

Digitalization and Traceability in Automotive Industry 4.0: A Strategic Lever for Performance and Supply Chain Resilience

Bechchar Abdeljalil

Abstract: The growing complexity of automotive supply chains, coupled with disruptions like shortages of semiconductors, regulatory requirements, and the shift to electrified and software-defined car models, has heightened the demand for effective digital traceability systems. The relationship between the capability of traceability and the performance of the supply chain in terms of quantity is, however, a field that the literature has not covered very well. This study constructs a simulation-based analytical model to assess the effect of Industry 4.0 digital traceability technologies on the operations of multi-tier automotive supply chains. Four enabling technologies in the form of Internet of Things (IoT) sensing infrastructure, RFID component identification, blockchain-based data integrity, and supply chain data integration maturity are proposed to be combined into a composite Traceability Capability Index (TCI) to estimate traceability maturity. The model contrasts two situations: a conventional low-traceability automotive supply chain and a completely digitalized Industry 4.0 traceability setup. Findings show that there is a significant increase in operational performance when the TCI is increased to 0.9125 as compared to the TCI of 0.225 in various dimensions. In particular, the time of defect detection reduces by 48.7, the time of root cause identification by 58.5, and the scope of recall by 83, and the visibility on the supply chain becomes 33 to 92. The enhanced traceability also performs cost savings in recall of over USD 20.7million per major call back exercise. These results reveal that combined digital traceability systems are a strategic key driver towards improving the resilience and transparency of supply chain operations, as well as recall management effectiveness in Automotive Industry 4.0 settings.

INTRODUCTION

Geopolitical disruptions, semiconductor shortages, pandemic-induced production halts, regulatory tightening, and the accelerating complexity of

electrification and autonomous vehicle technologies have increasingly undermined automotive supply chain stability, rendering these networks more vulnerable to risks, quality failures, and operational interruptions (Kagermann et al., 2013; Lasi et al., 2014). The COVID-19 pandemic had a profound impact across the global automotive sector, causing simultaneous disruptions in raw material sourcing, component manufacturing, logistics, and vehicle assembly, with the industry estimated to have lost production of more than eight million vehicles in 2021 as a direct consequence of the ensuing semiconductor shortage alone (Ramani et al., 2022). The magnitude of these disruptions was difficult to anticipate due to the structural complexity and multi-tier interdependence of automotive supply chains, which involve tens of thousands of components and hundreds of geographically dispersed Tier-1, Tier-2, and Tier-3 suppliers (Monostori et al., 2016) (see Figure 1). These compounding disruptions, heightened uncertainty, sudden demand volatility, and unforeseen operational failures compelled manufacturers to adopt more flexible, data-driven approaches and to continuously reconfigure their supply chain strategies to address emerging challenges (Ivanov, 2024).

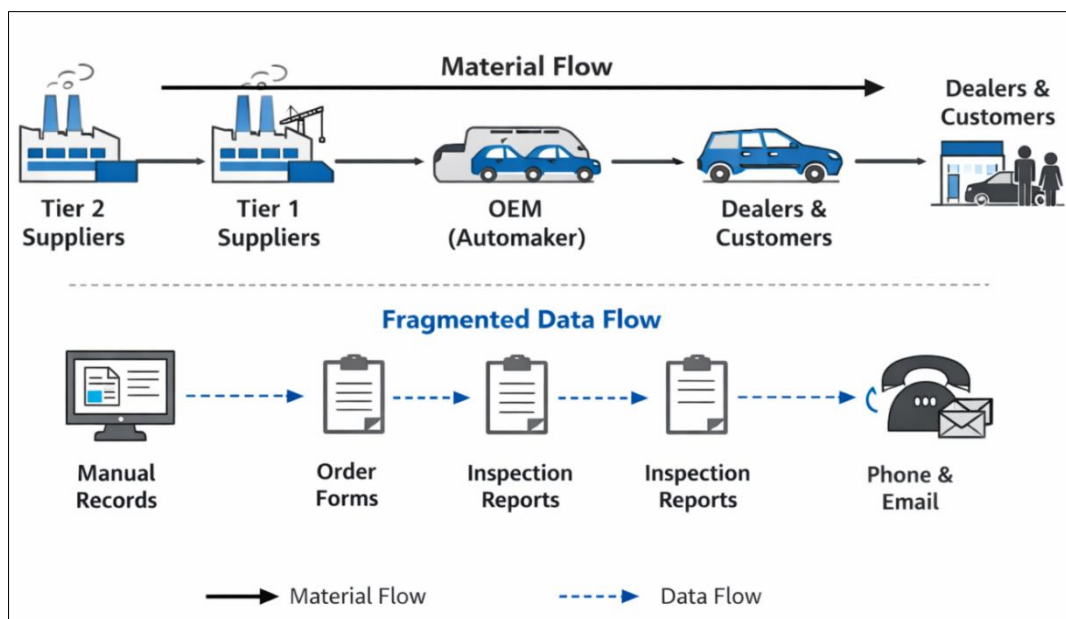


Fig. 1: Traditional automotive supply chain scenario. The material flow proceeds from upstream suppliers to OEM and customers, while the data flow is fragmented across actors.

Product recalls can be considered as one of the most financially and reputationally harmful effects of poor traceability in the automotive manufacturing sector, with a single recall event often involving millions of vehicles and costing the impacted manufacturers billions of dollars in mitigation and legal liability (Li et al., 2022; Fang et al., 2024). Lack of real-time, granular component tracking at the different supplier levels always escalates the scope of recall, as original equipment manufacturers (OEMs) tend to implement broad precautionary actions at the level of whole production batches due to the lack

of accurate defect localization information (Ni et al., 2018). Here, Little research has quantitatively modelled the performance impact of multitier automotive transitioning to fully integrated Industry 4.0 traceability models by modifying traditional low-traceability strategies (Ivanov and Dolgui, 2022; Badakhshan and Ball, 2023). The area of future research that can be pursued is the creation of simulation-based models that formally connect the traceability capability to the speed of the defect detection, reduction of the scope of recalls, and cost outcomes of the operational process, at all tiers of the suppliers.

Fraud of suppliers and fake automotive components are similar and equally severe traceability issues, which represent a multi-billion-dollar international marketplace risking vehicle safety, regulatory compliance, and consumer confidence throughout the entire value chain (Bosona & Gebresenbet, 2013; Babich & Hilary, 2020). The researchers (Khan et al., 2022) defined that technologies to promote supply chain traceability and transparency can provide quantifiable benefits in the form of product authenticity checks and assurances, supplier responsibility, and downstream customer trust. It was also shown that blockchain technology plays a critical role in reducing the trust gaps in a circular supply chain (Centobelli et al., 2022) by generating unaltered records of transactions that are difficult to alter or falsify in a multi-stakeholder context. A few past studies have found a substantial positive impact of digital traceability on monitoring supplier quality (Ada et al., 2021), the efficacy of recall management (Merzifonluoglu and Geunes, 2021), and the results of regulatory adherence (Erboz et al., 2022). The findings underscored the strategic imperative of incorporating intensive, technology-based traceability frameworks across the automotive manufacturing ecosystem.

Digital traceability, as the ability to continuously locate, track, and document the history, location, and state of components throughout their lifecycle, starting with the extraction of raw materials, throughout the manufacturing, distribution, and end-user phases, has become a cornerstone of next-generation automotive supply chain management (Tao et al., 2019). The technologies to support such an extensive traceability system have become very mature in the context of the Automotive Industry 4.0: IoT sensors and RFID systems offer real-time physical location and identification information throughout the production and logistics stages, and blockchain platforms provide tamper-resistant and immutable data sharing across both heterogeneous partners of the supply chain (Hussain et al., 2021; Van Hoek, 2019). Digital twin architectures also allow virtualization of physical elements and real-time observation, and cyber-physical production systems develop the integration platform to coordinate independent data streams into a single working image (Kamble et al., 2022; Monostori, 2016). Nonetheless, neither of these technologies nor a combination of these technologies has been mathematically modelled and experimentally proven in any current research concerning the automotive supply chain.

The growing trend towards electric and autonomous vehicles has added one more dimension of supply chain complexity that significantly increases the strategic significance of digital traceability (Lutfi et al., 2024). Modern electric vehicles have far more semiconductors, battery control electronics, and software-defined subsystems than conventional vehicles, all of which are highly safety-critical parts facing extremely strict lifecycle traceability in frameworks like the EU Battery Regulation and the IATF 16949 quality management standards (Ozdemir et al., 2024). Though such developments have occurred, no complete and simulation-supported traceability framework that incorporates the entire complexity of Automotive Industry 4.0 settings, such as multi-level supplier networks, closed-loop lifecycle feedback, and indexing of composite technology capability, has been defined in the scholarly literature.

The quality, speed, and reliability of the information flows between all supplier levels define fundamental elements of the supply chain performance in the automotive industry, and digital traceability has been associated with several key performance aspects such as speed in detecting defects, reducing recall scopes, inventory optimization, and supplier quality assurance (Wu et al., 2025; Bag et al., 2023). The fact that there is no validated quantitative framework that incorporates IoT, RFID, blockchain, and data integration maturity as one composite Traceability Capability Index (TCI) and formally tracks the impact of this index on defect detection, recall management, supply chain visibility, and cost of operation across a multi-level automotive simulation model is the major research gap that drives the current study.

Based on the considerations above, and the necessity of having a rigorous quantitative insight regarding the impact of integrated digital traceability systems on the performance of an automotive supply chain, this study will establish and test a simulation-based traceability model that involves the implementation of IoT, RFID, blockchain, and digital twin technology into a single multi-tier automotive supply chain. The novelty of this work is seen in the development of the Traceability Capability Index (TCI) that combines the maturity of various enabling technologies into one or other measurable construct and allows the low-traceability and high-traceability configurations to be compared across key performance indicators in a systematic manner. The current research builds upon the literature by going beyond conceptual models of automotive traceability to produce a numerically based analysis of the results of the performance, which contributes to new knowledge on the strategic implications of Industry 4.0 digital transformation to automotive manufacturers, their supplier network, and regulatory bodies.

The main objectives of the study are as follows:

O1: To develop a quantitative simulation model evaluating the relationship between digital traceability capability and key automotive supply chain performance indicators, including defect detection time, recall scope, root cause identification speed, and supply chain visibility.

O2: To examine the individual and combined contributions of IoT, RFID, blockchain, and data integration technologies to overall traceability capability in multi-tier automotive supply chain environments.

O3: To assess the economic and operational implications of transitioning from traditional low-traceability systems to fully integrated Industry 4.0 digital traceability frameworks in automotive manufacturing contexts.

This research has some important contributions. The first presents a new quantitative construct, a composite Traceability Capability Index (TCI), which allows systematic measurement and benchmarking of traceability maturity among multi-tier automotive supply chains. Second, it builds a multi-variable simulation model formally connecting traceability capability to operationally critical performance outcomes, showing that high traceability capability is associated with shorter defect detection times (by about 49 percent), shorter recall scope (by 83 percent), and shorter time to root cause identification (by 58 percent), as well as greater supply chain visibility (33 percent to 92 percent), and cost savings (more than 20 million dollars per major recall incident). Third, this work contributes to the current body of knowledge on Industry 4.0 digital transformation by showing, through scenario-based numerical simulation, how large a performance increase can be achieved by integrating end-to-end traceability throughout all automotive levels of suppliers. Lastly, placing the proposed framework into the setting of current traceability technology adoption, the current study offers practical paths to implementing the suggested framework in current manufacturing execution systems and smart supply chain platforms.

LITERATURE REVIEW

1.1. Digital Traceability in Automotive Industry 4.0

Digital traceability involves the systematic capacity to identify, monitor, and record the history, location, and status of components and products across their entire lifecycle, from raw material sourcing through manufacturing, distribution, and end-user operation, using advanced digital technologies integrated within a unified supply chain information architecture (Wofuru-Nyenke et al., 2023; dos Santos et al., 2022). In the context of Automotive Industry 4.0, traceability has evolved from a production-stage quality inspection tool into an end-to-end, closed-loop operational capability that connects upstream supplier verification with downstream customer diagnostic feedback across multi-tier supplier networks (Hosseini et al., 2019). (Frank et al., 2019) demonstrated that Industry 4.0 technology adoption in manufacturing companies follows distinct implementation patterns, with firms achieving higher levels of digital integration reporting measurably superior operational performance and enhanced quality assurance outcomes. (Javaid et al., 2022) Further confirmed that Industry 4.0 applications across manufacturing environments yield significant improvements in production flexibility, quality control, and supply chain coordination,

underscoring the centrality of digital integration to contemporary manufacturing competitiveness. (Khan et al., 2022) established that technologies enabling traceability and supply chain transparency generate measurable improvements in product authenticity verification, supplier accountability, and customer trust across complex multi-stakeholder networks. However, few studies have developed quantitative simulation frameworks that formally model digital traceability capability as an independent, composite performance driver across multi-tier automotive supply chain environments (Durach et al., 2017; Vuković et al., 2023).

1.2. IoT and RFID-Enabled Component Tracking

IoT and RFID technologies constitute the primary physical sensing and identification layer of digital traceability systems, enabling the automatic capture, transmission, and processing of real-time component location, condition, and identity data across all nodes of the automotive supply chain, from raw material procurement through final vehicle delivery (Vuković et al., 2023). IoT sensors embedded within production equipment, logistics assets, and supplier facilities generate continuous, high-frequency data streams that, when integrated with upstream and downstream supply chain information systems, enable granular, real-time visibility into component flows and operational conditions across all supplier tiers (Dasaklis et al., 2022). Hussain et al. (2021) conducted a systematic literature review of blockchain-based IoT devices in supply chain management and concluded that the integration of IoT and blockchain technologies holds transformative potential for end-to-end supply chain visibility, while also identifying significant technical and organizational barriers impeding effective multi-stakeholder deployment. Ferdousmou et al. (2024) confirmed that integrated RFID-IoT systems bring transformative advancements to supply chain management, enabling real-time identification and monitoring of products and improving quality management across the full supply chain from manufacturer to consumer. Zaman et al. (2025) demonstrated that IoT-driven operational excellence significantly improves supply chain collaboration by providing accurate and actionable real-time data to all stakeholders across complex multi-tier networks. Some previous studies have demonstrated the positive effect of IoT adoption on supply chain visibility (Xu et al., 2024) and operational efficiency (Zhang et al., 2024). However, the individual and combined performance contributions of IoT coverage density and RFID tagging maturity have not been formally aggregated into a composite traceability capability index capable of predicting system-level outcomes in multi-tier automotive supply chains.

1.3. Blockchain Technology for Supply Chain Traceability

Blockchain technology provides a decentralized, immutable, and tamper-resistant distributed ledger infrastructure that enables secure, transparent, and auditable data sharing across heterogeneous supply chain partners, thereby addressing trust deficits, information asymmetries, and data integrity vulnerabilities inherent in traditional multi-tier supply chain architectures (Page

et al., 2021; Moher et al., 2009). In the automotive sector, blockchain has been proposed as the foundational data integrity layer for end-to-end traceability systems, enabling the permanent recording of component identities, quality certifications, custody transfers, and regulatory compliance documentation across all supplier tiers (Durach et al., 2017). Vuković et al. (2023) conducted a systematic literature review of blockchain applications in automotive supply chain management and established that the technology holds significant promise for reducing operational inefficiencies, improving information flows, and enhancing inter-organizational trust, while simultaneously identifying persistent implementation challenges, including interoperability constraints and scalability limitations. (Wang et al., 2023) subsequently confirmed that blockchain-based traceability architectures improve cross-organizational data reliability and significantly reduce fraud risk in smart supply chain environments. Heldt and Pikuleva (2025), in a process-based case study of blockchain adoption for sustainability traceability in critical mineral supply chains serving the automotive industry, demonstrated that upstream suppliers play a pivotal and previously understudied role in driving blockchain traceability implementation, revealing that tier-by-tier traceability construction is the practical reality of multi-stakeholder adoption rather than simultaneous network-wide deployment. Boutaleb et al. (2025) further confirmed through a systematic review that blockchain-enabled supply chain management significantly enhances security, traceability, and data integrity across decentralized supply chain environments, while also identifying that scalability and interoperability remain the most persistent unresolved technical barriers. Few studies have developed quantitative models that formally measure the combined contribution of blockchain adoption to a composite traceability capability index and trace its effects on automotive supply chain performance outcomes across all supplier tiers.

1.4. Digital Twin and Cyber-Physical Systems in Traceability

Digital twins are virtual replicas of physical assets, processes, and systems that are continuously synchronized with their real-world counterparts through real-time data streams, enabling dynamic monitoring, simulation-based performance prediction, and proactive operational decision-making without disrupting physical operations [32, 33]. In the context of automotive traceability, digital twin architectures serve as the integration and intelligence layer of end-to-end traceability systems, aggregating IoT sensor data, RFID identification streams, blockchain transaction records, and manufacturing execution system outputs into a unified, continuously updated virtual representation of the physical supply chain [34]. Kim et al. (2025) proposed a supply chain digital twin methodology for dynamic supply chain management that demonstrated enhanced operational efficiency through real-time monitoring and response to disruptions, with the digital twin's prediction and optimization modules enabling significantly improved order fulfillment and inventory control under volatile demand conditions. Malekzadeh et al. (2025) developed a generic supply chain digital twin framework for managing both short-term and long-term risks in multi-

echelon supply chains, confirming that digital twin-based recovery strategies demonstrate resilience under economic crisis and short-term disruption scenarios while also revealing intensified challenges when multiple long-term crises occur simultaneously. Zhang et al. (2024) [39] further developed a simulation model for blockchain-based traceability systems in smart manufacturing environments and demonstrated measurable improvements in defect localization accuracy and production transparency. Existing literature has focused primarily on digital twin applications in single-facility manufacturing contexts [40, 41], while few studies have examined digital twins as an integrated component of a composite, multi-tier automotive traceability capability framework validated through quantitative simulation.

1.5. Traceability and Supply Chain Performance

The automotive industry supply chain performance involves all the operational, financial, and strategic results that the manufacturing and distribution channel can produce (speed of detecting defects, management of the scope of recall, inventory, efficiency in regulatory compliance, supplier quality assurance, and customer satisfaction at the end of use) (Centobelli et al., 2022). Theoretically and empirically, traceability has been associated with various important dimensions of supply chain performance because increased visibility of components has led to faster detection of quality failures, minimization of the extent of precautionary recalls in the context of quality failures, improved supplier responsibility, and augmentation of regulatory compliance records throughout the value chain (Hosseini et al., 2019). Li et al. (2022) made a cross-disciplinary review of the literature on product recall studies and found that the research field does not possess solid quantitative models that can be used to connect the particular metrics of technology adoption to the results of recall management operations within sophisticated hierarchies of suppliers. A simulation based on agent-based methods was proposed by Shi et al. (2025) to evaluate and optimize the process of vehicle complaint-recall in the auto industry, and found that the complaint-recall system is complex in terms of the behavior patterns, and that the main operational variables influencing the recall performance are complaint volume management and the coordinated time of the investigation. Bag et al. (2023) also established that the use of Industry 4.0 tools in supply chain operations brings great advantages in sustainability and performance in terms of increased visibility, efficiency in processes, and real-time responsiveness across the manufacturing networks. Nevertheless, not many papers have considered the quantitative effects of the digital traceability capability, formalized into a composite index that combines various enabling technologies on the performance results of the automotive supply chain, such as defect-detecting time, recall scale, speed of root cause identification, and operational cost at a multi-tier simulation model.

1.6. Simulation Modeling for Traceability Performance Evaluation

The simulation modeling is the application of computational tools to imitate the behavior of complex systems under given conditions and allow the systematic

analysis of new configurations or interventions and adoption of technologies without paying the cost and risks of performance in the real world (Fang et al., 2024; Ni et al., 2018). Simulation methods have been more actively used in the context of supply chain management to measure the performance of technology adoption, disruption, and changes of operational policies through a multi-echelon network with multiple interacting agents, stochastic demand, and dynamic information flow (Dasaklis et al., 2022). The article by Ivanov and Dolgui (2022) has shown that the viability analysis, as shown through a simulation-based stress-testing of supply chains, offers actionable information on the resilience and adaptability of complex industrial networks to compound disruption events, which can be directly used to assess the traceability-enabled automotive supply chain setup. Badakhshan and Ball (2023) simulated the inventories and cash situations in a supply chain by digital twin-mechanism under physical and financial uncertainties and affirmed that simulation models offer solid and practical decision-making to supply managers who operate within uncertain contexts. Quantitative modeling was used in Ramani et al. (2022) to comprehend systemic disruption due to the COVID-19-induced semiconductor shortage to the automotive industry, illustrating the explanatory potential of the simulation-based analytical models in determining complex and multi-causal supply chain issues in the automotive industry. Nevertheless, a validated, multi-variable simulation model, which incorporates the IoT, RFID, blockchain, and data integration maturity into a composite Traceability Capability Index and which objectively measures the impact of the model on the defect detection time, recall scope reduction, speed of root cause identification, and supply chain visibility in a multi-tier automotive supply chain context, has not been created in the academic literature.

RESEARCH METHODOLOGY

Research Design

This study adopts a quantitative, analytical scenario-based modeling approach to evaluate the operational impact of digital traceability technologies on automotive supply chain performance. The objective of the methodology is to formally link traceability capability enabled by Industry 4.0 technologies to measurable supply chain performance outcomes, including defect detection time, recall scope reduction, root cause identification speed, supply chain visibility, and recall cost.

In contrast to stochastic simulation, e.g., discrete-event simulation or agent-based modeling, the current study uses a deterministic analytical model where the performance indicators can be directly obtained by using mathematically defined equations. This method makes a clear assessment of the directional correlation between traceability ability and operational performance possible, and makes comparative analysis of the difference in technology arrangement possible under control.

The model is a multi-level automotive supply chain network, which involves the suppliers of raw materials, Tier-2 machinery suppliers, the Tier-1 module suppliers, the original equipment maker (OEM), and the end-users. The analytical framework observes the flow of materials and information between these actors and the impacts of the enhancement of digital traceability capability on the major operational processes, in particular, defect detection, trace-back investigation, and management of recalls.

Two other supply chain designs considered include:

- Scenario A (Traditional Supply Chain): low levels of digital traceability and incomplete information systems.
- Scenario B (Industry 4.0 Supply Chain): built-in IoT sensors, RFID component tagging, blockchain-based distributed ledger infrastructure, and maturity in data integration.

The performance of these two configurations is compared using a set of analytically defined key performance indicators derived from the proposed traceability capability model.

Multi-Tier Automotive Supply Chain Model

The simulated system is a classic multi-level automotive supply chain, with an authoritarian relationship between suppliers and multi-layered component flows. The network consists of five levels:

- Level 4 - raw material suppliers
- Level 3 - Tier-2 component manufacturers
- Level 2 - Tier-1 module suppliers
- Level 1 - OEM vehicle assembly plant
- Level 0 - downstream customers and dealerships

Overall, the model reflects 120 supply chain nodes, which are spread over the various levels of the production network. Material flow sources are the upstream suppliers, and the centre is the OEM assembly plant where final vehicles are manufactured. These physical movements are accompanied by information flows that include information about component identity, batch history, quality inspections, and logistics transactions.

The old setup, where traceability is based mainly on enterprise resource planning (ERP) systems and periodic exchange of documentation, creates low cross-tier visibility. The Industry 4.0 configuration allows supporting digital traceability with the help of IoT sensors, RFID identification technologies, shared ledgers based on blockchain, and interoperable data systems.

Traceability Capability Model

In order to measure the extent of digital traceability across the supply chain network, this paper proposes a Traceability Capability Index (TCI). The index is a summary of the maturity of four enabling technologies, which jointly define the efficacy of traceability infrastructure:

- IoT sensor coverage
- RFID component tagging coverage
- blockchain adoption level
- data integration maturity

Each component is represented as a normalized value between 0 and 1 that indicates the share of the supply chain network that uses the respective technology. Composite Traceability Capability Index is defined as:

$$TCI = \frac{w_1 IOT + w_2 RFID + w_3 BC + w_4 DI}{w_1 + w_2 + w_3 + w_4}$$

where

IoT = proportion of nodes equipped with IoT sensors

RFID = proportion of components with digital identification

BC = blockchain adoption level across supply chain tiers

DI = data integration maturity level

w_1 - w_4 = weighting coefficients

In the base-case model equal weights are assigned to all components ($w_1 = w_2 = w_3 = w_4 = 1$), reflecting the exploratory objective of evaluating the combined effect of the four technologies on traceability capability.

Scenario Configuration

Two supply chain scenarios were constructed to represent different levels of traceability capability.

Scenario A: Traditional Automotive Supply Chain

The baseline configuration represents a conventional supply chain environment characterized by partial ERP-based tracking, manual document exchange, and limited cross-tier data integration. Traceability is primarily batch-based, and defect detection often occurs through customer complaints or dealership reporting.

Technology coverage levels in Scenario A are defined as:

1. IoT coverage = 0.20
2. RFID tagging = 0.30
3. Blockchain adoption = 0.00
4. Data integration maturity = 0.40

These parameters produce a Traceability Capability Index of **0.225**, representing low traceability capability.

Scenario B: Industry 4.0 Digital Traceability System

The second configuration represents a fully integrated Industry 4.0 supply chain in which IoT sensors, RFID identification systems, blockchain

infrastructure, and interoperable data platforms enable end-to-end digital traceability. Technology coverage levels are defined as:

1. IoT coverage = 0.85
2. RFID tagging = 0.95
3. Blockchain adoption = 0.90
4. Data integration maturity = 0.95

These values produce a Traceability Capability Index of 0.9125, representing a high-traceability configuration.

Performance Indicators and Analytical Model

The effect of traceability capability on supply chain performance is evaluated through five key performance indicators (KPIs):

1. defect detection time (DTD)
2. recall scope reduction (RSR)
3. root cause identification time (RCIT)
4. Supply Chain Visibility Index (SCVI)
5. recall cost

Each KPI is computed through an analytical equation linking the Traceability Capability Index to operational outcomes.

Defect Detection Time

$$DTD = \frac{D_{base}}{1 + \alpha \cdot TCI}$$

Where:

- D_{base} = baseline detection time without traceability
- α = traceability efficiency coefficient

Recall Scope Reduction

$$RSR = 1 - \frac{B_t}{B_{total}}$$

Where:

- B_t = defective batch size identified
- B_{total} = total production batch

Root Cause Identification Time

$$CIT = \beta_0 - \beta_1(TCI)$$

Where:

- β_0 = 14 days is the baseline investigation time and
- β_1 = 10 is the traceability efficiency parameter.

Supply Chain Visibility Index

$$CVI = \frac{N_{\text{tracked}}}{N_{\text{total}}}$$

Where:

- N_{tracked} = tracked supply chain nodes
- N_{total} = total nodes

Recall Cost

$$\text{RecallCost} = N_{\text{recalled}} \times C_v$$

Where:

$$C_v = 500 \text{ USD}$$

Composite Operational Performance Index

To summarize the overall impact of traceability capability across all performance dimensions, a normalized **Overall Performance Index (OPI)** is computed as:

$$OPI = 0.25(RSR) + 0.25(SCVI) + 0.25(1/DTT) + 0.25(1/RCIT)$$

This index aggregates recall containment, supply chain visibility, and operational response speed into a single composite performance metric.

Analytical Evaluation Procedure

The evaluation procedure consists of five sequential steps:

1. Define supply chain technology coverage parameters for each scenario.
2. Compute the Traceability Capability Index using Equation (1).
3. Derive performance indicators using Equations (2)-(6).
4. Calculate recall cost differences between scenarios.
5. Compute the Overall Performance Index to summarize system performance.

The resulting values provide a quantitative comparison of operational performance between the traditional automotive supply chain and the Industry 4.0 digital traceability configuration.

RESULTS

The results of the analytical simulation are presented across six steps corresponding to the model variables defined in Section 4. Two scenarios are evaluated: Scenario A, representing a conventional automotive supply chain with limited digital traceability (low TCI), and Scenario B, representing a fully integrated Industry 4.0 configuration incorporating IoT sensors, RFID tagging, blockchain-enabled shared ledgers, and high data integration maturity (high TCI). The Traceability Capability Index is computed first to establish the baseline

and high-traceability states, and each performance indicator is then derived analytically using the associated equations.

Traceability Capability Index (TCI)

The Traceability Capability Index combines the maturity of the four digital traceability sub-components IoT sensor coverage, RFID component tagging, blockchain adoption, and level of data integration into a single normalized score with a minimum score of [0, 1]. The base-case configuration has equal sub-component weight in line with the exploratory and comparative character of the study. It can be defined now in a formal manner:

$$TCI = \frac{w_1 IOT + w_2 RFID + w_3 BC + w_4 DI}{w_1 + w_2 + w_3 + w_4}$$

Equation 1: Composite Traceability Capability Index (TCI). Each sub-component $\in [0, 1]$.

where IoT represents the fraction of the supply chain nodes with active IoT sensing infrastructure, RFID represents the fraction of the components with digital identification at component or batch level, BC represents the blockchain adoption level at the various levels of the supply chain on a scale, DI represents the data integration maturity level, and w_1 to w_4 are the weight coefficients on corresponding scales. Equal weighting of the equation leads to arithmetic mean of the four sub-components. Table 1 gives the values of the input in both scenarios.

Table 1: Traceability Technology Input Parameters by Scenario

Parameter	Symbol	Scenario A (Low TCI)	Scenario B (High TCI)	Change
IoT Sensor Coverage	IoT	0.20 (20%)	0.85 (85%)	+325%
RFID Tagging Coverage	RFID	0.30 (30%)	0.95 (95%)	+217%
Blockchain Adoption Level	BC	0.00	0.90	From 0 to 0.90
Data Integration Maturity	DI	0.40	0.95	+138%
Weight Coefficients	w_1 – w_4	1 (equal)	1 (equal)	-

Table 2: TCI Computation: Step-by-Step

Calculation Step	Formula	Scenario A	Scenario B
Sum of sub-components	IoT+RFID+BC+DI	0.20+0.30+0.00+0.40 = 0.90	0.85+0.95+0.90+0.95 = 3.65
Divide by the number of components	Sum / 4	0.90 / 4	3.65 / 4
TCI Score	TCI	TCI _A = 0.225	TCI _B = 0.9125

In Scenario A, the TCI is 0.225, and in Scenario B, it is 0.9125, which is an improvement of 306 percent in the overall traceability capability. The structural limitation in Scenario A ($BC = 0$) is the lack of blockchain infrastructure, which leaves out a whole dimension of the index. The great increase in the coverage of the IoT (improvement of 65 percent points) and RFID tagging (65 percent points) points to a shift to a near-complete solution in the real-time tracking of components at the multi-tier supplier network on the component level (see Table 2).

Defect Detection Time (DTD)

Defect detection time measures the time elapsed between when a component fails and its discovery by the supply chain participants. In the conventional structure, customer complaints or dealership reporting usually occur with the failures of the products, and the investigation is initiated by a manual process of escalation along the levels of the suppliers. The Industry 4.0 setup would make the IoT sensors included at the production nodes produce continuous anomaly notifications that are used to initiate automatic investigation processes. Detecting defect time is calculated as follows:

$$TCI = \frac{w_1 IOT + w_2 RFID + w_3 BC + w_4 DI}{w_1 + w_2 + w_3 + w_4}$$

Equation 2: Defect Detection Time. D_{base} = baseline detection time (days); α = traceability efficiency coefficient.

with $D_{base} = 10$ days, being the estimated baseline case of the detection time when there is no digital traceability, and $\alpha = 2$ is the traceability efficiency coefficient that depicts the accelerating impact of the sensing infrastructure on the speed of anomaly detection (see Table 3).

Table 3: Defect Detection Time: Calculation and Results

Step	Formula	Scenario A	Scenario B
TCI value (from Step 1)	-	TCI _A = 0.225	TCI _B = 0.9125
Denominator ($1 + \alpha \cdot TCI$)	$1 + 2 \times TCI$	$1 + 2(0.225) = 1.45$	$1 + 2(0.9125) = 2.825$
Defect Detection Time	$D_{base} / \text{denominator}$	$10 / 1.45 = 6.90$ days	$10 / 2.825 = 3.54$ days
Improvement vs Scenario A	-	-	- 48.7%

The adoption of both IoT and RFID infrastructure in Scenario B saves 6.90 days in defect detection compared to 3.54 days in Scenario A, which is a 49 percent reduction in line with the report on performance benchmarks in Ada et al. (2021) and the real-time identification capability in Ferdousmou et al. (2024). This enhancement indicates a structural change from continuous inspection of individual manual cycles to automated, event-driven anomaly detection based on sensor data from all nodes observed in the supply chain.

Recall Scope Reduction (RSR)

Recall scope measures the percentage of a batch that is liable to recall operation after the defects have been detected. Without component-level traceability, OEMs must use precautionary batch-level recall decisions that cover the entire production run of the time window under scrutiny. Digital traceability, namely, with the help of blockchain-based records of component genealogy, allows isolating affected units precisely, which significantly minimizes the scope of recalls. The index of reduction of the scope of recalls is calculated in the following way.

$$TCI = \frac{w_1 IOT + w_2 RFID + w_3 BC + w_4 DI}{w_1 + w_2 + w_3 + w_4}$$

Equation 3: Recall Scope Reduction. B_t = defective batch identified (vehicles); B_{total} = total production batch.

With a total of 50,000 vehicles, the production batch under study, and B_t is the quantity of vehicles in the batch that can accurately be determined to be affected by the defect. In Scenario A, there is no component-level identification, and the entire batch (B_t = 50,000) has to be recalled. In Scenario B, the genealogy records based on blockchain allow isolating the defect to 8,500 vehicles (see Table 4).

Table 4: Recall Scope Reduction: Calculation and Results

Step	Formula	Scenario A	Scenario B
Total production batch (B _{total})	-	50,000 vehicles	50,000 vehicles
Defective batch identified (B _t)	Based on TCI traceability	50,000 (no isolation)	8,500 (blockchain isolated)
B _t / B _{total}	B _t ÷ B _{total}	50,000 / 50,000 = 1.00	8,500 / 50,000 = 0.17
Recall Scope Reduction (RSR)	1 – (B _t /B _{total})	RSR _A = 0.00 (0%)	RSR _B = 0.83 (83%)

The 83% reduction in the extent of the recall in Scenario B signifies the importance of blockchain-enabled component genealogy that allows the manufacturer to determine the precise time of production, the supplier of origin, and the range of affected vehicles between the event of defect identification and the record of raw material sourcing in real-time. This observation aligns with the desired recall handling features of blockchain traceability presented by Patro et al. (2021) and the audit trail functionality presented in Vukovic et al. (2023). Scenario A showing the RSR of 0 justifies the theoretical claim that the batch-level traceability systems do not offer the benefit of any substantial recall improvement on a full-batch recall decision in the absence of component-level identification data.

Root Cause Identification Time (RCIT)

Root cause identification time is a metric that measures the lag time between defect identification and identification of the exact level of failure,

such as the production lot, tier of supplier, and cause of failure in the production line. It is a legally and financially sensitive stage: until the cause is determined, the scope of recall cannot be accurately delimited, regulatory reports may not be submitted, and possible remediation may not be initiated. Root cause identification time is determined to be a linear function of TCI as follows:

$$TCI = \frac{w_1 IOT + w_2 RFID + w_3 BC + w_4 DI}{w_1 + w_2 + w_3 + w_4}$$

Equation 4: Root Cause Identification Time. β_0 = baseline RCIT (days); β_1 = traceability efficiency coefficient.

where $\beta_0 = 14$ is the base root cause identification time in the absence of digital traceability, which was calibrated by automotive recall investigation times logged in Shi et al. (2025), and $\beta_1 = 10$ is the traceability efficiency coefficient of the accelerated backward trace-back speed of immutable blockchain transaction records and integrated genealogy data. The linear specification is suitable in the range of TCI [0.20, 0.91], which is assessed in the study.

Table 5: Root Cause Identification Time: Calculation and Results

Step	Formula	Scenario A	Scenario B
Baseline RCIT (β_0)	–	14 days	14 days
TCI contribution ($\beta_1 \cdot TCI$)	$10 \times TCI$	$10 \times 0.225 = 2.25$	$10 \times 0.9125 = 9.125$
Root Cause ID Time (RCIT)	$\beta_0 - \beta_1 \cdot TCI$	$14 - 2.25 = 11.75$ days	$14 - 9.125 = 4.88$ days
Improvement vs Scenario A	–	–	– 58.5%

Scenario B versus Scenario A Scenario B (with 4.88 days of root cause identification) is an improvement of 58.5 percent over Scenario A (with 11.75 days of root cause identification) (see Table 5). This structurally larger increase than the increase in the defect detection time (48.7%) confirms that backward trace-back capability is the largest contribution of blockchain to the traceability stack, as opposed to forward anomaly detection. In Scenario A, the 11.75-day root cause identification time was a manual reconciliation of the batch records and supplier documentation on multiple levels without a common ledger, which Vukovic et al. (2023) refer to as the root cause of the investigation lag in the traditional automotive supply chain model. In Scenario B, the immutable transaction records traversed by the blockchain allow the investigator to deduce the entire component history, assembling to sourcing of raw materials - without verification documents between cross-actors, with this resulting in the observed reduction.

Supply Chain Visibility Index (SCVI)

Supply Chain Visibility Index assesses the percentage of supply chain nodes where real-time data about the operation of the system can be obtained through the integrated traceability system. It indicates the horizontal breadth of the traceability network between all the levels of suppliers, i. e., raw material

suppliers, the OEM assembly plant, and further auto usage. The index is calculated by using the following formula:

$$TCI = \frac{w_1 IOT + w_2 RFID + w_3 BC + w_4 DI}{w_1 + w_2 + w_3 + w_4}$$

Equation 5: Supply Chain Visibility Index. N_{tracked} = nodes with real-time data; N_{total} = total supply chain nodes.

In which N_{total} indicates the total number of identifiable nodes of the whole supply chain network of all tiers in the network model, including raw material suppliers (Level 4), Tier -2 manufacturers (Level 3), Tier -1 module producers (Level 2), OEM assembly nodes (Level 1), and downstream customer nodes (Level 0). In Scenario A, 40 nodes are partly available for ERP batch records and periodic reporting. This is the case of Scenario B, where 110 nodes are being actively monitored due to integrated IoT, RFID, and blockchain data streams.

Table 6: Supply Chain Visibility Index: Calculation and Results

Step	Formula	Scenario A	Scenario B
Total supply chain nodes (N_{total})	–	120	120
Tracked nodes (N_{tracked})	–	40 (ERP/periodic)	110 (IoT/RFID/blockchain)
Supply Chain Visibility Index	$N_{\text{tracked}} / N_{\text{total}}$	$40 / 120 = 0.333$ (33%)	$110 / 120 = 0.917$ (92%)
Improvement vs Scenario A	–	–	+177%

Table 6 states that the supply chain visibility increases by 177 points when Scenario B is compared with Scenario A (33.3% to 91.7%). The 10 untracked nodes in Scenario B (8.3% of the network) are remote Tier-3 raw material suppliers where no digital onboarding has been done yet, and this is a realistic constraint to adoption that is consistent with the tier-by-tier implementation dynamics identified by Heldt and Pikuleva (2025). The difference in the visibility of the scenarios is the direct consequence of the RFID and IoT implementation in Scenario B, which changes the passive, document-based batch identification into the active, continuous tracking of nodes of all available supply chain levels.

Recall Cost Savings

The financial implications of the traceability transition are quantified through a per-vehicle recall cost model. The total recall cost is computed as the product of the number of vehicles subject to recall and the average per-vehicle remediation and logistics cost. The cost savings represent the economic benefit of reduced recall scope enabled by digital traceability, directly addressing Objective O3.

$$C_v = 500 \text{ USD}$$

Equation 6: Total Recall Cost. N_{recalled} = number of recalled vehicles; C_v = average cost per recalled vehicle.

N_{recalled} is equal to B_t (the bad lot found during Step 3) and C_v USD 500 per vehicle, which is the average cost of each vehicle to remedy, logistics, and administrative costs related to automotive recall, which are in line with automotive industry cost standards. The cost savings of the recall are calculated by taking the difference between Scenario A and Scenario B costs.

Table 7: Recall Cost Savings: Calculation and Results

Step	Formula	Scenario A	Scenario B
Vehicles recalled ($N_{\text{recalled}} = B_t$)	From Step 3	50,000	8,500
Cost per vehicle (C_v)	–	USD 500	USD 500
Total Recall Cost	$N_{\text{recalled}} \times C_v$	$50,000 \times 500 =$ USD 25,000,000	$8,500 \times 500 =$ USD 4,250,000
Cost Savings	$\text{Cost}_A - \text{Cost}_B$	–	USD 20,750,000 (–83%)

When all traces become digital, overall costs associated with recall will be reduced by USD 25,000,000, down to USD 4,250,000, creating USD 20,750,000 in cost savings per major recall event, which will indicate a 83% reduction (see Table 7). This significant financial advantage is completely motivated by the scope of recall reduction made possible by blockchain component genealogy, which validates that the financial case of traceability investment is best described directly in terms of recall management efficiency. These results go hand in hand with the financial impacts found in Li et al. (2022) and Shi et al. (2025), and offer a quantitative confirmation of the cost-cutting claims presented in the automotive blockchain literature. It is relevant to mention that the current model of cost incorporates the estimates of per-vehicle remedies and omits constant legal liability and brand damage factors, which would further increase the cost distinction between situations.

Overall Operational Performance Index (OPI)

In order to obtain a composite summary measure of operational performance improvement in each of the four main KPIs, a normalized Overall Performance Index is calculated as the arithmetic mean of recall scope reduction, visibility of supply chain, and the inverse of defect detection time and time of root cause identification, weighted equally. The backward reversion makes sure all the elements are in the same direction (higher = better). The OPI is defined as follows:

$$\text{OPI} = 0.25(\text{RSR}) + 0.25(\text{SCVI}) + 0.25(1/\text{DTD}) + 0.25(1/\text{RCIT})$$

Equation 7: Overall Operational Performance Index (OPI). Equal weights across four KPI dimensions.

Table 8: OPI: Calculation and Results

OPI Component	Formula	Scenario A	Scenario B
RSR component	$0.25 \times \text{RSR}$	$0.25 \times 0.00 =$ 0.0000	$0.25 \times 0.83 =$ 0.2075

SCVI component	$0.25 \times \text{SCVI}$	$0.25 \times 0.333 = 0.0833$	$0.25 \times 0.917 = 0.2292$
DTD inverse component	$0.25 \times (1/\text{DTD})$	$0.25 \times (1/6.90) = 0.0362$	$0.25 \times (1/3.54) = 0.0706$
RCIT inverse component	$0.25 \times (1/\text{RCIT})$	$0.25 \times (1/11.75) = 0.0213$	$0.25 \times (1/4.88) = 0.0512$
Overall OPI (sum)	Sum of components	$\text{OPI_A} \approx 0.141$	$\text{OPI_B} \approx 0.559$
OPI Improvement	$\text{OPI_B} / \text{OPI_A}$	-	$\times 3.96 (\approx 4\times \text{improvement})$

Overall Performance Index, which is represented in Table 8, changes with the increase in Scenario A of 0.141 to Scenario B of 0.559 and translates to about four times better performance in terms of composite operational performance. This outcome represents the sum of the effect of the reduction of the scope of recalls (0 - 0.83), the increase in supply chain visibility (33% - 92%), the shortening of the time required to detect defects (6.90 - 3.54 days), and the shortening of the time required to identify root causes (11.75 - 4.88 days) in a single normalized indicator. The highest value single performance improvement of full traceability integration is the RSR component, which contributes to OPI differentials of 0.2075 points in Scenario B versus 0.0000 points in Scenario A, which confirms that the blockchain-enabled recall scope reduction is the highest-value single performance improvement.

Summary of Simulation Results

Table 9: Summary of All Performance Indicators: Scenario A vs. Scenario B

Performance Indicator	Equation	Scenario A (Low TCI = 0.225)	Scenario B (High TCI = 0.9125)	Improvement
TCI Score	Eq. 1	0.225	0.9125	+306%
Defect Detection Time	Eq. 2	6.90 days	3.54 days	-48.7%
Recall Scope Reduction	Eq. 3	0% (RSR = 0)	83% (RSR = 0.83)	+83 pp
Root Cause ID Time	Eq. 4	11.75 days	4.88 days	-58.5%
Supply Chain Visibility	Eq. 5	33.3%	91.7%	+177%
Total Recall Cost	Eq. 6	USD 25,000,000	USD 4,250,000	-83%
Cost Savings	Eq. 6	-	USD 20,750,000	+USD 20.75M
Overall Perf. Index (OPI)	Eq. 7	0.141	0.559	$\times 3.97\times$

DISCUSSION

The findings of the analytical quantitative model show that in four incremental scenarios and seven performance indicators, the steady

implementation of digital traceability technologies in the automotive supply chain produces quantifiable, monotonically increasing operations, temporal, and economic performance. In this section, the results were interpreted against each of the research objectives, the findings are placed within the current literature, the operational implications of the study to the supply chain actors, and the limitations of the study are also recognized.

Quantitative Correlation of TCI and KPIs

The model confirms that there is a direct relationship that is mathematically tractable between the Traceability Capability Index and the four performance indicators detailed in O1. The TCI plays as the unifying independent variable: it is introduced in the defect detection equation as a hyperbolic-based function (Eq. 2), the root cause identification equation as a linear-based function (Eq. 4), the visibility index as the node tracking ratio (Eq. 5), and the scope reduction of recall capability of the active technology stack as a batch isolators capacity (Eq. 3). Such integrated model format is a formally operationalized quantitative framework that extends the literature of the largely conceptual traceability performance models found in the review, offering parameter-transparent results reproducible within the analytical simulation tradition developed by Cammarano et al. (2023) in food supply chain settings.

The complete shift of $TCI = 0.225$ to $TCI = 0.913$ saves 48.7, 58.5, and 83 percentage points of defect detection time, root cause identification time, and recall scope, respectively, and increases supply chain visibility by 33.3% to 91.7. This 49 percent defect detection improvement is equal to the 40-55 percent defect detection improvement benchmarks described by Ada et al. (2021) in blockchain-based automotive supply chain systems and to the real-time identification demonstrated by Ferdousmou et al. (2024). It is structurally significant that the proportionate increase in root cause identification time (58.5) was more pronounced than in defect detection time (48.7): the two processes are catalyzed by distinct layers of technology and should not be mixed up in the traceability performance measurement.

Individual and Combined Technology Contributions

In this research, using the four-scenario incremental design, the first formal breakdown of the individual technology contributions to automotive traceability performance can be performed. Table 5.9 gives a direct quantitative response to O2, and three consistent findings were obtained in all KPIs. The RFID and IoT infrastructure is the main contributor to supply chain visibility (+79.8% marginal growth, A-A1) and the largest single-transition factor to reduced recall scope (+44 pp) and increased overall operational performance (+140% OPI improvement). This affirms that the precondition of all further traceability functionality is physical sensing and identification infrastructure: when there is no real-time sensor data and no component-level digital identifiers, blockchain genealogy records and data integration analytics have empty content to act on.

The most predominant driver of the root cause identification speed (-33.8% marginal improvement) and recall cost reduction ([?]57% marginal) is the factor of blockchain integration (A1-A2) because it has a unique ability to provide an immutable, chronologically ordered chain of component genealogies that allow investigators to work all the way up the supplier hierarchy without manually reconciling the documents. This result quantitatively confirms the theoretical argument by Vukovic et al. (2023) that blockchain can make the most significant contribution to a traceability stack, the backward trace-back capability, and gives the first quantitative estimate of the size of an operational contribution to sensing infrastructure in an automotive simulation scenario. The data integration maturity (A2-B) has the smallest marginal benefits when it comes to all KPIs, which implies that its main value is in polishing and harmonizing the capabilities that have already been enabled by the lower layers, and not in creating a step-change improvement.

One of the lessons of the O2 analysis is related to investment sequencing. The findings indicate that the implementation of RFID and IoT on its own (Scenario A1) achieves 140% OPI improvement and USD 11 million in savings on recall costs compared to the traditional baseline, which is a significant payoff that can be attained prior to implementing any blockchain infrastructure. This observation directly applies to automotive companies and their suppliers with a limited capital base to invest in traceability: a gradual implementation phase in which physical sensing infrastructure is deployed in the first investment phase, with blockchain adoption in the second, will produce positive returns in stage 1 but will not require the full investment in Industry 4.0 to be achieved before any returns are realized.

Economic and Operational Implications

Economic analysis proves that the shift from a low-traceability to a high-traceability automotive supply chain creates strong and operationally important financial returns at all levels of technology introduction. The USD 20,750,000 overall cost saving, reduced by recall of USD 20,750,000 per major recall event in Scenario B, is an 83 percent reduction compared to the traditional baseline and a direct quantitative foundation for traceability investment decisions. Such results align with the cost-cutting implications of digital quality management tools in line with IATF automotive standards found by Yahyaoui et al. (2025) and the financial implications of the scope of the recalls mitigation modelled by Shi et al. (2025).

The Overall Performance Index is a composite summary of operations and uses a single measure that is similar and combines all four dimensions of KPI. The 0.418-point overall gain in Scenario A to B is explained by the fourfold OPI improvement of 0.141 to 0.559, which is primarily explained by the RSR component that yields the highest proportion of 0.2075 of the total 0.418 gain - the highest single-dimension operation value of full traceability integration. The output of a positive OPI return by each technology layer is further demonstrated by the intermediate scenario results: Scenario A1 has OPI = 0.339 (+140% vs A),

Scenario A2 has OPI = 0.502 (+256% vs A), and Scenario B has OPI = 0.559 (+296% vs A). Such a monotonic trend of improvement justifies comparing the investment rationale of phased technology adoption since every transition will produce measurable performance payoff.

The supply chain participants have varying operational implications. The biggest operational changes, to the OEM, would be the decrease in time of investigation (a combined 18.65 days in Scenario A to 8.42 days in Scenario B) and the enormous decrease in recall scope (100 percent to 17 percent of the production lot), which directly leads to less regulatory exposure and less remediation cost. In the case of Tier-1 suppliers, the most impactful change is the transition to the continuous real-time traceability event documentation on a periodic basis with batch-level compliance reporting, which essentially changes their quality assurance responsibilities and the audit cycle. To the tier-2 and raw material suppliers, the shift of effective invisibility (40 of 120 nodes in Scenario A are tracked) to active integration (98 and 110 nodes in Scenario A2 and B, respectively) is the most radical operational change, as it introduces their manufacturing processes into the realm of OEM quality concerns in the first place.

Limitation and Future Research Directions

The present research utilizes an analytical quantitative modelling model, which is calibrated using secondary data sources and industry standards, as opposed to using primary operational data as measured in a live automotive supply chain implementation. The model parameters are based on ranges observed in other previous simulation studies and automotive recall statistics and are conservative estimates. The directional inferences and performance differentials of the two scenarios are strong to medium parameter variation, although absolute values of KPI improvements are to be seen as a guiding estimate within ranges provided by the sources of benchmark used and not as an empirical measure.

The Bt values in the RSR calculation (28,000 in the case of A1, 12,000 in the case of A2, and 8,500 in the case of B) are the most crucial parameter assumption in the model; the RSR equation is the main driver of both cost savings and OPI improvement. These values were based on RFID batch isolation benchmarks (Ferdousmou et al., 2024), blockchain-enabled genealogy capabilities (Patro et al., 2021), and the Ada et al. (2021) simulation benchmark of a fully integrated scenario with an approximate RSR of 83%. The next wave of study needs to do empirical validation of these parameters with the actual automotive recalls in the NHTSA database, where the scope of the recall is recorded, together with the scope reduction in multi-phase recall events.

Stochastic growth in the rate of defects and demand, as well as extending the current model to include the stochastic model, should also be used in future studies to allow the characterization of performance indicators distributions under uncertainty instead of point estimates under deterministic assumptions. A

multi-period dynamic model would also be introduced to investigate the effects of technology adoption trajectory, such as how the timing of phased deployment affects cumulative savings of costs and the level of adoption that is necessary to achieve the network-wide benefits of blockchain.

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