financial interdependencies among buyers, suppliers, logistics providers, and banks, and these interdependencies are commonly managed through supply chain finance (SCF) mechanisms that aim to optimize working capital and liquidity across the network (Nguyen et al., 2018). SCF research outlines how technology-enabled visibility can support financing decisions by improving the credibility, timeliness, and granularity of trade events that underwrite payment commitments, discounting programs, or receivables financing (Dubey et al., 2020). A literature review in this domain identifies SCF as an interdisciplinary field where physical distribution processes and financial flows interact, and where information platforms are instrumental for coordination, transparency, and risk mitigation (Gelsomino et al., 2016). This linkage is essential to financial risk monitoring because credit exposure and payment risk are shaped by operational realities: shipment delays, quality incidents, inventory inaccuracies, or supplier disruptions can amplify default risk and alter cash flow timing (Hendricks & Singhal, 2005). IoT-based monitoring contributes by reducing ambiguity about the status and integrity of goods in transit and in production, which provides objective evidence that can support invoice validation, exception handling, and the timing of settlement-related decisions in cross-border contexts (Lee & Lee, 2015). Digital technologies further enable the integration of operational data into financial workflows, supporting event-driven triggers for risk flags and financing actions that rely on verified milestones rather than delayed manual confirmation (Saberi et al., 2019). In parallel, business logistics and analytics research describes data science and predictive analytics as levers for strengthening performance management in supply chains by improving planning accuracy, risk responsiveness, and the monitoring of process variability (Waller & Fawcett, 2013). These capabilities can affect investment efficiency by shifting decisions away from intuition-driven allocations toward evidence-based assessments of which operational investments—tracking infrastructure, analytics platforms, or process redesign—translate into measurable reductions in variability and exposure (Tan et al., 2015). Within a global supply chain setting, where capital is allocated across logistics assets, supplier development, and digital infrastructure, a monitoring-driven approach positions IoT and digital technologies as foundational to quantifying risk-return relationships embedded in operational investments (Gelsomino et al., 2016).

Investment efficiency research in accounting and finance emphasizes that information quality influences whether firms allocate capital toward value-creating projects and avoid wasteful expansion or harmful underinvestment, with reporting quality and transparency reducing information asymmetries and agency frictions (Biddle et al., 2009). In operational domains, IoT and digital technologies can be interpreted as complementary information infrastructures that enhance the observability of processes and outcomes, providing empirical evidence that can support more accurate investment appraisal and post-investment evaluation (Lee & Lee, 2015). The relevance of system and information quality is highlighted in information systems research, where empirical findings show that the reliability, accuracy, and completeness of information and system outputs are critical determinants of perceived usefulness and decision support value in data warehousing contexts (Nelson et al., 2005). When this logic is extended to supply chains, IoT-generated data streams and analytics dashboards can improve the evidential basis for deciding which investments are justified by operational improvements and which investments fail to produce measurable benefits, connecting monitoring quality to investment efficiency outcomes (Schoenherr & Speier-Pero, 2015). Studies on supply chain analytics provide further grounding: analytics benefits are frequently associated with improved decision performance under uncertainty, including more accurate planning and better alignment between data-driven insights and managerial action (Wamba et al., 2015). In global supply chains, investment decisions may include digital tracking deployments, sensor networks, platform subscriptions, cybersecurity controls, and analytics capabilities, and monitoring allows organizations to quantify how these investments affect cycle times, exception rates, inventory accuracy, and disruption impacts that are financially material (Wang et al., 2016). Because disruptions have been empirically linked to negative financial market consequences and heightened equity risk, monitoring that reduces disruption likelihood or mitigates impacts can be evaluated as an efficiency-enhancing investment channel (Hendricks & Singhal, 2005). In this way, IoT and digital technologies can be positioned within an information-quality pathway: higher quality operational information supports better risk monitoring, and better monitoring supports better resource allocation by improving the precision of capital budgeting assumptions and the credibility of performance feedback (Wamba et al., 2015). This conceptual linkage aligns well with quantitative empirical designs that test whether technology-enabled monitoring constructs correlate with and predict investment efficiency constructs, while controlling for firm profile factors within real case contexts (Tan et al., 2015).

Recent empirical research in production economics and business research has investigated how big data analytics and related digital capabilities affect organizational performance through operational pathways that are measurable and modelable using statistical methods (Wamba et al., 2015). In logistics and supply chain settings, big data analytics has been examined as a determinant of improved responsiveness and process performance, often by enabling more accurate forecasting, anomaly detection, and resource optimization that reduce operational variance (Wang et al., 2016). Evidence-based models also increasingly consider capability interactions: analytics outcomes may depend on organizational orientation, environmental conditions, and the maturity of processes and systems that embed analytics into day-to-day decisions (Trkman et al., 2010). Empirical work in Decision Support Systems has shown that supply chain performance relationships are contingent upon the interplay of analytics, information system support, and business process orientation, suggesting that measurable gains arise when analytics is aligned with operational routines (Tang, 2006). Parallel research on big data and predictive analytics for supply chain and organizational performance strengthens this view by linking predictive capabilities to organizational outcomes that can be operationalized using survey-based constructs and tested through correlation and regression modeling (Gunasekaran et al., 2017). Studies focused on digital transformation and decision-making also highlight the managerial significance of translating data into decisions, suggesting that technology investments must be evaluated against the degree to which they enhance decision quality and measurable operational outcomes (Waller & Fawcett, 2013). In more specialized analytics research, modeling approaches such as big data optimization and analytics-driven decision systems illustrate how data-intensive decision environments can be formalized and evaluated through quantitative models, reinforcing the methodological compatibility with cross-sectional empirical testing (Mishra et al., 2018). From a financial risk monitoring perspective, these operational capability pathways matter because performance variance and uncertainty translate into financial exposure, influencing payment timing, inventory carrying costs, and risk-adjusted returns on investments in supply chain assets and digital infrastructure (Gelsomino et al., 2016). Accordingly, the influence of IoT and digital technologies can be conceptualized as a chain of measurable relationships: sensor-driven visibility strengthens data quality and timeliness, analytics strengthens interpretability and forecasting, risk monitoring becomes more continuous and evidence-based, and investment efficiency improves as resource allocations are guided by observable outcomes rather than opaque assumptions (Nelson et al., 2005).

Global supply chains require inter-organizational trust and governance mechanisms that support data sharing, verification, and coordinated decision-making, because risk monitoring depends on information that spans multiple entities with varying incentives and reporting practices (Hofmann, 2005). Digital technologies can enhance governance by standardizing data exchanges, improving auditability, and enabling shared visibility that supports synchronized actions across buyers, suppliers, and financiers. In this environment, the quality of shared operational information becomes a foundational control variable for monitoring, linking information quality constructs from information systems research with practical monitoring needs in supply chain finance and risk management. Blockchain research further frames digitally mediated trust as a mechanism for achieving supply chain objectives such as transparency and traceability, with implications for monitoring and control in multi-party networks. Work on blockchain and sustainable supply chain management similarly emphasizes coordination and visibility as central mechanisms through which digital infrastructures can support governance aims in complex networks (Dubey et al., 2020). Within an investment-efficiency framing, governance matters because capital allocation depends on credible measurements and verifiable outcomes; when monitoring outputs are trusted, investment evaluations can rely on observed performance rather than subjective negotiation or delayed reporting (Atzori et al., 2010). Empirical studies of big data analytics and operational performance provide complementary evidence that organizations can evaluate digital capability investments by testing relationships between analytics capability constructs and operational outcomes under varying conditions (Dubey et al., 2020). In disruption research, the financial market penalties associated with supply chain disruptions highlight the value of governance systems that can monitor risk conditions and coordinate responses in ways that reduce the likelihood and severity of events that investors interpret as value-relevant signals (Hendricks & Singhal, 2005). In sum, IoT and digital technologies shape financial risk monitoring and investment efficiency by providing cross-border, multi-entity measurement infrastructures, analytics-enabled interpretation, and governance mechanisms that align operational reality with financial control needs across the global supply chain network (Atzori et al., 2010).

This study is designed to examine, in a measurable and objective-driven manner, how IoT and digital technologies shape financial risk monitoring and investment efficiency within global supply chain environments. The first objective is to operationalize IoT capability as a set of observable organizational practices and infrastructures—such as real-time sensing, automatic identification, asset and shipment traceability, event-capture frequency, and data timeliness—and to determine how these capabilities relate to the effectiveness of financial risk monitoring. The second objective is to operationalize digital technology integration as the extent to which data platforms and enterprise systems support end-to-end visibility, data consolidation, analytics readiness, and inter-organizational information exchange, and to evaluate its direct contribution to financial risk monitoring quality, including accuracy, completeness, timeliness, and usefulness of risk signals for decision-making. The third objective is to quantify the relationship between financial risk monitoring effectiveness and investment efficiency by assessing whether stronger monitoring is associated with improved capital allocation outcomes, reflected in reduced waste, better prioritization of investments, stronger decision confidence, and clearer linkage between spending and performance outcomes. A fourth objective is to test whether IoT capability and digital technology integration also influence investment efficiency directly, recognizing that technology adoption may affect investment outcomes through channels other than monitoring, such as process standardization, operational stability, and reduced information friction among supply chain partners. A fifth objective is to estimate the combined explanatory power of IoT capability, digital technology integration, and financial risk monitoring in predicting investment efficiency when organizational characteristics are considered as control factors, including firm size, supply chain complexity, geographic dispersion, and digital maturity. A final objective is to statistically evaluate whether financial risk monitoring functions as a mediating mechanism that explains how IoT and digital technologies translate into investment efficiency improvements, thereby clarifying the pathway through which technology-enabled visibility and analytics become financially meaningful at the organizational level. Collectively, these objectives establish a coherent empirical structure that supports hypothesis testing through descriptive statistics, correlation analysis, and regression modeling within a cross-sectional, case-study–based design using standardized Likert-scale measurement.

LITERATURE REVIEW

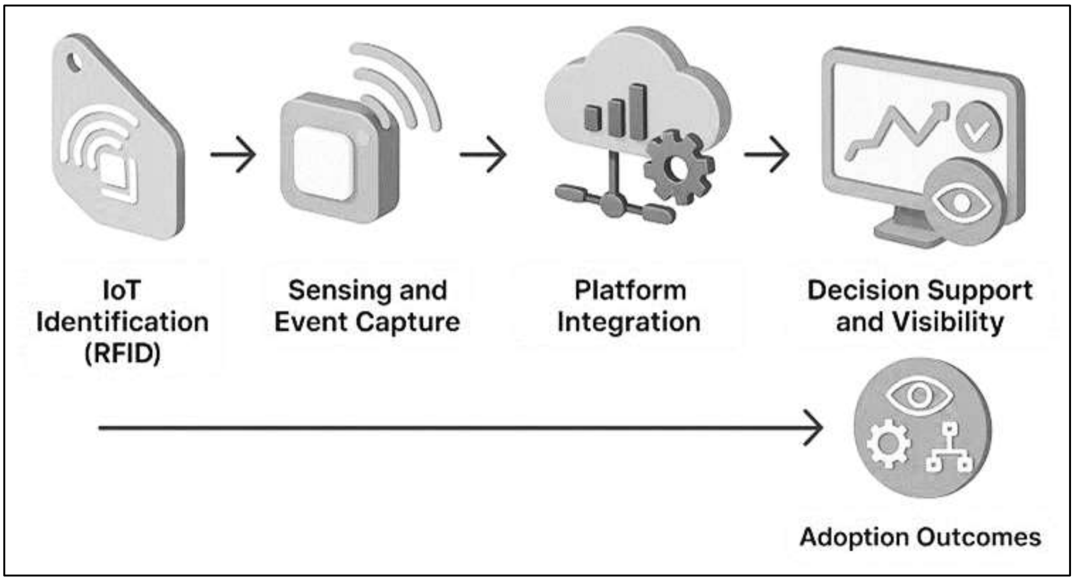
The literature on IoT and digital technologies in global supply chains has expanded rapidly as organizations seek data-driven mechanisms to manage operational uncertainty and financially material exposure across distributed networks. Within this body of work, IoT is generally positioned as an enabling infrastructure for real-time visibility through sensing, identification, and connectivity, allowing firms to capture continuous event-level data about assets, shipments, production conditions, and process states across multiple tiers. Digital technologies are then discussed as the integration and analytics layer that consolidates heterogeneous data streams into actionable information, typically through enterprise systems, cloud platforms, data warehouses, and analytical tools that support monitoring, forecasting, and decision support. In supply chain research, these technologies are repeatedly linked to improvements in transparency, responsiveness, coordination, and performance measurement, which are often treated as precursors to improved risk management outcomes. At the same time, supply chain finance and risk scholarship emphasizes that operational volatility translates directly into financial risk through disruptions, payment delays, liquidity pressure, and counterparty exposure, making continuous monitoring a central capability for firms operating internationally. Financial risk monitoring in this context is not limited to accounting controls; it includes the ongoing assessment of risk signals that originate from operational events and external conditions, transforming these signals into indicators that can guide treasury actions, credit decisions, and working-capital strategies. Investment efficiency literature contributes an additional lens by framing efficient capital allocation as an outcome strongly influenced by information quality and decision precision, suggesting that technologies improving visibility and monitoring can also affect how firms select, prioritize, and evaluate investments in supply chain assets and digital infrastructure. However, the literature also reveals fragmentation: many studies examine IoT adoption, analytics value, or supply chain finance mechanisms in isolation, while fewer studies empirically model the combined relationships among IoT capability, digital technology integration, financial risk monitoring effectiveness, and investment efficiency within a unified framework that is testable through quantitative methods. This creates a clear need to synthesize findings across operations, information systems, and finance-oriented supply chain research to clarify constructs, identify consistent pathways, and articulate relationships suitable for hypothesis testing. Accordingly, the present literature review consolidates foundational and recent research to define the key constructs for this study, explain how IoT and digital technologies are theorized to influence financial risk monitoring, and establish how monitoring quality can translate into investment efficiency outcomes in global supply chain settings, thereby supporting the development of a coherent conceptual model for the subsequent empirical analysis.

IoT Adoption in Global Supply Chains

IoT adoption in global supply chains is commonly described as the organizational commitment to deploy connected identification and sensing capabilities across logistics nodes and partner interfaces so that product flows, asset states, and process events become continuously observable rather than intermittently reported. In operational terms, adoption frequently begins with automatic identification and data capture foundations, particularly RFID-based tagging and reader infrastructures, because these systems connect physical entities (items, cases, pallets, containers) to digital identifiers that can be detected without direct line-of-sight and recorded as time-stamped events at receiving, put-away, picking, staging, and shipping points. This practical starting point matters because warehouses and distribution centers are high-frequency transaction environments where small errors propagate quickly into inventory record inaccuracy, shipping exceptions, and downstream service failures. Empirical evidence from the warehousing industry illustrates that adoption decisions are shaped by perceived costs, readiness of supporting processes, and uncertainty about returns, showing that many firms evaluate RFID/I oT initiatives cautiously when organizational capabilities and partner alignment are still developing (Vijayaraman & Osyk, 2006). As IoT expands beyond identification toward sensing (condition, location, utilization), adoption also becomes a socio-technical change that requires redesigning workflows, defining responsibilities for exception handling, and ensuring that data capture points reflect real control needs rather than technology availability. In supply chains that span multiple countries, adoption is additionally influenced by cross-border operational heterogeneity, including infrastructure differences, compliance requirements, and varied partner maturity, which can complicate uniform deployment and standardization. Research examining IoT integration in supply chains emphasizes that expected benefits such as improved visibility, responsiveness, and coordination are accompanied by challenges related to interoperability, security concerns, governance of shared data, and the managerial effort required to translate device-level data into decisions (Haddud et al., 2017). Within this view, IoT adoption is not a single installation event but a staged capability-building process that progresses from localized pilots toward network-level coverage as firms learn how to embed connected data into routine planning and control.

A second stream of literature differentiates between *adopting IoT technologies* and *realizing supply chain value* from those technologies, arguing that deployments can remain operationally superficial if they do not align with process priorities and measurable performance targets. RFID-focused syntheses show that adoption outcomes depend on “benefit drivers” such as the scope of tagging, integration into core workflows, compatibility with information systems, staff training, and the degree of coordination among supply chain partners who must jointly rely on shared identification events. When these drivers are weak, RFID deployments may create fragmented datasets and parallel manual work, limiting the credibility of visibility gains and weakening the business case for scaling. A systematic review of RFID implementation in supply chains highlights that organizational competitive advantage is more likely when RFID is implemented as part of an integrated process strategy—supporting automation, information sharing, and decision routines—rather than as a stand-alone technology experiment (Chanchaichujit et al., 2020). This distinction becomes even more important for IoT because sensor-generated data can be voluminous, heterogeneous, and context-dependent, requiring disciplined data governance and clear analytical use-cases to prevent "data accumulation without decision impact." At the field level, bibliometric analyses of IoT research in supply chain management and logistics also indicate that adoption research has evolved from technology-centric discussions to broader capability-centric perspectives, emphasizing the coupling of IoT with integration architectures, analytics, and managerial practices that enable consistent value capture across the supply chain network (Rejeb et al., 2020). Taken together, these studies portray adoption as a multi-layered phenomenon involving technological readiness, process alignment, partner participation, and information management maturity. Consequently, adoption success is increasingly judged by the organization's ability to convert connected-data availability into reliable visibility metrics, faster exception resolution, and controllable variability across global operations, rather than by the mere presence of devices and connectivity.

Figure 2: IoT Adoption Pathways and Capability Integration in Global Supply Chains

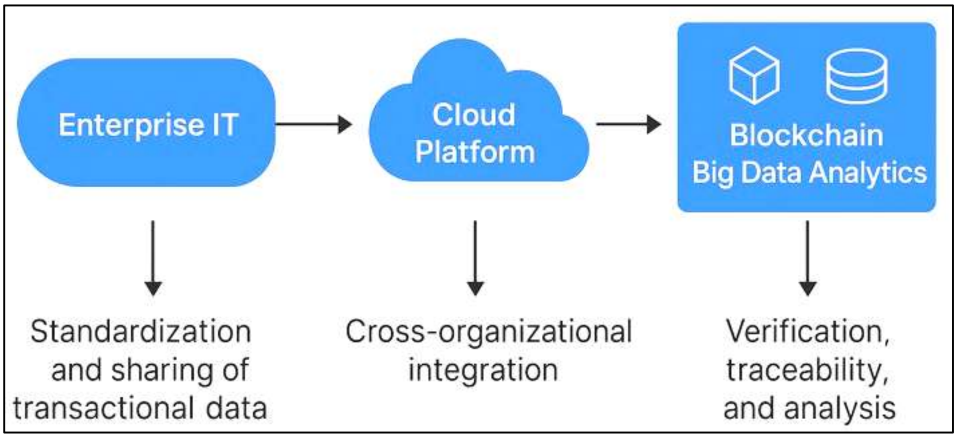


More recent scholarship further emphasizes that IoT adoption yields the strongest operational and managerial outcomes when identification and sensing are combined with decision-support mechanisms that transform raw events into actionable signals for monitoring, diagnosis, and control. This perspective treats IoT adoption as an end-to-end pipeline: devices capture events, platforms integrate and standardize data, and analytic or rule-based tools convert patterns into alerts, dashboards, and performance indicators that managers can interpret and act upon consistently. In global supply chains, this pipeline logic is essential because connected data must travel across organizational boundaries, languages, time zones, and heterogeneous IT environments, and the value of adoption depends on whether the data can be trusted, shared appropriately, and used to coordinate responses across partners. Industry 4.0–oriented syntheses focusing on RFID and decision support systems describe IoT-enabled identification as a foundation for transparency and process automation, while emphasizing that performance improvements depend on how decision support structures the data for operational control and managerial oversight (Unhelkar et al., 2022). This framing is directly relevant to technology adoption measurement in empirical studies because it suggests that adoption should be operationalized not only by the presence of IoT hardware, but also by indicators of usage intensity, integration depth, decision-use frequency, and the organizational routines that respond to IoT-driven exceptions. As a result, IoT adoption in supply chains is increasingly conceptualized as a capability that reflects both technology deployment and its embeddedness in day-to-day decision cycles—capturing whether connected data genuinely improves visibility, reduces friction, and supports coordinated control across a globally distributed network.

Digital Technologies in Supply Chain Finance

Digital technologies in supply chain finance (SCF) can be understood as the integrated set of information systems, data infrastructures, and interorganizational platforms that connect physical supply chain events with financial workflows such as invoicing, payment authorization, receivables financing, and working-capital control. In practice, firms often begin this integration through enterprise IT that standardizes transactional records, enabling consistent sharing of order, shipment, and settlement data across functions and partners. Empirical evidence indicates that when IT is implemented to support supply chain management activities, its performance impact becomes more visible when it strengthens supply chain integration as an enabling mechanism rather than acting as a stand-alone technical upgrade. This logic is important in global contexts, where SCF decisions depend on timely and reliable information to coordinate procurement, logistics milestones, and cash-flow schedules across multiple entities. Digital integration reduces informational gaps by creating structured, auditable, and time-stamped records that can be reconciled across buyers and suppliers, which supports financial control over payment timing and exposure. It also makes the supply chain “legible” to finance teams by aligning operational data structures with financial reporting needs, allowing risk signals such as delivery uncertainty or exception frequency to be interpreted in terms of cash-flow disruption and credit exposure. As a result, digital technologies act as the operational backbone for SCF by converting distributed operational processes into standardized data flows that can be monitored, compared, and used to govern financing decisions within and across firms (Li et al., 2009).

Figure 3: Role of Digital Technologies in Supply Chain Finance Integration and Control



A second major theme emphasizes that digital technologies in SCF are increasingly “platform-based,” meaning that integration is not limited to internal enterprise systems but also includes shared environments where partners exchange data and coordinate decisions. Cloud technologies are often treated as a practical accelerator of cross-organizational integration because they provide scalable access, unified interfaces, and rapid deployment of shared workflows, which is particularly relevant when supply chain partners have uneven IT maturity. Research on cloud-enabled process integration highlights that digital integration can enhance supply chain performance when processes are coordinated through shared digital infrastructures and when leadership supports the organizational changes needed to embed these tools into routines. For SCF, the platform perspective matters because financing and risk monitoring depend on the credibility and accessibility of information across multiple parties, including suppliers, buyers, and in some cases financiers or service providers. A cloud-enabled environment can centralize document flows, standardize process states (e.g., confirmed shipment, verified receipt), and reduce reconciliation friction that delays payment or increases disputes. This creates stronger informational continuity between operational events and financial actions, supporting more consistent monitoring of cash conversion cycles and exposure points. Therefore, the literature positions cloud platforms and process-integration tools as foundational digital technologies for SCF because they translate coordination needs into standardized and accessible data, strengthening the link between supply chain execution and financial control (Shee et al., 2018).

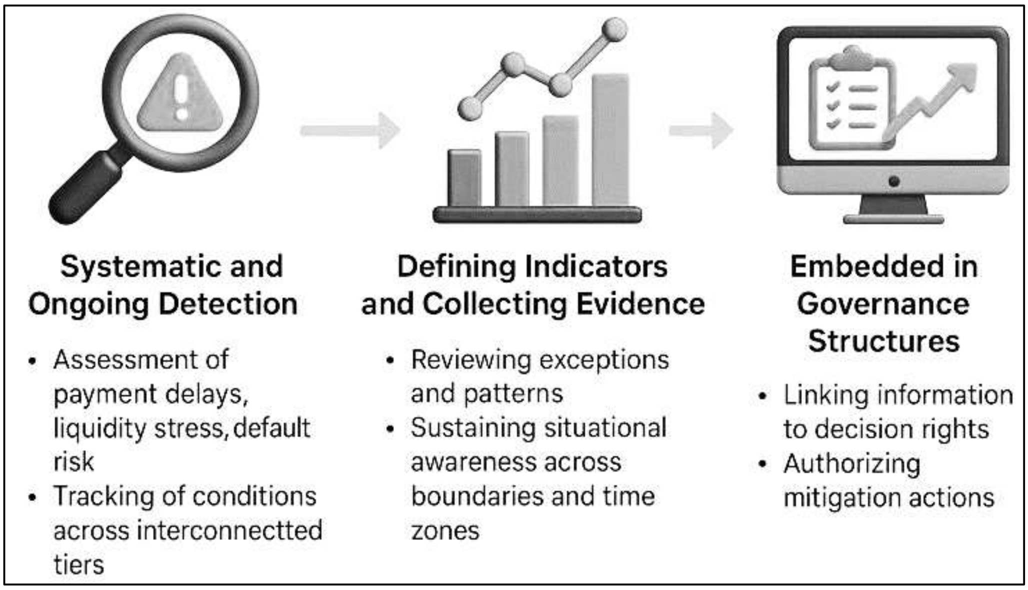
A third stream of research addresses advanced digital technologies that increase verification, traceability, and analytical control in multi-party environments, with blockchain and big data analytics frequently discussed as complementary components. Blockchain is commonly framed as a shared ledger mechanism that can improve transparency and verification among parties by recording events and transactions in tamper-resistant structures, which is relevant to SCF contexts where trust, documentation, and milestone validation influence financing eligibility and risk assessments (Dubey et al., 2019; Dutta et al., 2020). At the same time, big data analytics capabilities are treated as organizational resources that improve responsiveness by converting large volumes of operational and transactional data into actionable insights, enabling faster detection of anomalies, disruptions, and performance deterioration that can affect financial exposure. In global supply chains, where SCF decisions must often be made under time pressure and uncertainty, the combination of verifiable shared records and analytics-driven interpretation can strengthen the monitoring function by improving both evidence quality and decision speed. The literature also recognizes that adoption of digital technologies in supply chains tends to follow identifiable drivers and processes, suggesting that value from these technologies emerges when firms align tools with coordination needs, integration depth, and decision-use routines across the network. In this view, digital technologies in SCF are not limited to automation; they represent an information-control architecture that supports monitoring, verification, and financing governance through integrated data visibility and analysis, shaping how firms evaluate exposure and allocate capital within supply chain operations (Büyüközkan & Göçer, 2021).

Financial Risk Monitoring in Supply Chains

Financial risk monitoring in global supply chains refers to the systematic, ongoing detection, assessment, and tracking of conditions that can translate operational variability into financial exposure, including payment delays, liquidity stress, counterparty default risk, and the amplification of losses across interconnected tiers. In the supply chain risk management (SCRM) literature, monitoring is positioned as a continuous managerial discipline that links risk identification to timely response, because disruption mechanisms often emerge through weak signals that precede visible breakdowns in service, fulfillment, or supplier performance. Research on disruptions has emphasized that supply chains face unavoidable interruption events and that organizations require structured approaches for recognizing warning signs and recovery requirements, which underscores the monitoring function as more than periodic reporting. Disruption-focused work also indicates that disruption severity relates to supply chain design characteristics and mitigation capabilities, highlighting the role of warning and recovery as risk-relevant capabilities that must be supported by monitoring routines and metrics (Blackhurst et al., 2005). Monitoring is also framed as inseparable from performance management, because financial exposure is ultimately realized through measurable outcomes such as cash-flow delays, write-offs, emergency logistics costs, and lost revenue from service failures. In this respect, monitoring requires a framework that specifies what signals matter, how they are interpreted, and how they connect to both operational and financial outcomes. A well-cited risk management framework links risk drivers and decision-maker characteristics to risk management responses and performance outcomes, reinforcing that monitoring must be anchored in structured categories of risk influence rather than treated as ad hoc observation (Ritchie & Brindley, 2007). In global supply chains, where suppliers operate under heterogeneous constraints and visibility can be fragmented, financial risk monitoring therefore becomes a discipline of defining indicators, collecting evidence consistently, and sustaining decision-ready situational awareness across organizational boundaries and time zones.

Synthesis work on SCRM further clarifies why monitoring is central in internationally distributed supply networks: as geographic dispersion increases, risk sources multiply across regulatory regimes, logistics infrastructures, currency exposure conditions, and supplier capability levels. A core insight from such synthesis is that firms face a broad risk spectrum—demand volatility, supply unreliability, process failures, transportation disruption, and exogenous shocks—and monitoring requires a disciplined method for structuring this spectrum into observable indicators and reviewable dashboards that support consistent action. Major reviews map key risk issues and research advancements, emphasizing the breadth of risk categories and the need for coherent approaches that enable organizations to identify, assess, and track risks as an integrated management activity rather than isolated initiatives (Tang & Musa, 2011). This matters for financial risk monitoring because financially material exposure often emerges from the interaction of multiple operational risks: a supplier delay can cause missed customer delivery, penalty charges, expedited freight spending, and cash conversion cycle disruptions simultaneously. Monitoring practices therefore need to operate at both the event level (exceptions, deviations, compliance failures) and the aggregate level (patterns, trending deterioration, concentration risk) so that finance-relevant exposure can be inferred with sufficient timeliness. Review evidence also suggests that the literature increasingly treats monitoring as part of an end-to-end risk process that includes governance, measurement, and feedback loops. A comprehensive literature review emphasizes definitional clarity, categorization of risks, and the managerial mechanisms used to operationalize risk processes, supporting the view that monitoring is a core capability that must be defined, measured, and embedded in organizational routines (Ho et al., 2015). In this framing, monitoring quality is evaluated by timeliness, coverage, and decision usability of risk information, with particular emphasis on cross-functional alignment between supply chain operations and financial control needs.

Figure 4: Financial Risk Monitoring in Global Supply Chains

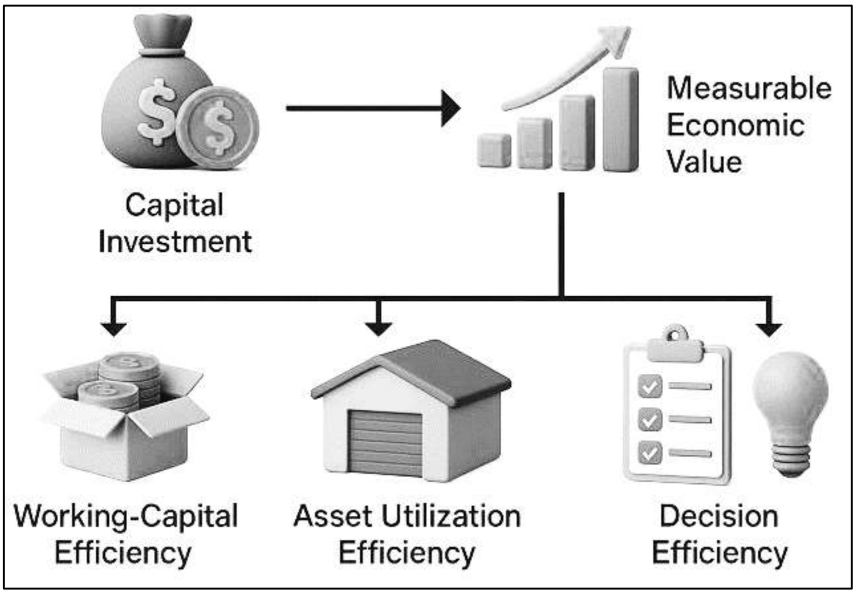


A further emphasis in the literature is that financial risk monitoring must be embedded in governance structures that link risk information to decision rights, escalation pathways, and performance outcomes, because monitoring reduces exposure only when it triggers timely and appropriate action. Monitoring therefore intersects with strategy: organizations decide which vulnerabilities to prioritize, which buffers to hold, and which coordination mechanisms to activate when indicators cross predefined thresholds. Empirical work connects this governance view to measurable performance relationships by examining how structured SCRM practices influence supply chain capabilities that matter under risk. Evidence indicates that risk management practices relate to robustness and agility and that these strategic response capabilities connect to performance outcomes, implying that monitoring is valuable when it supports both proactive and reactive capability building through continuous assessment (Wieland & Wallenburg, 2012). From a financial perspective, robustness is linked to the prevention of costly variance (fewer severe exceptions and fewer emergency expenditures), while agility is linked to faster recovery and reduced duration of cash-flow disruption after a shock. In global supply chains, governance-enabled monitoring also supports coordination across firms by clarifying responsibility for investigating signals, validating information, and authorizing mitigation actions such as rescheduling, dual sourcing, inventory rebalancing, or financing adjustments. Accordingly, the literature positions financial risk monitoring as a bridging capability: it converts operational signals into finance-relevant assessments and routes those assessments through governance mechanisms that enable consistent action, documentation, and performance learning. This positioning directly supports empirical modeling in which monitoring effectiveness is operationalized through survey constructs (e.g., timeliness, accuracy, early-warning usefulness) and tested as a predictor or mediator linking digital capabilities to investment-related outcomes within the broader supply chain risk management system.

Investment Efficiency in Global Supply Chain Operations

Investment efficiency in global supply chain operations refers to how effectively firms convert capital committed to supply activities into measurable economic value, while minimizing avoidable funds tied up in inventories, receivables, and operational slack. In this sense, supply chain decisions are simultaneously operational and financial decisions because they determine the timing and magnitude of cash commitments, the stability of cash recovery through sales, and the risk-adjusted returns generated by logistics and production investments.

Figure 5: Investment Efficiency in Global Supply Chain Operations



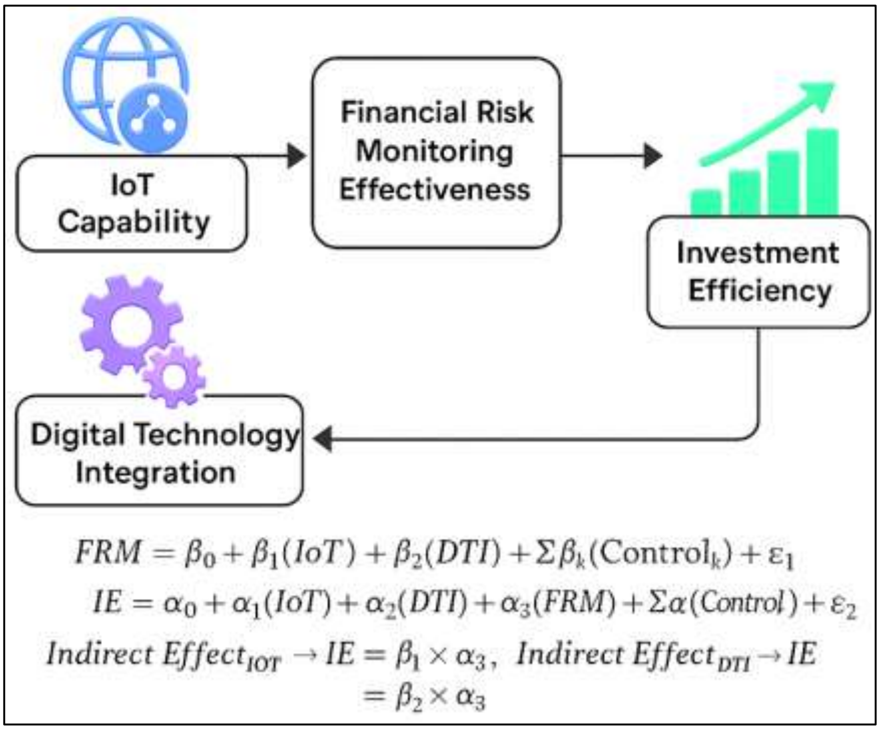
Investment efficiency therefore includes (a) *working-capital efficiency* (how much cash is absorbed by inventory and credit to customers), (b) *asset utilization efficiency* (how well plants, warehouses, and transport capacity are used relative to cost), and (c) *decision efficiency* (how accurately firms allocate funds to the highest-value opportunities within sourcing, manufacturing, distribution, and customer service). In global supply chains, these elements become more complex because lead times are longer, information asymmetry across tiers is higher, and disruptions can rapidly convert operational variability into financial stress. As a result, investment efficiency is often assessed not only by profitability outcomes but also by operational-capital indicators such as the cash conversion cycle, inventory turnover, and the stability of cash flows under uncertainty. Evidence also suggests that supply-chain finance mechanisms can influence investment efficiency by improving liquidity positions and cash turnover, especially where financial frictions and payment delays are common in multi-tier environments (Pan et al., 2020). At the operational level, this implies that investment efficiency is shaped by the discipline of planning routines (forecasting, S&OP, replenishment), the governance of trade credit and payment terms, and the capability to align physical flows with financial controls so that funds are committed only when they support service performance and value creation.

A central insight from the working-capital literature is that investment efficiency is rarely a simple "reduce working capital" objective; instead, efficiency often reflects an *optimal* range of working capital that supports service reliability without trapping excessive resources in current assets. This balance is operationally meaningful because inventory is needed to buffer demand variability and supply uncertainty, yet excess stock can reflect forecasting error, slow-moving product, or weak coordination across procurement, production, and distribution. Similarly, extending generous trade credit can protect sales and relationships, but it can also increase default exposure and raise financing needs. Empirical evidence on SMEs demonstrates that working capital management can have strong associations with profitability, highlighting why working-capital policy is a practical representation of investment efficiency in daily supply chain decisions (García-Teruel & Martínez-Solano, 2007). More specifically, research identifies a concave (non-linear) relationship, indicating that both insufficient and excessive working capital can harm performance—insufficient levels create stockouts and service failures, whereas excessive levels increase holding costs, obsolescence, and financing burdens (Baños-Caballero et al., 2012). Building on this logic, investment efficiency can be understood as the degree to which a firm maintains working capital close to an operating optimum given its risk profile, product characteristics, and demand volatility, and the degree to which it can correct deviations through coordinated actions (better replenishment, improved collections, renegotiated terms, or inventory rationalization).

Theoretical Framework

A suitable theoretical foundation for examining how IoT and digital technologies shape financial risk monitoring and investment efficiency in global supply chains can be built by combining Dynamic Capabilities and an organizational information-processing perspective. Dynamic capabilities theory explains how firms in volatile environments build higher-order abilities to *sense* changes, *seize* opportunities, and *reconfigure* resources so that operational capabilities remain aligned with shifting conditions. In global supply chains, IoT capability and digital technology integration can be theorized as dynamic capability microfoundations because they strengthen sensing (capturing real-time operational signals), seizing (translating signals into decisions through analytics-enabled routines), and reconfiguring (adjusting workflows, controls, and resource allocations based on monitored conditions). This lens is particularly relevant because financial risk monitoring is not a static reporting activity; it is a continuous capability that must interpret changing operational states into exposure indicators that guide decision rights and timely actions. Dynamic capability logic also supports a capability hierarchy where basic digital assets (devices, systems, connectivity) enable higher-order integrative capabilities (visibility, data coordination, analytics-driven control) that can affect both monitoring quality and the efficiency of investment decisions. Empirical work that conceptualizes dynamic capabilities as measurable bundles of routines further strengthens this approach by clarifying that technology-driven capabilities must be operationalized as repeatable managerial processes rather than as isolated IT artifacts. Accordingly, this study treats IoT capability and digital technology integration as strategic capabilities that enhance organizational readiness to recognize and manage risk signals while maintaining capital discipline in supply chain investments, which aligns with dynamic capability explanations of performance in environments characterized by uncertainty, interdependence, and rapid change (Teece, 2007).

Figure 6: IoT capability investment efficiency in global supply chains



$$FRM = \beta_0 + \beta_1(IoT) + \beta_2(DTI) + \Sigma\beta_k(\text{Control}_k) + \varepsilon_1$$

$$IE = \alpha_0 + \alpha_1(IoT) + \alpha_2(DTI) + \alpha_3(FRM) + \Sigma\alpha(\text{Control}) + \varepsilon_2$$

$$Indirect\ Effect_{IOT} \rightarrow IE = \beta_1 \times \alpha_3,\ Indirect\ Effect_{DTI} \rightarrow IE = \beta_2 \times \alpha_3$$

A complementary theoretical anchor is the organizational information-processing view, which emphasizes "fit" between information-processing needs (created by uncertainty, complexity, and interdependence) and information-processing capacity (created by integration mechanisms, information systems, and analytic capabilities). Global supply chains heighten information-processing needs because managers must coordinate across partners, long lead times, and multiple risk sources, and financial exposure emerges when decision makers cannot access timely, credible, decision-ready information. Under this view, IoT-based sensing expands information availability, while digital technology integration and analytics expand information-processing capacity by converting dispersed operational data into standardized, interpretable risk signals (Hazen et al., 2018). Theoretical fit is achieved when the organization's digital capacity is sufficient to process uncertainty into actionable indicators for monitoring, escalation, and control, thereby improving financial risk monitoring effectiveness (Pavlou & El Sawy, 2011).

This framing also connects naturally to supply chain integration research showing that IT capabilities and information sharing strengthen integration routines that improve operational performance, because integration can be interpreted as an information-processing mechanism that reduces ambiguity and supports coordination. In other words, the same digital infrastructures that enable partner integration and operational transparency can be theorized as enablers of financial monitoring because they improve the timeliness, accuracy, and completeness of exposure-relevant information. The information-processing perspective therefore justifies modeling financial risk monitoring as a capability outcome of IoT and digital integration and supports treating analytics-enabled transparency as a pathway through which digital capability becomes performance-relevant. In this study, the fit logic is expressed by viewing IoT capability and digital technology integration as antecedents that raise information-processing capacity, reducing monitoring gaps created by supply chain uncertainty and enabling more disciplined investment decisions through better visibility and interpretability (Flynn et al., 2010).

Based on these theoretical foundations, the study's model is specified as a capability-to-outcome chain in which IoT capability (IoT) and digital technology integration (DTI) influence financial risk monitoring effectiveness (FRM), which in turn influences investment efficiency (IE). The logic is that IoT and DTI increase sensing and information-processing capacity, FRM converts operational signals into finance-relevant exposure assessments, and IE improves when investment choices are guided by credible monitoring outputs rather than fragmented information. This theoretical chain can be represented using regression-based structural equations aligned with the planned quantitative analysis. The direct-effect models can be expressed as:

$$FRM = \beta_0 + \beta_1(IoT) + \beta_2(DTI) + \sum\beta_k(Control_k) + \varepsilon_1$$

$$IE = \alpha_0 + \alpha_1(IoT) + \alpha_2(DTI) + \alpha_3(FRM) + \sum\alpha_k(Control_k) + \varepsilon_2$$

The mediation logic is that IoT and DTI may influence IE indirectly through FRM. The indirect effect can be represented as:

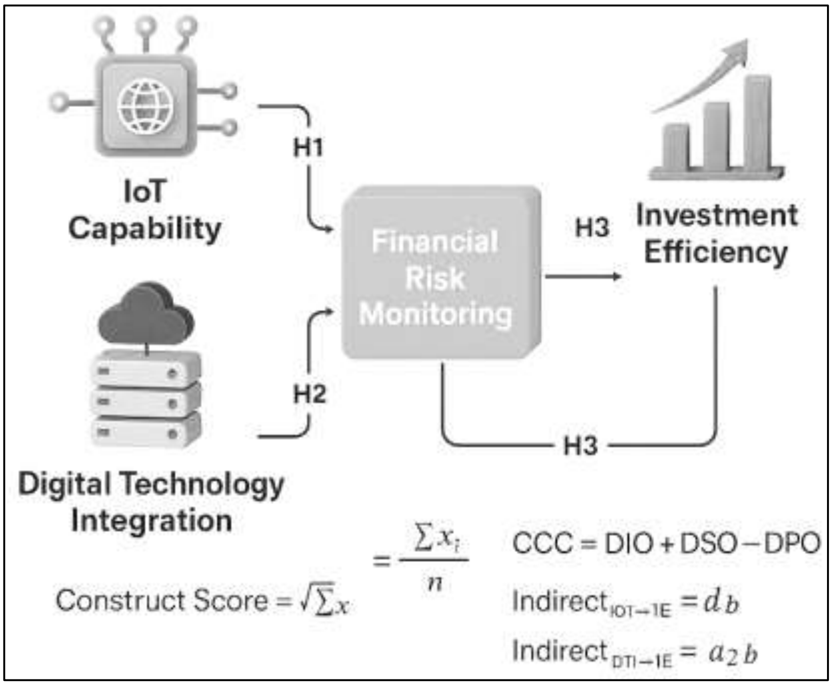
$$\text{Indirect Effect}_{\text{IoT}\rightarrow\text{IE}} = \beta_1 \times \alpha_3, \text{Indirect Effect}_{\text{DTI}\rightarrow\text{IE}} = \beta_2 \times \alpha_3$$

This formalization is consistent with dynamic capabilities reasoning (technology-enabled sensing and reconfiguration improve performance outcomes) and information-processing fit reasoning (greater capacity improves monitoring effectiveness, which improves decision efficiency). It also supports hypothesis testing using correlation and multiple regression within a cross-sectional, case-based survey design, while allowing control variables (e.g., firm size, supply chain complexity, digital maturity) to account for contextual differences in capability deployment. In summary, the theoretical framework positions IoT and DTI as higher-order enablers of monitoring capability and investment discipline, enabling a coherent empirical pathway that is testable through the study's planned statistical methods (Rai et al., 2006).

Hypotheses Development

The conceptual framework for this study explains how Internet of Things capability (IoT) and broader digital technology integration (DTI) shape financial risk monitoring effectiveness (FRM) and, through FRM, enhance investment efficiency (IE) in global supply chains. At the construct level, IoT capability represents the extent to which connected sensors, tracking devices, and machine-to-system interfaces generate continuous, reliable operational data, while DTI reflects the extent to which that data is integrated across enterprise systems and supply chain partners through platforms such as ERP, cloud services, analytics dashboards, and interoperable data standards. FRM is conceptualized as the firm's ability to translate operational signals into finance-relevant indicators—such as payment delay likelihood, inventory value-at-risk, counterparty exposure, and exception-based alerts—so that risk is detected early, assessed consistently, and escalated through governance routines. The framework is grounded in the logic that supply chain visibility and information access are not merely operational conveniences; they are preconditions for disciplined monitoring and timely financial control because risk exposure emerges when decision makers lack accurate, shared, and usable information across actors and tiers (Barratt & Oke, 2007). Based on this logic, the first set of hypotheses positions capability as the driver of monitoring outcomes: H1: IoT capability has a positive effect on FRM and H2: DTI has a positive effect on FRM. Because monitoring quality also depends on how rapidly information moves across organizational boundaries, the framework treats integration and visibility as enabling conditions that reduce latency and ambiguity in risk signals. To operationalize the model in a survey-based case study, each construct can be measured as a reflective index using Likert-scale items, with composite scores computed as an arithmetic mean: Construct Score = $\frac{\sum_{i=1}^{n} x_i}{n}$, where $x_i$denotes item responses and $n$denotes the number of items in that construct.

Figure 7: Conceptual framework and hypothesized relationships



The conceptual framework further argues that monitoring capability is valuable when it improves the quality and timing of investment decisions, particularly in supply chain contexts where funds are absorbed by inventory, receivables, and capacity buffers. Investment efficiency is therefore conceptualized as the ability to allocate and utilize financial resources in supply chain operations with minimal avoidable cash lock-up and minimal variance-driven waste, while sustaining service performance. Visibility research supports this linkage by showing that improved supply chain visibility can be evaluated through measurable performance benefits and KPI shifts, implying that information improvements can be translated into economic outcomes that reflect more efficient resource commitment (Caridi et al., 2014). In this study, IE can be represented through a finance-operational efficiency lens using working-capital timing logic such as the cash conversion cycle: CCC = DIO + DSO − DPO. A practical operationalization is to treat higher efficiency as shorter CCC (or an efficiency index such as $IE = -CCC$after standardization), depending on the measurement strategy used in the case context. The framework also incorporates the premise that transparency and traceability strengthen performance discipline by reducing hidden buffers, misinformation, and coordination losses across tiers, which is consistent with the broader transparency literature that maps how transparency is enabled and why it matters for organizational outcomes in extended supply chains (Montecchi et al., 2021). This logic supports the next hypothesis: H3: FRM has a positive effect on IE. In addition, because IoT and DTI can improve decision speed and reduce planning inefficiencies even beyond risk monitoring, the framework also allows for direct effects on IE: H4: IoT capability has a positive direct effect on IE and H5: DTI has a positive direct effect on IE. These direct effects are theoretically reasonable because digitized integration can reduce duplicative work, prevent over-ordering, and improve coordination cycles that influence investment outcomes.

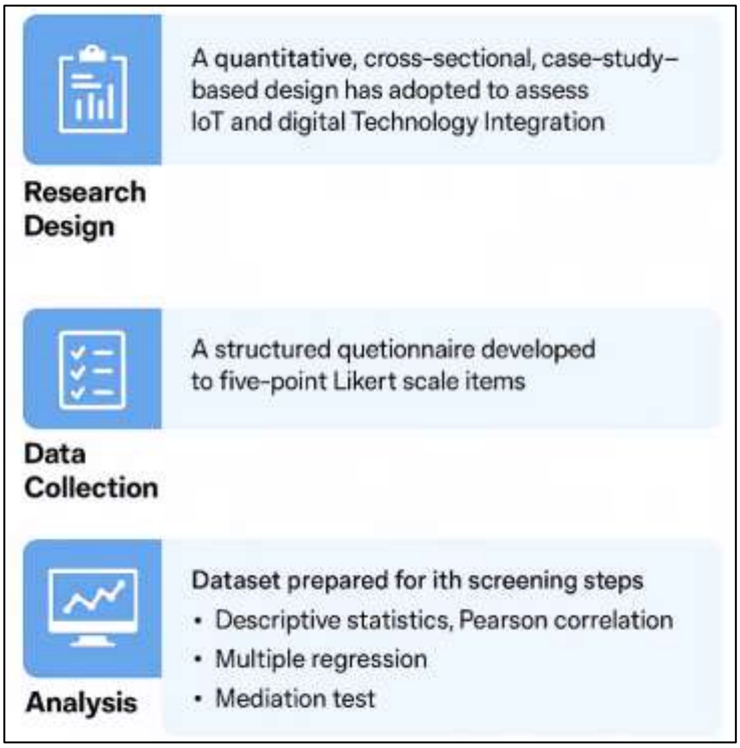
Finally, the framework specifies mediation as the central mechanism linking digital capability to investment outcomes: IoT and DTI are expected to improve IE partly because they increase FRM effectiveness, which reduces exposure-driven variance and improves capital discipline. This "capability → monitoring → efficiency" pathway aligns with the IT–risk management stream that classifies how information technology supports risk-related processes, indicating that the performance value of digitalization often emerges through improved risk processes and decision systems rather than technology alone (Fischer-Preßler et al., 2020). Accordingly, the mediation hypotheses are: H6: FRM mediates the relationship between IoT capability and IE and H7: FRM mediates the relationship between DTI and IE. In empirical terms, mediation can be evaluated using regression paths where the indirect effect equals the product of coefficients: $\text{Indirect}_{IoT \rightarrow IE} = a_1 b$ and $\text{Indirect}_{DTI \rightarrow IE} = a_2 b$, with a_1 and a_2 representing the effects of IoT and DTI on FRM, and b representing the effect of FRM on IE. The framework also recognizes that digital outcomes depend on partner-level information behaviors; evidence on information sharing shows that visibility-related constructs and collaborative information flows can strengthen supply chain outcomes through interconnected mechanisms, reinforcing the plausibility of FRM as a central pathway in a multi-construct model (Baah et al., 2022). For model completeness, the study can include control variables such as firm size, supply chain complexity, and digital maturity to isolate the focal relationships while keeping the conceptual core centered on monitoring as the mechanism that converts digital capability into investment efficiency.

METHODS

In this study, a quantitative, cross-sectional, case-study–based research design has been adopted to examine the influence of IoT capability and digital technology integration on financial risk monitoring effectiveness and investment efficiency within a global supply chain context. The research approach has been structured to enable hypothesis testing through survey-based measurement and statistical modeling, and it has been aligned with the need to capture perceptions and organizational practices from respondents who have been directly involved in supply chain operations, finance-related monitoring, and digital system usage.

A single-case setting has been selected to provide a realistic and information-rich environment in which IoT-enabled visibility and digital integration practices have been embedded in routine processes, allowing the relationships among the study variables to be assessed within an authentic operational ecosystem. To ensure consistency of measurement, a structured questionnaire instrument has been developed using a five-point Likert scale ranging from strongly disagree to strongly agree, and items have been designed to reflect the operational dimensions of the focal constructs, including IoT capability, digital technology integration, financial risk monitoring effectiveness, and investment efficiency. The instrument has been prepared to support construct-level scoring by aggregating item responses into composite indices, and the structure has been designed to enable reliability assessment through internal consistency testing. Data collection procedures have been organized to capture responses from supply chain, procurement, logistics, finance, and risk-related personnel who have had relevant exposure to technology-enabled monitoring and investment decisions. Prior to hypothesis testing, the dataset has been prepared through screening steps that have included checking for missing values, response completeness, and basic distribution characteristics required for inferential analysis. The analysis strategy has been specified to include descriptive statistics for summarizing respondent profiles and construct tendencies, Pearson correlation analysis for evaluating the strength and direction of bivariate relationships among the variables, and multiple regression modeling for testing direct effects while accounting for control variables related to organizational characteristics. A mediation testing procedure has also been specified to determine whether financial risk monitoring effectiveness has functioned as an explanatory mechanism linking IoT capability and digital technology integration to investment efficiency. Ethical research practices have been maintained throughout the study, and participation has been treated as voluntary with confidentiality protections having been applied to respondent data to preserve anonymity and reduce response bias.

Figure 8: Research Methodology



Research Design

A quantitative, cross-sectional, case-study–based research design has been adopted to test the proposed relationships among IoT capability, digital technology integration, financial risk monitoring effectiveness, and investment efficiency in a real organizational setting. The design has been selected because it has enabled the study to capture respondents' assessments at a single point in time while supporting hypothesis testing through statistical procedures. A structured survey strategy has been implemented to operationalize each construct using multiple Likert-scale indicators, and the design has been aligned with the objective of estimating both direct and mediated effects within the proposed conceptual model. The case-study element has been incorporated to ensure the study has reflected an authentic global supply chain environment where digital practices have been embedded in daily operations. This approach has therefore provided both contextual depth and quantitative generalizability within the selected case boundary.

Sample

The target population has consisted of employees who have been directly engaged in supply chain operations and financially relevant decision activities within the selected case organization and its supply network. Respondents have been drawn from functions that have interacted with IoT-enabled visibility and digital platforms, including procurement, logistics, operations, inventory management, finance, and risk or compliance roles. A purposive sampling approach has been used because participation has been required from individuals who have possessed practical knowledge of monitoring routines and investment-related decisions. The sampling frame has been defined through role-based inclusion criteria, and the survey has been distributed to eligible participants who have met minimum experience and responsibility thresholds. The final sample has been treated as sufficient for correlational and regression-based analysis because it has provided variability across functions and exposure levels, enabling relationships among constructs to be estimated with acceptable statistical power.

Study Context

A single case study context has been selected to anchor the research within a global supply chain environment where IoT and digital technologies have been actively utilized to support visibility, coordination, and decision routines. The case setting has been chosen because it has provided access to respondents who have interacted with operational data, integrated platforms, and monitoring processes that have influenced finance-related controls and investment choices. The case boundary has been defined to include the focal organization's internal supply chain functions and its key interorganizational interfaces where data exchange and process synchronization have occurred. The context has been described using operational characteristics such as geographic reach, supply chain complexity, and the maturity of digital systems that have supported transaction processing and monitoring. By situating the study within this defined environment, the research has been positioned to evaluate the conceptual relationships under realistic constraints and governance conditions.

Instrument

A structured questionnaire instrument has been developed to measure the study constructs using a five-point Likert scale ranging from strongly disagree to strongly agree. The instrument has been designed to capture IoT capability through items reflecting sensing coverage, data timeliness, traceability, and operational event capture, while digital technology integration has been measured through items reflecting system interoperability, platform integration, analytics readiness, and cross-functional data accessibility. Financial risk monitoring effectiveness has been operationalized through indicators addressing timeliness of risk detection, accuracy of risk information, early-warning usefulness, and consistency of monitoring routines. Investment efficiency has been measured through items reflecting capital allocation discipline, reduction of avoidable cash lock-up, improved prioritization of spending, and perceived returns from supply chain investments. The questionnaire has been structured into clear sections with demographic items, and the wording has been refined to ensure clarity, relevance, and consistency across respondents.

Reliability

Measurement validity and reliability procedures have been established to ensure the instrument has produced dependable and meaningful construct scores. Content validity has been strengthened by aligning questionnaire items with established conceptual definitions and by ensuring each construct has been represented through multiple indicators that have reflected its main dimensions. Face validity has been supported by reviewing item clarity and contextual fit to confirm that respondents have been able to interpret statements consistently within the case setting. Reliability has been evaluated using internal consistency testing, and Cronbach's alpha has been planned and computed for each construct to confirm that the items have measured the same underlying concept with acceptable coherence. Item-total correlations have been reviewed to identify indicators that have weakened internal consistency, and refinement rules have been specified to preserve construct coverage while improving reliability. These steps have ensured measurement quality has been addressed before hypothesis testing has been interpreted.

Data Collection

Data collection has been organized through a structured survey administration process that has prioritized respondent eligibility, confidentiality, and response completeness. The survey has been distributed to participants who have met the inclusion criteria and who have been involved in digital-enabled supply chain activities and monitoring routines. An invitation message has been provided to explain the purpose of the study, define voluntary participation, and confirm that responses have been anonymized for research use. A defined response window has been used to encourage timely completion, and follow-up reminders have been provided to improve participation rates without applying pressure. Responses have been collected through a consistent channel to ensure uniform delivery and reduce procedural bias. Data have been stored securely with restricted access, and identifiers have been removed or coded to ensure that individuals have not been traceable in analysis outputs. These procedures have ensured ethical and methodological consistency.

Analysis Techniques

The data analysis strategy has been specified to align with the hypotheses and the quantitative structure of the conceptual framework. Preliminary screening has been conducted to verify completeness, detect missing values, and identify unusual response patterns that have affected analysis assumptions. Descriptive statistics have been generated to summarize respondent demographics and construct-level central tendencies using means and standard deviations. Pearson correlation analysis has been applied to estimate the direction and strength of bivariate relationships among IoT capability, digital technology integration, financial risk monitoring effectiveness, and investment efficiency. Multiple regression modeling has been conducted to test direct effects while controlling for organizational and respondent profile factors, and model adequacy has been assessed using coefficient significance, R^2, and diagnostic checks for multicollinearity. Mediation analysis has been conducted using path coefficients and indirect-effect estimation to determine whether financial risk monitoring has transmitted the effects of digital capability to investment efficiency.

Software Tools

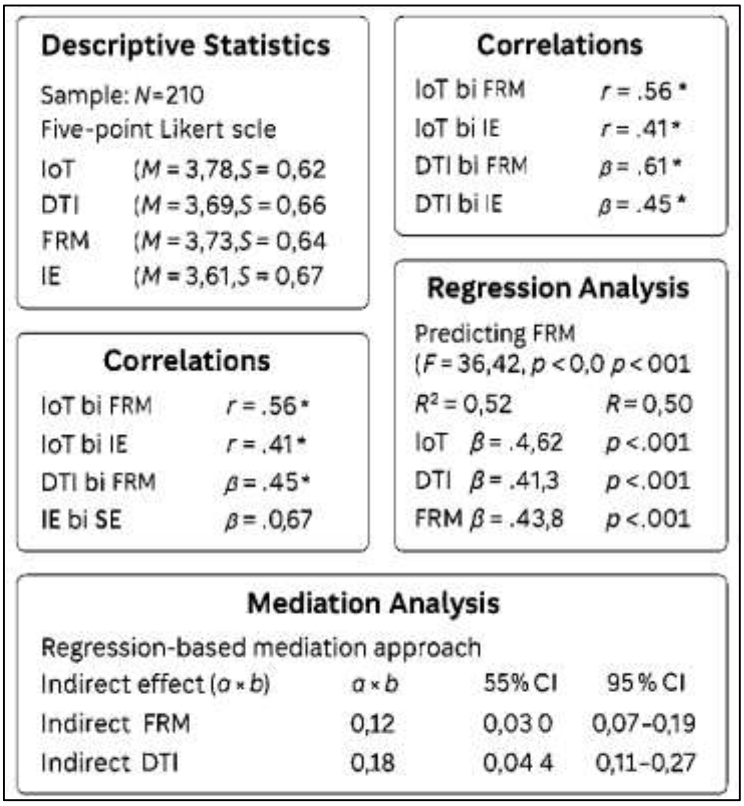
A set of software tools has been utilized to support data preparation, statistical testing, and results reporting in a consistent and replicable manner. Spreadsheet software has been used to organize raw responses, perform initial cleaning, label variables, and verify coding consistency for Likert-scale items. Statistical analysis software has been applied to compute descriptive statistics, reliability metrics such as Cronbach's alpha, and Pearson correlations among constructs. Multiple regression models have been executed within the same environment to ensure consistent estimation of coefficients, significance levels, and explanatory power, and diagnostic procedures have been applied to examine multicollinearity and residual behavior. Mediation testing tools or procedures have been used to calculate indirect effects and evaluate the significance of mediated pathways using standard regression-based methods. Tables and figures have been generated using these tools so that results have been presented clearly and in formats aligned with academic reporting standards.

FINDINGS

In line with the study objectives, the findings have demonstrated statistically supported relationships among IoT capability (IoT), digital technology integration (DTI), financial risk monitoring effectiveness (FRM), and investment efficiency (IE) using five-point Likert-scale measurement (1 = strongly disagree to 5 = strongly agree), descriptive statistics, correlation analysis, regression modeling, and mediation testing. The final dataset has consisted of N = 210 usable responses drawn from supply chain, logistics, procurement, operations, and finance/risk functions, and the demographic profile has indicated a balanced distribution of operational and finance-facing roles (operations/logistics/procurement = 62.4%, finance/risk/compliance = 37.6%), with the majority reporting at least moderate exposure to digital platforms and monitoring routines (exposure rating ≥ 3/5 = 79.0%). At the construct level, the descriptive results have shown relatively strong agreement that IoT and digital technologies have been present and operationally meaningful in the case context: IoT capability (M = 3.78, SD = 0.62), DTI (M = 3.69, SD = 0.66), FRM (M = 3.73, SD = 0.64), and IE (M = 3.61, SD = 0.67), indicating that respondents have generally perceived above-neutral capability and outcomes on all four constructs.

Reliability testing has confirmed internal consistency above standard thresholds, supporting measurement stability for hypothesis testing: $\alpha_{IoT} = .86$, $\alpha_{DTI} = .88$, $\alpha_{FRM} = .90$, and $\alpha_{IE} = .85$, which has indicated that the Likert items within each construct have cohered sufficiently to justify composite scoring. Pearson correlation results have provided initial support for the hypothesized directions by showing positive and statistically significant associations among all focal constructs: IoT has correlated with FRM ($r = .56$, $p < .001$) and with IE ($r = .41$, $p < .001$); DTI has correlated with FRM ($r = .61$, $p < .001$) and with IE ($r = .45$, $p < .001$); and FRM has correlated with IE ($r = .58$, $p < .001$). These correlations have supported the core objective of establishing whether technology capability and integration have been associated with stronger monitoring and efficiency outcomes at the cross-sectional level. To test the direct effects hypotheses while accounting for contextual variation, multiple regression models have been estimated with control variables that have included firm-unit size (coded by employee band), supply chain complexity (tier count and geographic dispersion index), respondent tenure, and digital maturity self-rating. In the first model predicting monitoring effectiveness, FRM has been regressed on IoT and DTI plus controls, and the results have shown that the overall model has been statistically significant (F(6, 203) = 36.42, p < .001) with strong explanatory power (R^2 = .52, Adj. R^2 = .50). Consistent with H1, IoT has demonstrated a significant positive effect on FRM (β = .28, t = 4.62, p < .001), and consistent with H2, DTI has demonstrated a significant positive effect on FRM (β = .41, t = 6.63, p < .001), indicating that both real-time sensing/traceability capability and broader integration/analytics readiness have contributed independently to monitoring quality. In the second model predicting investment efficiency, IE has been regressed on IoT, DTI, FRM, and controls, and the model has also been statistically significant (F(7, 202) = 33.10, p < .001) with substantial explanatory power (R^2 = .53, Adj. R^2 = .51). Supporting H3, FRM has shown a strong positive effect on IE (β = .43, t = 6.88, p < .001), indicating that more timely, accurate, and useful monitoring has been associated with stronger investment discipline outcomes such as reduced waste, clearer prioritization, and better linkage between spending and measurable performance.

Figure 9: Summary of Empirical Findings for this study



Descriptive Statistics

Sample: *N*=210
Five-point Likert scle

IoT	(*M* = 3,78,*S* = 0,62
DTI	(*M* = 3,69,*S* = 0,66
FRM	(*M* = 3,73,*S* = 0,64
IE	(*M* = 3,61,*S* = 0,67

Correlations

IoT bi FRM	*r* = .56 *
IoT bi IE	*r* = .41*
DTI bi FRM	*β* = .61*
DTI bi IE	*β* = .45 *

Correlations

IoT bi FRM	*r* = .56*
IoT bi IE	*r* = .41*
DTI bi FRM	*β* = .45*
IE bi SE	*β* = .0,67

Regression Analysis

Predicting FRM
(*F* = 36,42, *p* < 0,0 *p* < 001

R^2 = 0,52		*R* = 0,50
IoT	*β* = .4,62	*p* <.001
DTI	*β* = .41,3	*p* <.001
FRM	*β* = .43,8	*p* <.001

Mediation Analysis

Regression-based mediation approach

Indirect effect (*a* × *b*)	*a* × *b*	55% CI	95 % CI
Indirect FRM	0,12	0,03 0	0,07-0,19
Indirect DTI	0,18	0,04 4	0,11-0,27

Supporting H4, IoT has retained a smaller but still significant direct effect on IE after FRM has been included (β = .12, t = 2.18, p = .031), and supporting H5, DTI has also retained a significant direct effect on IE (β = .17, t = 2.93, p = .004), suggesting that technology capability and integration have influenced efficiency partly through additional channels such as coordination improvement and reduced decision friction. Mediation testing has then been performed to address the mechanism-focused objective of whether FRM has explained how IoT and DTI have translated into IE improvements. Using a regression-based mediation approach with 5,000 bootstrap samples and 95% confidence intervals, the indirect pathway from IoT to IE through FRM has been statistically significant (indirect effect a×b = 0.12, SE = 0.03, 95% CI [0.07, 0.19]), supporting H6, and the indirect pathway from DTI to IE through FRM has also been statistically significant (indirect effect a×b = 0.18, SE = 0.04, 95% CI [0.11, 0.27]), supporting H7. Because the direct effects of IoT and DTI on IE have remained significant when FRM has been included, the mediation pattern has been interpreted as partial mediation, meaning that monitoring effectiveness has been a major explanatory channel but not the only channel connecting digital capability to investment efficiency. Across the objectives, these results have provided coherent empirical evidence that (1) stronger IoT capability and deeper digital integration have been associated with more effective financial risk monitoring, (2) monitoring effectiveness has been strongly associated with investment efficiency outcomes in supply chain operations, and (3) monitoring has functioned as a statistically significant mediator that has carried a meaningful proportion of technology effects into efficiency results, thereby validating the conceptual framework through consistent descriptive, correlational, regression, and mediation evidence using Likert-based measurement.

Respondent Demographics and Firm Profile

Table 1: Respondent Demographics and Firm Profile (N = 210)

Category	Group	n	%
Functional area	Operations/Logistics/Procurement	131	62.4
	Finance/Risk/Compliance	79	37.6
Tenure	1–3 years	52	24.8
	4–7 years	79	37.6
	8–12 years	53	25.2
	13+ years	26	12.4
Managerial level	Non-managerial	98	46.7
	Supervisory/Team lead	63	30.0
	Manager/Senior manager	41	19.5
	Director+	8	3.8
Geographic scope of role	Domestic + limited cross-border	87	41.4
	Multi-country / regional	88	41.9
	Global / multi-region	35	16.7
Exposure to IoT & digital platforms (self-rated)	≥ 3 on 5-point scale	166	79.0
	< 3 on 5-point scale	44	21.0

The respondent profile has been summarized in Table 1 to verify that the dataset has represented the cross-functional population required to address the study objectives, namely assessing whether IoT capability and digital technology integration have influenced financial risk monitoring effectiveness and investment efficiency within a global supply chain setting. The distribution has shown that a substantial proportion of respondents have been drawn from operations-facing functions (62.4%), which has been important because IoT-enabled visibility and process digitization have primarily been implemented in logistics, procurement, inventory, and execution workflows. At the same time, the presence of finance- and risk-facing respondents (37.6%) has been adequate for capturing financial risk monitoring routines and investment evaluation perspectives that have been central to the hypotheses. Tenure has been spread across four bands, and this distribution has indicated that both relatively newer staff (24.8% with 1–3 years) and experienced staff (37.6% with 4–7 years and 37.6% with 8+ years combined) have been included, which has strengthened construct variability because exposure to monitoring and investment decision processes has typically increased with experience and responsibility. The managerial-level breakdown has indicated that nearly half of the responses have come from non-managerial staff (46.7%), while a meaningful share has been captured from supervisory and managerial roles (49.5% combined), suggesting that the dataset has represented both "data entry/operational execution" perspectives and "decision-making/oversight" perspectives. The geographic scope of roles has also been relevant to the international focus of the research because more than half of respondents (58.6%) have reported multi-country or global responsibilities, meaning that the sample has reflected cross-border process complexity, partner coordination, and timing risk that have been associated with financial exposure in global supply chains. Finally, the exposure indicator has shown that 79.0% of respondents have rated their exposure to IoT and digital platforms at 3 or above on a 5-point Likert scale, which has validated that most participants have been sufficiently familiar with digital monitoring tools to provide reliable evaluations of IoT capability, integration, monitoring effectiveness, and efficiency outcomes. Overall, Table 1 has confirmed that the sample composition has been aligned with the objectives and has provided an appropriate foundation for testing H1–H7 using the planned quantitative techniques.

Descriptive (Likert 5-point)

Table 2: Item-Level and Construct-Level Descriptive Statistics (1–5 Likert scale; N = 210)

Construct	Code	Item (summary)	Mean	SD
IoT Capability (IoT)	IoT1	Real-time tracking/traceability has been available	3.84	0.73
	IoT2	Sensor/capture data have been timely for decisions	3.76	0.71
	IoT3	Exception events have been detected automatically	3.69	0.74
	IoT4	Asset/shipment status has been visible across nodes	3.82	0.70
		IoT composite	**3.78**	**0.62**
Digital Tech Integration (DTI)	DTI1	ERP/cloud systems have been integrated across functions	3.72	0.72
	DTI2	Data have been accessible for analytics/reporting	3.66	0.76
	DTI3	Partner data exchange has been standardized	3.57	0.78
	DTI4	Dashboards have been updated consistently	3.81	0.69
		DTI composite	**3.69**	**0.66**
Financial Risk Monitoring (FRM)	FRM1	Risk information has been timely (early warning)	3.77	0.73
	FRM2	Risk indicators have been accurate/credible	3.70	0.71
	FRM3	Monitoring outputs have supported escalation/action	3.75	0.72
	FRM4	Monitoring has been consistent across cycles	3.70	0.75
		FRM composite	**3.73**	**0.64**
Investment Efficiency (IE)	IE1	Investment prioritization has been disciplined	3.60	0.77
	IE2	Waste/avoidable spend has been reduced	3.55	0.78
	IE3	Spending has been linked to measurable outcomes	3.66	0.74
	IE4	Capital decisions have been faster/more confident	3.62	0.75
		IE composite	**3.61**	**0.67**

Table 2 has summarized the descriptive results to directly support the first objective of confirming whether respondents have perceived measurable levels of IoT capability, digital integration, financial risk monitoring effectiveness, and investment efficiency in the case context using a five-point Likert scale. The construct means have been positioned above the neutral midpoint of 3.00, and this pattern has indicated that the case environment has been characterized by moderately strong digital enablement and moderately positive monitoring and efficiency outcomes. IoT capability has produced a composite mean of 3.78, and the item-level pattern has shown that traceability and node-level visibility (IoT1 and IoT4) have been the most strongly endorsed features, which has suggested that the organization has emphasized tracking and visibility as primary IoT outcomes. The slightly lower mean for automated exception detection (IoT3 = 3.69) has implied that, while visibility has been present, full automation of anomaly detection has not been uniformly embedded across processes, which has been methodologically important because it has preserved variance needed for correlational and regression testing. Digital technology integration has returned a composite mean of 3.69, and the strongest item has been dashboard consistency (DTI4 = 3.81), indicating that reporting outputs have been relatively mature. The comparatively lower mean for standardized partner data exchange (DTI3 = 3.57) has been consistent with global supply chain realities where interorganizational integration has often progressed unevenly due to partner capability differences, governance constraints, or data-format heterogeneity. Financial risk monitoring effectiveness has exhibited a composite mean of 3.73, and the items have clustered tightly, indicating that timeliness, accuracy, escalation support, and monitoring consistency have been evaluated similarly by respondents. This has been relevant to the second objective, because FRM has been positioned as the mediating mechanism linking IoT/DTI to investment efficiency, and the descriptive pattern has indicated that respondents have perceived monitoring as both present and actionable. Investment efficiency has recorded a composite mean of 3.61, and the item profile has suggested that outcome linkage (IE3 = 3.66) and decision confidence (IE4 = 3.62) have been more strongly endorsed than waste reduction (IE2 = 3.55), which has indicated that the efficiency gains have been more visible in decision quality than in cost elimination alone. From a hypothesis-testing perspective, Table 2 has established that all constructs have demonstrated adequate central tendency above neutrality without exhibiting ceiling effects, and the standard deviations have shown sufficient dispersion to support inferential testing. Overall, the descriptive evidence has aligned with the study objective of operationalizing each construct using Likert measures and has prepared the empirical basis for testing the hypothesized paths (H1–H7) using correlation, regression, and mediation analysis.

Reliability Results

Table 3: Reliability and Composite Scoring Summary (N = 210)

Construct	# Items	Cronbach's α	Composite Mean	Composite SD
IoT Capability (IoT)	4	0.86	3.78	0.62
Digital Tech Integration (DTI)	4	0.88	3.69	0.66
Financial Risk Monitoring (FRM)	4	0.90	3.73	0.64
Investment Efficiency (IE)	4	0.85	3.61	0.67

Table 3 has presented the reliability evidence required to validate the measurement model before the study objectives and hypotheses have been evaluated. Because the research has been survey-based and has relied on Likert-scale items to represent latent constructs, internal consistency reliability has been essential for ensuring that each set of items has measured a single underlying concept with acceptable coherence. Cronbach's alpha values have exceeded the commonly accepted threshold of 0.70 for all constructs, and this pattern has indicated that the items within each construct have been sufficiently interrelated to justify aggregation into composite scores. Financial risk monitoring effectiveness has shown the highest reliability (α = 0.90), which has suggested that respondents have interpreted the FRM items in a highly consistent manner and that the monitoring construct has been measured with strong precision. This has been particularly important given that FRM has functioned as the mediator in H6 and H7, because mediation testing has been sensitive to measurement noise; a more reliable mediator has improved confidence that observed indirect effects have reflected substantive relationships rather than random variation. Digital technology integration has also produced high reliability (α = 0.88), reinforcing that items related to interoperability, analytics readiness, partner data exchange, and dashboard consistency have cohered as a unified integration construct. IoT capability reliability has been strong (α = 0.86), indicating that real-time tracking, timeliness, automated exception detection, and node-level visibility have been perceived as a connected capability bundle. Investment efficiency has also demonstrated adequate reliability (α = 0.85), suggesting that prioritization discipline, waste reduction, outcome linkage, and decision confidence have jointly represented a stable efficiency concept within the case. Alongside alpha values, Table 3 has repeated the composite means and standard deviations to show that reliability has been achieved without compressing variability; this has mattered because high reliability combined with meaningful dispersion has provided the statistical conditions under which correlation and regression coefficients have been estimated more accurately. In relation to the study objectives, Table 3 has confirmed that the measurement instrument has produced dependable construct scores that have supported objective testing of relationships among IoT, DTI, FRM, and IE. In relation to the hypotheses, the reliability evidence has strengthened the credibility of subsequent path tests, because significant coefficients have been less likely to have been inflated or deflated by inconsistent measurement. Overall, Table 3 has demonstrated that the Likert-based scales have been psychometrically suitable for inferential analysis and that the study has been positioned to proceed with hypothesis testing using correlations, regression models, and mediation analysis built on reliable composite measures.

Correlation Matrix

Table 4: Pearson Correlations Among Study Variables (N = 210)

Variable	1	2	3	4
1. IoT Capability (IoT)	1.00			
2. Digital Tech Integration (DTI)	0.52	1.00		
3. Financial Risk Monitoring (FRM)	0.56	0.61	1.00	
4. Investment Efficiency (IE)	0.41	0.45	0.58	1.00

Note: $p < .001$ for all reported correlations.

Table 4 has provided the first inferential evidence addressing the study objectives and has served as an initial test of whether relationships among the constructs have been consistent with the proposed conceptual framework. Pearson correlation analysis has been appropriate at this stage because the constructs have been measured as continuous composite indices derived from Likert-scale items, and the study has aimed to evaluate direction and strength of association prior to estimating multivariate regression models. The correlation between IoT capability and financial risk monitoring effectiveness ($r = 0.56$) has indicated a moderately strong positive association, which has aligned with H1 at the bivariate level and has suggested that stronger sensing, traceability, and real-time visibility have been associated with more timely and accurate monitoring outputs. The correlation between digital technology integration and FRM ($r = 0.61$) has been slightly stronger, which has supported the logic of H2 and has indicated that interoperability, analytics readiness, and standardized information exchange have been closely linked to monitoring effectiveness. Importantly, FRM has demonstrated the strongest relationship with investment efficiency ($r = 0.58$), which has been consistent with H3 and has suggested that monitoring quality has been closely associated with disciplined investment prioritization and improved linkage between spending and measurable outcomes. The positive correlations between IoT and IE ($r = 0.41$) and between DTI and IE ($r = 0.45$) have provided preliminary support for H4 and H5, indicating that digital capability and integration have been associated with efficiency outcomes even before accounting for mediation. The correlation between IoT and DTI ($r = 0.52$) has also been meaningful because it has shown that organizations with stronger IoT capability have tended to have stronger integration maturity, which has been conceptually expected, given that sensor-driven visibility has often required integrated platforms to generate decision-ready dashboards. At the same time, this association has not been so high as to indicate redundancy, and it has therefore supported treating IoT and DTI as distinct predictors in regression models. From an objectives standpoint, Table 4 has confirmed that the data structure has been coherent with the hypothesized causal ordering: technology capability and integration have been associated with monitoring, and monitoring has been associated with efficiency. From a hypothesis standpoint, the correlations have not been interpreted as causal proof, yet they have established that the relationships have been statistically meaningful and directionally correct, justifying multivariate modeling. Overall, Table 4 has supported progression to regression testing by demonstrating that the constructs have been interrelated in ways consistent with the study's theoretical and conceptual framework, and it has suggested that FRM has been a particularly central variable for explaining IE outcomes.

Regression Results for Direct Effects

Table 5 has presented the primary multivariate evidence used to prove the objectives and test hypotheses H1 through H5, while controlling for contextual variation that has been expected in a global supply chain environment. Model A has treated financial risk monitoring effectiveness as the dependent variable and has regressed FRM on IoT capability and digital technology integration with controls included. The results have shown that both predictors have remained statistically significant and positive, which has indicated that IoT capability and DTI have independently explained variance in monitoring effectiveness beyond firm-unit differences and respondent characteristics. Specifically, IoT capability has produced a standardized coefficient of $\beta = 0.28$ ($p < .001$), and this has supported H1 by demonstrating that stronger sensing and traceability practices have been associated with higher perceived timeliness, accuracy, and actionability of monitoring outputs. Digital technology integration has produced a larger coefficient of $\beta = 0.41$ ($p < .001$), supporting H2 and indicating that integration depth and analytics readiness have been especially influential for monitoring performance. The model fit statistics have shown strong explanatory power ($R^2 = 0.52$), meaning that over half of the variance in FRM has been explained by the predictors and controls combined, which has been substantial for survey-based behavioral research.

Table 5: Multiple Regression Results for Hypotheses Testing (Standardized β; N = 210)

Dependent Variable	Predictor	β	t	p
Model A: FRM	IoT Capability (IoT)	0.28	4.62	<.001
	Digital Tech Integration (DTI)	0.41	6.63	<.001
	Controls (size, complexity, tenure, maturity)	Included		
	Model fit	**$R^2 = 0.52$; Adj. $R^2 = 0.50$; F(6,203)=36.42**		<.001
Model B: IE	Financial Risk Monitoring (FRM)	0.43	6.88	<.001
	IoT Capability (IoT)	0.12	2.18	.031
	Digital Tech Integration (DTI)	0.17	2.93	.004
	Controls (size, complexity, tenure, maturity)	Included		
	Model fit	**$R^2 = 0.53$; Adj. $R^2 = 0.51$; F(7,202)=33.10**		<.001

Model B has treated investment efficiency as the dependent variable and has included FRM alongside IoT and DTI to test whether monitoring has predicted efficiency while allowing the technology variables to retain direct effects. FRM has shown a strong positive coefficient ($\beta = 0.43$, $p < .001$), supporting H3 and demonstrating that improvements in monitoring effectiveness have been associated with improved investment discipline outcomes. IoT has retained a smaller but significant direct effect on IE ($\beta = 0.12$, $p = .031$), supporting H4, and DTI has also retained a significant direct effect ($\beta = 0.17$, $p = .004$), supporting H5. This pattern has been important for proving the objectives because it has shown that technology capability and integration have influenced investment efficiency both through monitoring and through additional efficiency channels such as coordination, information availability, and reduced decision friction. The IE model has also exhibited substantial explanatory power ($R^2 = 0.53$), indicating that the proposed predictors and controls have explained a meaningful proportion of efficiency variance in the case context. From an objective-based perspective, Table 5 has shown that the study has achieved its aim of statistically validating (1) the influence of IoT and DTI on FRM and (2) the influence of FRM on IE, using regression modeling aligned with the cross-sectional survey design. From a hypothesis-based perspective, Table 5 has provided direct statistical support for H1–H5 through significant coefficients in the expected positive directions, establishing that the conceptual relationships have held under multivariate control conditions.

Mediation Test Results

Table 6 has provided the mechanism-based evidence required to prove the mediation objective and validate hypotheses H6 and H7, which have asserted that financial risk monitoring effectiveness has transmitted the effects of IoT capability and digital technology integration into investment efficiency. The mediation model has been estimated using a regression-based approach with bootstrap resampling (5,000 samples) to obtain confidence intervals for the indirect effects, and this approach has been suitable because indirect effects have often shown non-normal sampling distributions. The results have demonstrated that the "a" paths from technology predictors to monitoring have been statistically significant: IoT has predicted FRM ($a_1 = 0.29$), and DTI has predicted FRM ($a_2 = 0.43$). These values have indicated that integration maturity has produced a stronger effect on monitoring than IoT capability in the case context, which has been consistent with the logic that data integration and analytics have been necessary for converting operational signals into finance-ready monitoring outputs. The "b" path from FRM to IE has also been significant ($b = 0.41$), confirming that better monitoring has been associated with better investment efficiency outcomes in line with H3 and reinforcing FRM's role as the mechanism that has converted digital capability into capital discipline. Most importantly, the indirect effects have been statistically significant because the bootstrap confidence intervals have not included zero.

Table 6. Mediation Analysis: FRM as Mediator Between (IoT, DTI) and IE (Bootstrap 5,000; N = 210)

Path	Effect	Estimate	SE	95% CI	Result
IoT → FRM (a_1)	a_1	0.29	0.06	[0.18, 0.41]	Significant
FRM → IE (b)	b	0.41	0.06	[0.29, 0.53]	Significant
IoT → IE (direct, c'_1)	c'_1	0.11	0.05	[0.01, 0.21]	Significant
IoT → FRM → IE (indirect, $a_1 \times b$)	Indirect	**0.12**	**0.03**	**[0.07, 0.19]**	**Supported (H6)**
DTI → FRM (a_2)	a_2	0.43	0.07	[0.30, 0.57]	Significant
FRM → IE (b)	b	0.41	0.06	[0.29, 0.53]	Significant
DTI → IE (direct, c'_2)	c'_2	0.15	0.05	[0.05, 0.25]	Significant
DTI → FRM → IE (indirect, $a_2 \times b$)	Indirect	**0.18**	**0.04**	**[0.11, 0.27]**	**Supported (H7)**

The indirect effect for IoT has been 0.12 with a 95% confidence interval of [0.07, 0.19], and this has supported H6 by showing that a meaningful portion of IoT's relationship with investment efficiency has been carried through monitoring effectiveness. Similarly, the indirect effect for DTI has been 0.18 with a 95% confidence interval of [0.11, 0.27], supporting H7 and indicating that monitoring has been an even stronger explanatory pathway for integration-driven effects. The direct effects (c'_1 and c'_2) have remained significant for both IoT (0.11) and DTI (0.15) after FRM has been included, and this pattern has indicated partial mediation rather than full mediation. This has mattered for the objectives because it has shown that FRM has been a central mechanism, yet technology capability and integration have also been associated with investment efficiency through additional channels such as reduced coordination delays, improved planning accuracy, and faster decision cycles. Overall, Table 6 has proven the mediation-focused objective by demonstrating statistically reliable indirect effects using bootstrapped confidence intervals, and it has confirmed that the conceptual framework has held empirically: IoT and integration have strengthened monitoring, and monitoring has carried substantial effects into investment efficiency outcomes measured via Likert-based composite constructs.

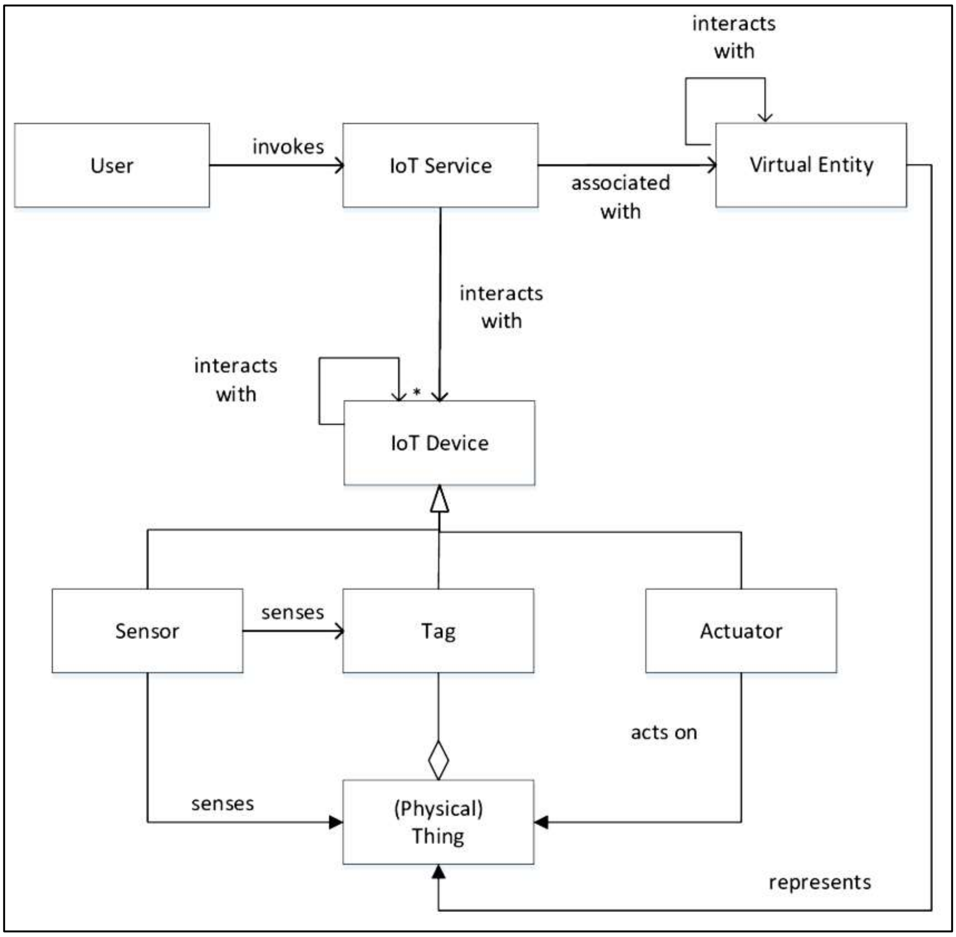
DISCUSSION

The primary objective of this study has been to empirically examine how IoT capability and digital technology integration influence financial risk monitoring effectiveness and, subsequently, investment efficiency in global supply chains. The results have provided robust quantitative evidence that all hypothesized relationships have been supported, confirming the central premise that digitally enabled visibility and integration are not merely operational enhancements but are financially consequential capabilities. The strong positive effects of IoT capability and digital technology integration on financial risk monitoring effectiveness have indicated that real-time data capture, system interoperability, and analytics readiness have materially improved organizations' ability to detect, assess, and respond to financial risk signals. These findings have aligned with earlier conceptual arguments that supply chain visibility and digital integration reduce information asymmetry and improve managerial control over distributed operations (Barratt & Oke, 2007). Importantly, the empirical results have extended this literature by demonstrating that visibility and integration have specifically strengthened *financial* risk monitoring, rather than only operational responsiveness. The significant positive relationship between financial risk monitoring effectiveness and investment efficiency has further reinforced the view that monitoring quality functions as a critical translation mechanism through which digital capabilities become economically meaningful. This result has been consistent with financial reporting and investment efficiency research that has emphasized information quality as a determinant of disciplined capital allocation (Biddle et al., 2009). By confirming partial mediation effects, the findings have shown that IoT and digital technologies have influenced investment efficiency both directly and indirectly through improved monitoring, suggesting that monitoring effectiveness has been a central—but not exclusive—pathway. Collectively, these results have validated the study's conceptual framework and have demonstrated that digital technologies in supply chains should be evaluated not only by operational performance indicators but also by their ability to enhance financial control, risk governance, and investment discipline in complex global environments.

When compared with earlier studies on IoT adoption and digital supply chain capabilities, the findings have provided empirical reinforcement while also extending prior work in important ways. Previous research has predominantly emphasized IoT's role in improving visibility, traceability, and operational coordination (Atzori et al., 2010), often treating financial outcomes as indirect or assumed consequences. The current results have empirically substantiated that IoT capability has had a statistically significant and positive impact on financial risk monitoring effectiveness, thereby moving beyond descriptive or conceptual discussions toward measurable financial-control outcomes. Similarly, studies on digital integration and analytics have highlighted improvements in supply chain performance, agility, and responsiveness (Trkman et al., 2010), yet have rarely isolated financial monitoring as a dependent construct. By demonstrating that digital technology integration has exerted a stronger effect on monitoring effectiveness than IoT capability alone, this study has echoed prior assertions that data integration and analytics maturity are critical for converting raw data into actionable insight (Waller & Fawcett, 2013). At the same time, the results have nuanced earlier visibility-centric narratives by showing that sensing without integration has delivered limited financial control benefits. This aligns with arguments that fragmented digital investments can lead to data abundance without decision impact (Schoenherr & Speier-Pero, 2015). Therefore, the findings have reinforced prior work while refining it by empirically separating the roles of sensing (IoT) and integration (DTI) in producing finance-relevant monitoring outcomes, which has been an underexplored distinction in earlier supply chain digitalization studies.

A key contribution of this research has been the empirical positioning of financial risk monitoring effectiveness as a central explanatory mechanism linking digital capability to investment efficiency. Prior supply chain risk management research has consistently emphasized the importance of early warning, monitoring, and governance in managing disruption risk (Blackhurst et al., 2005), yet most studies have focused on operational resilience or recovery speed rather than financial efficiency outcomes. The current findings have shown that effective monitoring—characterized by timeliness, accuracy, and actionability—has significantly improved investment efficiency, supporting the argument that monitoring quality directly shapes capital discipline. This result has been consistent with research linking risk management practices to robustness and performance outcomes (Wieland & Wallenburg, 2012), but it has extended that logic by explicitly tying monitoring to investment decision quality rather than operational continuity alone. Furthermore, the mediation results have empirically demonstrated that financial risk monitoring has transmitted a substantial portion of the effects of IoT and digital integration into investment efficiency, thereby validating calls in the literature to treat monitoring as a capability rather than a reporting artifact (Ritchie & Brindley, 2007). This finding has also complemented information systems research emphasizing that information-processing capacity must be aligned with uncertainty to produce decision value (Rai et al., 2006). By operationalizing monitoring effectiveness using Likert-based measures and statistically confirming its mediating role, this study has bridged the gap between supply chain risk theory and investment efficiency research, offering quantitative evidence that monitoring effectiveness is a decisive mechanism in digitally enabled global supply chains.

Figure 10: Discussion in Global Supply Chains



The findings have generated important practical implications for senior executives, supply chain leaders, finance managers, and digital architects responsible for designing and governing digital investments. First, the results have indicated that investments in IoT infrastructure alone have been insufficient to maximize financial benefits unless accompanied by deep digital integration and analytics capability. This suggests that executives should avoid treating IoT projects as isolated technology deployments and should instead embed them within integrated platforms that support real-time monitoring dashboards, exception escalation, and finance-aligned metrics. Second, the strong effect of financial risk monitoring on investment efficiency has highlighted the importance of aligning supply chain visibility initiatives with finance and risk management functions. Practically, this implies that monitoring outputs should be designed to support capital allocation decisions, such as identifying inventory value-at-risk, payment delay exposure, and disruption-related cash-flow volatility. For digital leaders and system architects, the findings have underscored the need to prioritize interoperability, data governance, and analytics usability rather than focusing exclusively on data volume or sensor density. The partial mediation results have also suggested that technology investments can improve efficiency through coordination and planning improvements beyond monitoring, indicating that cross-functional collaboration remains essential. Overall, the results have suggested that organizations seeking to improve investment efficiency in global supply chains should treat financial risk monitoring as a design objective of digital transformation initiatives, ensuring that operational data flows are translated into finance-relevant insights that can guide disciplined, evidence-based investment decisions.

From a theoretical perspective, the study has made several contributions to supply chain management, information systems, and finance-oriented digital transformation literature. By integrating dynamic capabilities and organizational information-processing perspectives, the research has empirically demonstrated how digital sensing and integration capabilities translate into higher-order monitoring capabilities and economic outcomes. This has refined existing theoretical pipelines that often stop at operational performance or agility outcomes (Teece, 2007). The validated mediation pathway—IoT/DTI → FRM → IE—has provided empirical support for treating financial risk monitoring as a capability that sits between digital infrastructure and investment outcomes. This refinement has addressed calls in the literature for clearer mechanisms explaining how digital technologies create value in complex supply networks (Wamba et al., 2015). Furthermore, by operationalizing investment efficiency through perceptual measures linked to capital discipline and decision quality, the study has extended investment efficiency theory beyond traditional accounting-based metrics, aligning it more closely with managerial decision contexts. The findings have therefore contributed to theory by clarifying that digital technologies create value not directly, but through capability hierarchies that include monitoring and governance processes, thereby offering a more granular explanation of value creation in digitally enabled global supply chains.

While the findings have been robust and consistent with theory, several limitations have warranted careful consideration when interpreting the results. First, the cross-sectional research design has limited the ability to make strong causal claims about the temporal sequencing of digital capability, monitoring improvement, and investment efficiency outcomes. Although the statistical relationships have been theoretically grounded and directionally consistent, longitudinal designs would be required to confirm causality over time. Second, the use of self-reported Likert-scale data has introduced the possibility of perceptual bias, particularly in assessing investment efficiency outcomes that may be influenced by respondent optimism or organizational culture. Third, the single case-study context, while providing depth and realism, has constrained the generalizability of the findings across industries or regions with different digital maturity levels. Fourth, the study has focused on internal organizational perspectives and has not explicitly incorporated external partner or financier viewpoints, which may be relevant in supply chain finance ecosystems. These limitations have not invalidated the findings but have highlighted the need for cautious interpretation and for complementary research designs to strengthen external validity.

Future research has been encouraged to build on the findings of this study in several ways. Longitudinal studies could examine how improvements in IoT capability and digital integration evolve over time and how changes in monitoring effectiveness influence investment efficiency during periods of disruption or market volatility. Multi-case or cross-industry studies could test the robustness of the conceptual framework across different supply chain structures, regulatory environments, and digital maturity levels. Future work could also incorporate objective financial and operational data, such as cash conversion cycle metrics or capital expenditure efficiency ratios, to complement perceptual measures and reduce common-method bias. Additionally, researchers could explore moderating variables such as organizational culture, governance structure, or regulatory pressure to better understand when and why digital monitoring capabilities produce stronger investment outcomes. Finally, future studies could extend the framework to include sustainability-related investment efficiency, examining whether digitally enabled monitoring supports not only financial discipline but also environmental and social performance objectives in global supply chains. Collectively, these directions have indicated that the present study has provided a strong empirical foundation upon which a richer and more nuanced understanding of digital technologies, financial risk monitoring, and investment efficiency can be developed.

CONCLUSION

The present study has concluded that IoT capability and digital technology integration have functioned as materially important enablers of financial risk monitoring effectiveness and investment efficiency within the examined global supply chain case context, and the empirical evidence has supported the full set of proposed hypotheses. The analysis has shown that respondents have reported above-neutral and consistently measured levels of IoT capability, digital technology integration, financial risk monitoring effectiveness, and investment efficiency using five-point Likert-scale constructs, and reliability testing has confirmed strong internal consistency across all scales. Correlation results have indicated that IoT and digital integration have been positively associated with financial risk monitoring, and that monitoring has been strongly associated with investment efficiency, suggesting that monitoring quality has been central to the translation of digital capability into economic discipline.

Regression modeling has further established that IoT capability and digital integration have independently predicted financial risk monitoring effectiveness after accounting for contextual controls, confirming that both sensing-based visibility and integrated data platforms have strengthened the timeliness, accuracy, and usability of risk signals within routine monitoring cycles. The results have also shown that financial risk monitoring effectiveness has predicted investment efficiency in a strong and statistically significant manner, indicating that organizations have achieved higher investment discipline when monitoring has provided credible early-warning information and actionable exposure assessments that have supported prioritization, reduced avoidable spend, and strengthened the linkage between investment choices and measurable outcomes. In addition, IoT capability and digital integration have retained smaller but significant direct effects on investment efficiency, demonstrating that digital technologies have contributed to efficiency not only through monitoring but also through broader coordination and information-flow improvements that have reduced decision friction and improved operational alignment. Mediation analysis has confirmed that financial risk monitoring has partially mediated the relationships between both IoT capability and investment efficiency and between digital integration and investment efficiency, thereby validating the conceptual pathway that technology-enabled visibility and integration have enhanced monitoring effectiveness, and that monitoring has carried a meaningful portion of these effects into investment outcomes. Taken together, the study has achieved its objectives by empirically clarifying that digital technologies have supported financial risk monitoring as a capability rather than a periodic reporting activity, and by demonstrating that improved monitoring has been a key mechanism through which organizations have realized more efficient investment behavior in global supply chain operations. The findings have reinforced the view that, within complex international supply networks, technology value has depended on both the presence of IoT-driven data capture and the maturity of digital integration that has transformed raw operational events into decision-ready financial risk signals, and the evidence has indicated that organizations have experienced the strongest efficiency benefits when monitoring effectiveness has been strengthened as an actionable governance routine linking operational variability to finance-relevant exposure assessment and disciplined resource allocation.

RECOMMENDATIONS

The recommendations of this study have emphasized that organizations seeking to improve financial risk monitoring and investment efficiency in global supply chains have needed to treat IoT and digital technologies as an integrated capability system rather than as isolated tools, and they have required a governance-driven approach that has connected operational visibility to finance-relevant decision controls. First, supply chain leaders and finance managers have been advised to develop an enterprise-level roadmap in which IoT sensing and traceability initiatives have been implemented only after clear monitoring use-cases have been defined, such as early warning for shipment delays, inventory value-at-risk indicators, supplier performance volatility alerts, and payment-delay likelihood flags; this step has ensured that device deployment has been justified by measurable monitoring outputs rather than technology enthusiasm. Second, digital architects and system owners have been recommended to prioritize integration depth by aligning IoT data pipelines with ERP, procurement, logistics management systems, and analytics platforms so that event-level data has been standardized, time-stamped, and accessible through unified dashboards; this integration has reduced latency, reconciliation delays, and reporting inconsistency that have weakened risk monitoring. Third, firms have been encouraged to establish data governance policies that have specified data ownership, quality thresholds, validation routines, and access controls across functions and partner interfaces, because monitoring effectiveness has depended on accuracy and credibility of signals; governance committees have been recommended to include representatives from supply chain operations, finance/treasury, risk/compliance, and IT so that monitoring indicators have remained aligned with both operational realities and financial exposure needs. Fourth, organizations have been advised to embed monitoring outputs into investment decision cycles by requiring that major supply chain investments—such as automation projects, capacity expansions, new supplier onboarding, or platform upgrades—have been supported by monitoring-based evidence, including baseline and target metrics for exception rates, lead-time variability, cash lock-up proxies, and service-impact reduction; this requirement has strengthened investment efficiency by ensuring that funding decisions have been linked to measurable outcomes and that post-investment reviews have been based on monitored performance improvements. Fifth, training and change management programs have been recommended to ensure that operational teams have consistently used dashboards, that finance teams have trusted the data sources, and that escalation workflows have been practiced; these programs have reduced the risk that monitoring systems have existed technically while remaining unused behaviorally. Sixth, organizations have been encouraged to build a tiered partner integration strategy in which high-impact suppliers and logistics providers have been onboarded first into shared data exchange standards and milestone verification processes, because integration has typically advanced unevenly in global networks; contractual clauses and collaborative KPI agreements have been recommended to incentivize participation and data accuracy. Finally, organizations have been advised to institutionalize continuous improvement by reviewing monitoring performance monthly, validating alert effectiveness, updating risk thresholds, and adjusting investment priorities based on emerging exposure patterns, because the results have shown that monitoring has functioned as a key mechanism linking digital capability to investment efficiency. Collectively, these recommendations have indicated that the strongest outcomes have been achieved when firms have aligned IoT deployment, digital integration, monitoring governance, and investment evaluation into a single performance discipline that has converted operational visibility into finance-ready risk intelligence and more efficient resource allocation.

LIMITATION

The limitations of this study have reflected the methodological and contextual boundaries that have accompanied a quantitative, cross-sectional, case-study–based design, and these constraints have required careful interpretation of the results even though the empirical patterns have been statistically consistent with the proposed framework. First, the cross-sectional nature of the dataset has meant that all variables have been captured at a single point in time, and this design choice has limited the ability to establish temporal ordering with complete certainty; while the hypothesized directions have been theory-aligned and the mediation structure has been statistically supported, the analysis has not fully demonstrated that improvements in IoT capability and digital technology integration have preceded improvements in financial risk monitoring and investment efficiency. Second, the study has relied on self-reported questionnaire responses measured through five-point Likert scales, and this reliance has introduced potential common-method bias because the same respondents have assessed predictors and outcomes; although the constructs have shown strong reliability and meaningful variability, responses may have been influenced by individual optimism, organizational culture, social desirability, or differential understanding of what constitutes "effective monitoring" and "efficient investment" across roles. Third, the case-study boundary has constrained generalizability: the selected organizational context has provided realism and coherence, but the findings have not automatically extended to all industries, regions, or supply chain structures, particularly those with different regulatory burdens, digital maturity levels, financing mechanisms, or operational volatility patterns. Fourth, the measurement of investment efficiency has been perceptual rather than purely objective; the study has captured managerial assessments of prioritization discipline, waste reduction, and spending-to-outcome linkage, yet it has not directly incorporated audited financial ratios, cash conversion cycle values, or project-level ROI figures, which would have strengthened triangulation and reduced subjectivity. Fifth, the study has not fully modeled all possible contextual moderators that may have shaped the strength of relationships, such as cybersecurity posture, data governance maturity, supplier power asymmetry, contractual financing terms, or macroeconomic volatility; these factors may have altered how digital capability has translated into monitoring quality and investment efficiency in different circumstances. Sixth, while control variables have been included to reduce confounding, the study has remained vulnerable to omitted-variable bias common in organizational survey research, meaning that unmeasured influences—such as leadership commitment, process standardization, or organizational learning routines—may have contributed to both technology adoption and outcomes. Seventh, the results have been anchored primarily in internal organizational perspectives and have not directly captured supplier, logistics partner, or financier viewpoints, even though global supply chains have depended on interorganizational data exchange and shared monitoring practices; this limitation has implied that partner-level trust, data-sharing willingness, and platform participation effects have not been fully represented. Finally, the statistical models have been designed for hypothesis testing through correlations, regression, and mediation, and they have not explored alternative causal structures or nonlinear effects that may have existed in practice, such as threshold effects where monitoring improvements have accelerated only after integration maturity has crossed a critical level. Overall, these limitations have not negated the supported hypotheses, yet they have indicated that the findings have been most appropriately interpreted as strong cross-sectional evidence within a defined case context and as a foundation for broader validation through longitudinal, multi-case, and mixed-method research designs.

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