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Conceptualization and validation of an intelligent digital twin design framework for supply chain risk management

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ABSTRACT

Intelligent digital twins for supply chain risk management have recently gained attention due to rising disruptions, increasing supply chain complexity, and the need for advanced tools. Although various frameworks exist, few clearly identify the necessary data, predictions, and decision-making problems for their development, and even fewer have been validated in real-world case studies. This study fills those gaps by proposing and validating a comprehensive design framework in the automotive sector. The results show that the prototypes developed based on the framework effectively support tasks such as predicting supply chain performance and guiding supplier selection and order allocation while significantly reducing the time needed for risk management tasks.

1. Introduction

In recent years, the growing complexity and volatility of global Supply Chains (SC) have significantly increased the need for advanced tools to mitigate risks. Indeed, traditional risk management approaches often fall short in addressing the dynamics of modern SCs and their interconnected nature (Manuj et al., 2014). On the contrary, Intelligent Digital Twins (IDTs) have emerged as powerful solutions in this context. As digital replicas of a physical SC, they enable descriptive, predictive and prescriptive analytics, allowing continuous monitoring, prediction of potential disruptions and providing a comprehensive, dynamic view of the entire SC ecosystem (Ivanov, 2023; Moshood et al., 2021).

In addition, the importance of IDTs in Supply Chain Risk Management (SCRM) extends beyond their ability to monitor and react to disruptions. These advanced systems provide a proactive approach, enabling organizations to forecast and prepare for potential risks before they materialize. The ability to model complex SC networks in real-time and simulate various risk scenarios is essential for businesses to anticipate challenges such as supply shortages, transportation delays, geopolitical disruptions, and fluctuations in demand. By integrating real-time data streams from suppliers, customers, and operational systems, IDTs allow for dynamic modeling of SC behaviors, enhancing the ability to identify and assess risk factors with unprecedented accuracy. Additionally, implementing IDTs enables a more holistic and interconnected view of the SC. Traditional Supply Chain Management (SCM) approaches often treat components in isolation, which can lead to inefficient risk mitigation strategies. In contrast, IDTs facilitate a systems-level understanding by linking different elements of the SC—from raw materials sourcing to production, distribution, and end-user delivery. This integration allows for more accurate predictions and better-informed decision-making, reducing the impact of risks across the entire SC.

The development of frameworks for the design and deployment of these systems is thus of paramount importance. Without a structured, standardized framework, the implementation of IDTs can become fragmented and inconsistent, limiting their effectiveness (Butt, 2020). A comprehensive framework ensures that the complexities of the SC and the risk management processes are properly addressed, providing a clear path for integrating these technologies into existing SC operations. Such frameworks also allow organizations to scale these solutions across diverse business environments, adapting them to their specific risks and challenges.

Unfortunately, providing a unified framework for designing IDTs in SCRM is particularly challenging due to several complexities. The first challenge lies in determining which entities within the supply chain need to be mapped in the system. A SC is an interconnected network of various stakeholders, such as suppliers, manufacturers, distributors, and retailers, each with its own processes, characteristics, and interactions with other entities. Mapping these relationships is difficult due to the diversity in SC structures, which can vary greatly depending on the SC's industry, size, or geographic scope. Additionally, the relationships between entities are often nonlinear, dynamic, and subject to frequent

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changes (Gabellini et al., 2024; Gabellini et al., 2024; Matteo et al., 2024), making it challenging to determine which entities are essential to model and at what level of granularity.

Once the relevant entities are identified, the next challenge is determining which data should be collected. SC generates overwhelming data from various sources, including transactional, operational, and environmental data (Gabellini, Civolani, et al., 2023; Gabellini et al., 2023). The difficulty in identifying which data to collect stems from the need to ensure both comprehensiveness and focus. Collecting too much data can lead to information overload, making it difficult for decision-makers to extract actionable insights. Collecting too little data can result in an incomplete or biased understanding of risks. Furthermore, data may come from disparate sources with different formats or systems, making integration and harmonization a major challenge. Reliable, accurate, and timely data is essential for effective decision support, and ensuring the quality of this data is a persistent concern in the design of IDTs.

The complexity continues when selecting which metrics to predict. Identifying the right metrics to focus on is difficult because different SCs have different priorities, and the metrics that matter most may vary widely. For example, inventory levels and shelf-life metrics may be critical in a perishable goods SC, while in automotive or electronics SC, the availability of specific components and logistics efficiency may take precedence. Moreover, predicting risk-related metrics is often a difficult task due to the inherent unpredictability of certain metrics (Gabellini, Calabrese, et al., 2023; Gabellini et al., 2022). This uncertainty makes it particularly difficult to determine which metrics are most crucial to track and predict in order to support effective risk management and which are not useful to predict because of their unpredictability.

Lastly, another challenge arises from the complexity of identifying which decision-making problems IDTs should support. SC decision-making spans various levels, from strategic decisions to operational decisions. Each type of decision involves different data inputs, decision-making criteria, and time horizons. The difficulty in identifying which decision problems an IDT should address lies in ensuring that the system is flexible enough to support multiple types of decisions while also being focused enough to provide meaningful guidance on the most critical issues. Additionally, decisions are made by various stakeholders with different perspectives and priorities, further complicating the design of IDTs that meet the diverse needs of decision-makers. Thus, identifying which decision-making problems to focus on requires careful consideration of the risk landscape, the organizational objectives, and the specific requirements of decision-makers.

Due to the significance of the issue, numerous studies have thus proposed frameworks to guide practitioners in the development of SCRM-IDTs. These frameworks vary in nature, ranging from conceptual ones to those focused on validation, implementation, and governance. However, while these frameworks provide a solid foundation for the conceptualization, validation, implementation, and governance of such tools, they do not specifically address the core issues previously highlighted, namely the identification of the data to collect, the predictions to generate, and the decisions to make. Furthermore, many of the existing frameworks lack validation in real-world settings. This limitation has also been noted in the manufacturing context, as highlighted by Bitencourt et al. (2024)

Based on these evidences, the main contributions of this paper are thus twofold:

- Framework Definition: The study introduces a new design framework for developing IDTs within the context of SCRM. This framework explicitly outlines which data should be collected, which predictions need to be generated, and which decisions are to be supported.
- Framework Validation: The study validates the proposed framework in a real automotive case study, demonstrating its ability to support SCRM-IDTs that generate effective predictions, facilitate decision-making, and reduce the time required to perform SCRM tasks.

The papers' structure unfolds as follows. Section 2 will revise the literature on the topic. Section 3 will present the proposed framework and the implementation and validation strategy adopted to develop and test a prototype based on the proposed framework in a real automotive company. Section 4 will present the prototype, its technical results in solving specific tasks and its overall contribution in the examined case study. Section 5 discusses the results by highlighting the main managerial implications. Lastly, Section 6 summarizes the main conclusion of the work.

2. Literature review

This Section reviews the existing literature on frameworks for developing Digital Twins (DT) and IDTs in SCM and SCRM. We then present a schematic classification of these studies based on the type of framework proposed, the thematic focus, and the presence or absence of a validation case study. This classification reveals the gaps in the current literature and clarifies the motivation and originality of our research. Lastly, following this classification, a theoretical background is presented by drawing on relevant studies that are instrumental in informing the design of the proposed framework.

2.1. Frameworks for supply chain and supply chain risk management Digital Twins

Design science research emphasizes creating and evaluating innovative artifacts that address real-world problems. Frameworks, in particular, play a central role in guiding researchers and practitioners through systematic processes of conceptualizing, designing, implementing, and assessing these artifacts, ensuring both rigor (through alignment with existing theory and methodology) and relevance (through practical applicability and demonstrable utility). In designing digital twins for SCM and SCRM, frameworks can be conceptual, architectural, technological, implementation-oriented, or governance-related, among other forms. Each type provides a structured viewpoint for tackling specific challenges and ensures that the resulting digital twin meets established scientific standards while effectively solving pressing industry needs.

Conceptual frameworks are especially important because they articulate the core elements, relationships, and objectives that underpin a twin's design and operation. Several recent studies have thus put forward conceptual frameworks of digital twins in SCM (Busse et al., 2021; Freese & Ludwig, 2024; Le & Fan, 2024; Zaidi et al., 2024) and SCRM (Ivanov, 2023; Ivanov & Dolgui, 2021; Ogunsoto et al., 2025).

Specifically, Busse et al. (2021) propose an initial framework for a digital supply chain twin that spans multimodal supply chains. By capturing an entire logistics network, their digital twin is intended to enhance both simulation and real-time optimization capacities, thereby identifying potential issues and improving the robustness of multi- and intermodal operations. Freese and Ludwig (2024) also emphasize the need for a specialized framework in SC contexts, given the process-driven nature, diverse stakeholder involvement, and heavy reliance on up-to-date information. Their proposal identifies the layers, dimensions, and technology dependencies critical for early-phase adoption of digital twins, seeking to guide planners in introducing new twin solutions while accommodating ongoing advancements in data-intensive and collaborative logistics environments. Le and Fan (2024) adopt a similar stance in advocating for clear conceptual structures. They propose a framework of digital twins for logistics and SC systems that addresses efficiency, transparency, and timeliness in decision-making, noting both the research gaps and the practical challenges that arise when new modeling techniques and analytics are introduced. Zaidi et al. (2024) add nuance by highlighting the challenges of real-time synchronization and autonomous decisions in digital twin systems for SCM. Their three-layered conceptual structure incorporates external and internal supply chain links, blending IoT, RFID, and cyber-physical systems to facilitate data-driven disruption management.

Considering DT for SCRM, Ivanov and Dolgui (2021) instead proposed a computerized model that merges data-driven and model-based approaches to enhance predictive and reactive responses. The argument that real-time visibility into supply network states can be a game changer is reinforced by Ivanov (2023), who introduces the notion of an IDT as a human-AI collaboration platform that can also be utilized for stress testing and improving resilience. By integrating monitoring, early warning signals, and proactive learning, the authors posit that an IDT can transform unknown risks into manageable scenarios. In a more specialized context, Ogunsoto et al. (2025) outline a three-phase DT design that anticipates a common form of natural disaster—-flooding—using discrete event simulation and neural networks. Their conceptual approach coordinates predictive analytics, simulation-based breakdown modeling, and neural network-driven recovery forecasting, extending the digital twin concept from simple real-time tracking to an actionable crisis anticipation and remediation method. A recurring theme across all of these perspectives is the recognition that SC-DT requires meticulously structured conceptual frameworks to handle myriad data sources, stakeholder inputs, and volatile conditions. By clarifying the structural dimensions, data flow requirements, and decision-making processes in the early stages of development, these frameworks are invaluable tools for ensuring both the technical coherence and the practical efficacy of digital twin implementations in supply chain contexts.

While conceptual frameworks establish the foundational logic and scope of DT, additional types of frameworks address distinct yet equally critical aspects of designing and managing such systems. Architectural frameworks, for instance, focus on structuring the technical components and interactions that underlie DT operations. Park et al. (2020) propose a multi-level framework for a cyber-physical logistics system capable of handling resilience in a make-to-order environment. By coordinating different cyber-physical system layers, their approach offers functionalities for managing the bullwhip and ripple effects, suggesting that a well-devised system architecture can align distributed DT simulations and service composition to mitigate common SC disturbances.

Implementation frameworks bring an applied perspective, illustrating how firms might move from conceptual ideas to actual deployment. Kamble et al. (2022) argue that IoT, cloud computing, and blockchain technologies have enhanced the potential of DT and conclude with a sustainable DT implementation framework. This framework urges the inclusion of people, processes, and physical assets from across the entire chain, highlighting the practical steps and considerations that turn a DT design into a functioning, value-added system.

Development frameworks shed light on the iterative processes and tools used to build and refine DT. Biller & Biller, (2023) define process DT and discuss their core elements, underscoring the importance of simulation and AI for describing, predicting, and optimizing SC behavior. By integrating these enabling technologies, their approach clarifies how DT evolves from standalone models into sophisticated, data-driven environments capable of replaying histories, anticipating future disruptions, and guiding performance optimization.

Governance frameworks ensure that DT continues to operate effectively, ethically, and in alignment with organizational or industry objectives over time. Kalaboukas et al. (2023) propose a governance model for DT within SC by integrating three views: business and sustainability, data governance, and AI model governance. Their work reveals the importance of structures and policies coordinating multiple entities—assets, processes, organizations—so that each twin collaborates safely and transparently, ultimately contributing to improved sustainability and decision-making.

Lastly, utilization frameworks examine how DT can be leveraged in ongoing operations and strategic planning once they are up and running. Cimino et al. (2024) describe a cyclical and holistic methodology that applies SC-DT to enhance resilience and sustainability. By focusing on how organizations exploit the twin's capabilities, their framework clarifies how insights gathered from simulations or predictive analytics feed back into continuous improvement, ensuring that the DT remains a dynamic, evolving resource.

2.2. Gaps in the current literature and innovative contributions of the proposed study

According to Table 1, existing literature highlights the growing interest in harnessing frameworks for developing DTs and IDTs in SCM and SCRM. However, a critical gap persists regarding design frameworks that specify which data should be collected, which metrics should be predicted, and which decision-making processes ought to be supported. This absence of a dedicated framework poses challenges for practitioners and researchers attempting to design such IDTs that yield measurable performance improvements practically. Moreover, although previous works have proposed various frameworks to conceptualize or implement DT, most have not been validated in real-world scenarios. In design science research, meaningful validation is paramount; it offers robust evidence of an artifact's utility, bridging the space between theoretical constructs and tangible outcomes.

Motivated by these gaps, our study thus presents a design framework that explicitly identifies the necessary data to collect, the key performance metrics to predict, and the decision-making problems to address and validate its effectiveness in a real automotive case study. This approach addresses the dearth of validated frameworks and responds to the practical need for actionable guidance on deploying IDTs effectively in complex SC environments.

2.3. Theoretical background: foundations of the proposed SCRM-IDT framework

The proposed framework for a SCRM-IDT is grounded in the extensive body of literature addressing decision-making, predictive analytics and risk monitoring in supply chain. This section provides the theoretical foundations for each of these components and synthesizes the rationale for their inclusion in the framework.

According to Rajagopal et al. (2017), The Supplier Selection and Order Allocation (SSOA) problem, the Inventory Management (IM) problem, and the Supply Chain Network Design (SCND) problem are considered the most critical areas in which firms must act decisively when facing disruptions or uncertainty in supply chains. In the context of supplier selection, scholars such as Demirtas & Üstün, (2008); Islam et al. (2021, 2024); Sawik, (2013) emphasize the importance of identifying reliable suppliers and allocating orders dynamically to ensure continuity of supply. Inventory management decisions require optimal policies for safety stock, reorder points, and replenishment frequencies, which must be calibrated to dynamic risk conditions, as noted by Araya-Sassi et al. (2020); Berling & Sonntag, (2022); Feng et al. (2022). In parallel, the design of the supply chain network itself, encompassing facility location, transportation flows, and structural flexibility, is a long-term strategic problem that requires robust treatment under uncertainty, as summarized by Govindan et al. (2017).

Supporting these decision problems requires the generation of accurate predictions for specific metrics. The literature identifies a range of predictive variables necessary for decision-making. On the supply side, relevant forecasts include supplier purchasing costs, quality performance, delivery punctuality, production capacity, transportation availability, and associated logistics costs (Ali & Zhang, 2023; Esmaeili-Najafabadi et al., 2021; Feng et al., 2023). In the production domain, predictions of production capacity, fixed and variable costs, and the cost of opening new facilities are crucial inputs for capacity planning and network expansion decisions (Lee & Moon, 2024; Mahapatra et al.,

Table 1
Summary of the literature review related to DTs and IDTs framework for SC and SCRM.

Study	Thematic area	Digital twin type	Framework type	Validation approach	Assumptions	Limitations
Park et al. (2020)	SCM	DT	Architectural	Real-world Implementation and Simulation in an automotive case study	– Assumes Make-to-Order – No Forecasting or Inventory Features – Only Internal SC Agents Considered	– Lacks Process Planning Functionality
Busse et al. (2021)	SCM	DT	Conceptual	Theoretical validation against functional criteria	– Assumes stakeholder data sharing and continuous updates	– Lack of detailed architecture; – Cost-benefit unknown;
Kamble et al. (2022)	SCM	DT	Implementation	Validated by industry practitioners	– Reliance on vendor-specific AI and simulation methodologies	– Product life cycle scope, cybersecurity, IP protection, unstructured data sources
Biller & Biller, (2023)	SCM	DT	Development	Validation with Static Historical Data	– Represents Physical Manufacturing Resources and Processes	– Challenge of Standardization Due to Use-Case-Driven Customization
Kalaboukas et al. (2023)	SCM	DT	Governance	Validated based on a refrigerator Supply Chain Scenario	– DTs of All Stakeholders Linked via Information Sharing and Cognition	– Lack of Practical Implementations
Freese & Ludwig, (2024)	SCM	DT	Conceptual	Expert interviews and illustrative example	– N/A	– Limited literature database scope
Le & Fan, (2024)	SCM	DT	Conceptual	N/A	– Assumptions on SKU count, area size, cycle time, policy	– Assumptions may limit flexibility
Zaidi et al. (2024)	SCM	DT	Conceptual	Case study	– Data availability	– Single case study
Ivanov & Dolgui, (2021)	SCRM	DT	Conceptual	Developed and tested a decision support system for disruption risk management	– Viable System Model with pre-, during-, and post-disruption stages	– Technical data processing requirements not discussed
Ivanov, (2023)	SCRM	IDT	Conceptual	anyLogistix-based evidence	– Human-in-the-loop, not fully automated	– Potential barriers and shortcomings not considered
Cimino et al. (2024)	SCRM	DT	Utilization	Case study using anyLogistix	– Continuous improvement via cyclic structure	– Low number of disruptions and solutions considered
Ogunsoto et al. (2025)	SCRM	DT	Conceptual	Scenario simulation	– Single-enterprise supply chain	– Single-vendor assumption, no backorders
This study	**SCRM**	**IDT**	**Design**	**Automotive case study**	**– Assumes access to ERP and external data, capability to model SC decision problems, and stakeholder willingness to use AI-based tools**	**– Single-industry case**

2022; Mohammed et al., 2021). Inventory management relies on forecasts of inventory holding and shortage costs, storage capacity, and expansion needs, as well as stock obsolescence trends (Pathy & Rahimian, 2023; Qiu & Shang, 2014). On the demand side, predictive capabilities must encompass final product and component demand, pricing trends, customer purchasing behavior, logistics costs, and the financial feasibility of retail expansion, as observed in the works of Chen et al. (2021); Wang et al. (2024); Zheng et al. (2023).

To support these predictions, the digital twin must store and process data about the key structural entities within the supply chain. These include suppliers, industrial plants, sectors, customers, final products, components, raw materials, and the countries in which operations are embedded. The literature highlights the relevance of modeling such entities across multiple decision problems. For example, Kellner & Utz, (2019) and Vahidi et al. (2018) demonstrate that supplier-level modeling is essential for both sourcing and logistics optimization. Similarly, Lotfi et al. (2024) and Saputro et al. (2021) show how plant-level and product-level data structures are critical for design optimal decision making systems.

Another essential dimension of the framework design involves identifying and classifying the risk factors that influence each predictive variable. Literature consistently categorizes risks into two broad types: exogenous and endogenous. Exogenous risks refer to those external to the firm and beyond its direct control. Chopra and Sodhi (2004); Ho et al. (2015); Pandey et al. (2020) and Yun & Ülkü, (2023) identify several critical sources of exogenous risk, such as climate change and its associated natural disasters, political instability, financial market volatility, cybersecurity threats, labor disputes, and pandemics. These risks affect upstream supply continuity, logistics reliability, and cost stability. Zimmer et al. (2017) further highlight ethical and social risks, such as labor exploitation and health and safety violations, which carry reputational consequences and potential disruptions.

Endogenous risks, by contrast, are internal to the firm and its supply chain partners. These include issues such as limited supplier capacity, poor responsiveness, lack of flexibility, contract rigidity, and low integration among partners. Chopra and Sodhi (2004) emphasize that such internal risks can be equally disruptive if not monitored and mitigated. Ho et al. (2015) extend this classification by including operational issues such as inadequate visibility, unbalanced inventory policies, poor demand forecasting, and underinvestment in maintenance. Additionally, Malik & Sarkar, (2018); Qian et al. (2022) note that customer dependency, long credit cycles, and low employee engagement can create systemic vulnerabilities that propagate across the supply chain.

3. Materials and methods

This section presents the research process adopted to validate the proposed framework, following a design science research approach. While the framework itself constitutes a research output, it is included here to clearly describe its structure, implementation, and validation process. The actual results of its evaluation are discussed later, in the Section 4. As illustrated in Fig. 1, the research process unfolds in three phases: framework design, implementation, and validation through a real automotive case study. These phases are detailed in the following subsections: Section 3.1 describes the design of the framework, Section 3.2 explains its implementation through a working prototype, and Section 3.3 outlines the evaluation process used to assess its performance.

3.1. New SCRM-IDT design framework

The development of the framework followed a top-down methodology, starting from the identification of the primary decision problems that an SCRM-IDT. Drawing on Rajagopal et al. (2017), three key decision domains were identified as foundational: SCND, SSOA, IM. These

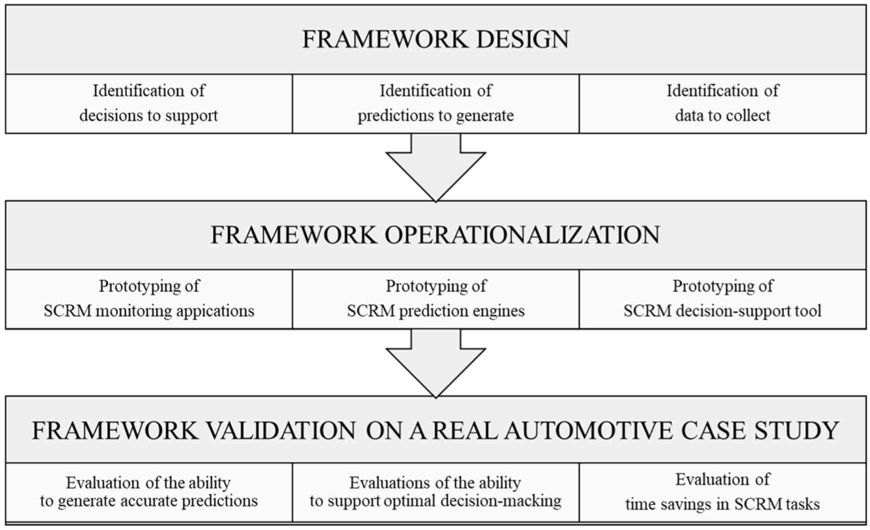

Fig. 1. Methodological approach followed to test and validate the proposed SCRM-IDT framework.

domains form the prescriptive core of the framework and guide the structure of the subsequent analytical layers.

To inform these decision domains, a systematic evaluation of the existing models in the review of Rajagopal et al. (2017) was conducted. This evaluation allowed for the extraction of the main parameters required for decision-making, which were grouped into four categories of predictions to generate: supply-related, production-related, inventory-related, and demand-related. These predictive categories and their associated elements are detailed and substantiated through a literature-mapping in Table 2.

In parallel, the analysis also revealed the core entities and sets involved in supply chain operations. These include suppliers, facilities, customers, products, and components. Each of these entities defines a data object that the IDT must monitor over time. Table 3 links these sets to key literature sources, highlighting their critical role in informing data collection and model formulation.

Finally, the framework incorporates a classification of the metrics to collect to enable risk-aware predictions. These metrics, reported in Table 4, are divided into exogenous risk factors (e.g., natural disasters, geopolitical instability, exchange rate volatility) and endogenous risk factors (e.g., machine failures, labor shortages, supplier reliability). The selection of these metrics is again grounded in a comprehensive literature synthesis, and maps relevant studies to the metrics used.

The resulting framework is thus structured into three interdependent layers. The data layer defines the entities that need to be monitored and specifies the required input data, the prediction layer incorporates forecasting modules designed to generate the necessary estimates and the prescriptive layer integrates optimization components that leverage the prediction outputs to support key decision. The overall structure is illustrated in Fig. 2, which captures the relationships among decisions, predictions, data entities, and risk factors.

3.2. Framework implementation

A prototype of an IDT for SCRM based on the proposed framework has been developed utilizing several open-source tools and external data providers, ensuring both efficiency and scalability in addressing various aspects of supply chain performance and risk analysis.

The proposed IDT database management system was implemented using PostgreSQL. Django was selected for the web application framework. For data visualization, the integration of Chart.js and OpenStreetMap provided dynamic and interactive capabilities to represent complex information. The predictive models were developed using the Darts library, a Python-based tool specializing in time series forecasting.

Table 2
Key literature sources linked to predictive metrics.

Prediction Area	Predicted Metric	Representative Literature
Supply-side forecasts	Supplier purchasing costs	Ali & Zhang, (2023), Esmaeili-Najafabadi et al. (2021), Kayani et al. (2023), Mahapatra et al. (2022), Mohammed et al. (2021)
	Supplier quality	Ali & Zhang, (2023)
	Supplier lead times	Ali & Zhang, (2023), Saputro et al. (2021)
	Supplier production capacity	Mahapatra et al. (2022), Lee & Moon, (2024), Esmaeili-Najafabadi et al. (2021)
	Supplier transportation capacity	Mohammed et al. (2021)
	Supplier transportation cost	Kayani et al. (2023), Lee & Moon, (2024)
Production-side forecast	Production capacity	Amiri, (2006)
	Fixed production cost	Amiri, (2006)
	Variable production cost	Esmaeili-Najafabadi et al. (2021), Du et al. (2015)
	Cost of open a production facility	Amiri, (2006)
Inventory-side forecast	Holding costs	Pathy & Rahimian, (2023), Qiu & Shang, (2014), Chen et al. (2021)
	Shortage costs	Pathy & Rahimian, (2023), Chen et al. (2021)
	Capacity	Pathy & Rahimian, (2023), Qiu & Shang, (2014)
	Cost of open a warehouse	Amiri, (2006)
Demand-side forecast	Final product demand	Chen et al. (2021), Zheng et al. (2023)
	Components demand	Hosseini et al. (2022)
	Selling price	Chen et al. (2021), Zheng et al. (2023)
	Customer transportation cost	Chen et al. (2021)
	Customer transportation capacity	Zheng et al. (2023)
	Cost of open a retailer	Ahmadi-Javid & Hoseinpour, (2015)

For the prescriptive part, Pyomo and Gurobi were utilized. Based on this combination of hardware and software choices, the user interface was designed with a focus on three core functionalities:

Table 3
Reference literature for defining supply chain sets and entities.

Entities	Representative Literature
Countries	Esmaeili-Najafabadi et al. (2021), Lee & Moon, (2024)
Sector	Srivastava & Rogers, (2022)
Facility	Saputro et al. (2021)
Suppliers	Vahidi et al. (2018), Kellner & Utz, (2019)
Customers	Kayani et al. (2023)
Final products	Lotfi et al. (2024)
Components	Vahidi et al. (2018)
Raw materials	Islam et al. (2024)

Table 4
Mapping of risk factors to foundational literature sources.

Risk type	Risk metrics	Representative Literature
Exogenous risks factors	natural disaster, labour disputes, war and terrorism, supplier finance, Exchange rate	Chopra & Sodhi (2004)
	Geopolitical instability, Sovereign risks, Government regulations, transportation cost and strikes, economic downtimes	Ho et al. (2015)
	Child and forced labour, Occupational health and safety, Unfair wages and working hours, lack of employee training	Zimmer et al. (2017)
	Commodity price and availability	Ballinger et al. (2019)
	Cybersecurity	Pandey et al. (2020)
	Contagious deseas	Dias et al. (2020)
Endogenous risks factors	Supplier capacity, Supplier responsiveness, Supplier flexibility, Sourcing alternatives, Supplier visibility, Supplier integration, Supplier contract type, Number of transportation modes, Supplier lead time, Product life cycle obsolescence, Sales promotion, Customer number,	Chopra & Sodhi (2004)
	Supplier credit periods, Customer dependency, Customer credit periods, Customer financial strength, Employee accidents, Exployee absence, Employee experience,	Ho et al. (2015)

- Monitoring SC performance and risks;
- Predicting future performance based on identified risks;
- Supporting decision-making problems considering previously monitored risk elements.

This design ensured that users could access detailed insights into past performance metrics, identify potential risks, and make informed decisions to improve SC efficiency. In doing these, tabular, time-series and geo-mapping visualization have been adopted.

Lastly, internal and external data sources have been collected inside the database management system of the proposed SCRM-IDT. A summary of the main tools and data sources adopted for its implementation are reported in Table 5.

3.3. Framework validation

The validation of the proposed framework considered its ability to generate effective SCRM-IDTs from both the technical and socio-technical points of view. This comprehensive evaluation aligns with the recent suggestion Chua & Niederman, (2025) reported. Authors indeed argue that a narrow focus on technical systems in decision-support literature overlooks the critical role of sociotechnical factors. They emphasize that addressing complex organizational problems requires technically accurate systems and those that support decision-making in

Table 5
Tools and data sources adopted to implement the proposed framework.

IDT ELEMENTS/DATA	TOOLS/DATA SOURCE
Database Management System	PostgreSQL
WebApp	Django
Descriptive models	Chartjs, OpenStreetMap
Predictive models	Darts library
Prescriptive models	Pyomo, Gurobi
Supply chain indicators data sources	Company ERP and WMS
External data providers	https://data.humdata.org/dataset/worldriskindex https://ec.europa.eu/eurostat https://login.bvdinfo.com/R1/Orbis https://www.imf.org/ https://www.who.int/data/collections

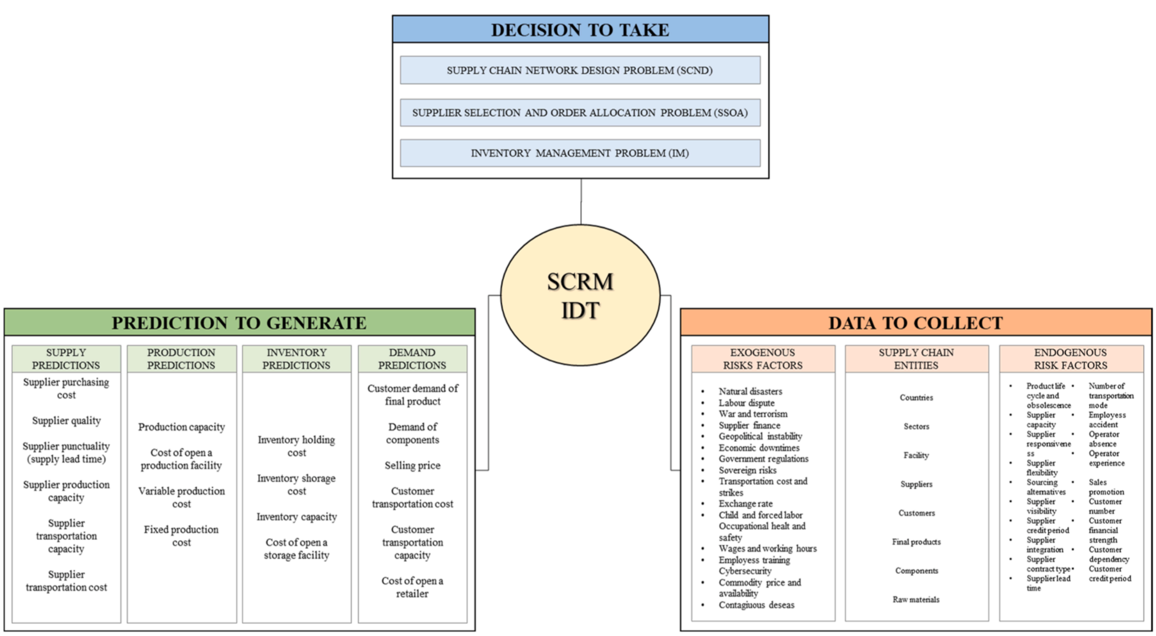

Fig. 2. The proposed SCRM-IDT design framework.

uncertain environments, which involves human interaction. With this in mind, the evaluation of the IDT involves both its technical efficiency and its interaction with human decision-making processes. The case study was conducted in the automotive industry, which was selected for its high exposure to global supply chain risks, structural complexity, and interdependence across suppliers and markets. These characteristics make it an especially suitable context for evaluating the framework's capacity to support risk-informed, real-time decisions. However, we acknowledge that relying on a single-industry case limits the generalizability of the findings. Nonetheless, the purpose of the case was to demonstrate the framework's applicability and internal coherence, laying the groundwork for future multi-sector validations.

3.3.1. Technical validation

Two tasks have been selected to assess the technical dimension: predicting typical supply chain key performance indicators exposed to risk elements and solving the SSOA problem, which are key challenges in SCRM as identified in the proposed framework. Details about the dataset adopted for the experiments have been reported in Table 6. Similarly, details on the experimental settings adopted to investigate prediction generation are reported in Table 7 and Table 8. Specifically, Table 7 details the predicted metrics, the forecasting aggregation and length and the models and data collection examined. Table 8 provides deeper details about which data were considered in each examined data collection.

To build a risk-aware predictive setup, internal company data were enriched with external risk indicators. These external datasets were aligned temporally with the ERP data, and joined using shared attributes such as supplier, sector, country of origin or time.

Prior to model training, input variables were preprocessed as follows: numerical features were normalized using min-max scaling. Time series were chronologically ordered and resampled and interpolated where necessary to ensure uniform time steps and data consistency across forecasting horizons.

The forecasting models employed—ARIMA, CatBoost, and LSTM—were selected for their methodological complementarity and alignment with the characteristics of the prediction tasks. ARIMA was included as a well-established baseline for time series modeling with strong performance on stationary data. CatBoost, a gradient boosting method optimized for categorical features and small datasets, was chosen due to its ability to handle complex feature interactions with limited tuning. LSTM, as a recurrent neural network architecture, was selected for its capacity to model long-term temporal dependencies and capture non-linear patterns in sequential data. While other models such as Prophet or XGBoost could have been considered, the selected models offered a balanced mix of interpretability, accuracy, and adaptability across the varied scenarios examined in this study. The focus was not on benchmarking the full model landscape but on validating the framework's ability to accommodate multiple modeling approaches relevant to practical SCRM settings.

All models were implemented using the Darts Python library, which provides a unified interface for time series modeling and evaluation. For

Table 6
Details on the dataset adopted for the experiments.

Sector	Automotive
Number of countries involved in supply activities	27
Number of sectors involved in supply activities	101
Number of suppliers involved	415
Number of components supplied	17'403
Mean value of delivery punctuality	4.9 [days]
Standard deviation of delivery punctuality	19.3
Mean value of purchasing cost	761 [euro]
Standard deviation of purchasing cost	1763
Mean value of delivery quality	0.01 [pieces]
Standard deviation of delivery quality	0.6

Table 7
Details of the predictive tasks examined.

Training set split	01/2021-01/2023
Test set split	01/2023-12/2023
Predicted metrics	• Delivery punctuality • (days between actual and planned delivery) • Purchasing cost • Delivery quality • (quantity of defective components delivered)
Forecasting physical aggregation	Component level
Forecasting temporal aggregation	Daily level
Forecasting length	Short term: component lead time Long term: 1 year
Forecasting models examined	ARIMA; CatBoost; LSTM
Input data examined	Historical only (HIST); Historical and other data from ERP (HIST+ERP); Historical and other data from ERP and external data provider (HIST+ERP+EXT)

Table 8
Indicators adopted to train predictive models based on the considered data collection.

DATA	HIST	HIST+ERP	HIST+ERP+EXT
Target variable history	•	•	•
Monthly ordered quantity from suppliers		•	•
Trimester ordered quantity from suppliers		•	•
Monthly ordered variety from suppliers		•	•
Trimester ordered variety from suppliers		•	•
Monthly ordered value from suppliers		•	•
Trimester ordered value from suppliers		•	•
Coal price			•
Natural gas price			•
Spot crude price			•
Propane price			•
Aluminum price			•
Cobalt price			•
Copper price			•
Iron ore price			•
Lead price			•
Molybdenum price			•
Nickel price			•
Tin price			•
Uranium price			•
Zinc price			•
Gold price			•
Palladium price			•
Platinum price			•
Silver price			•
Geopolitical risk index of supplier			•
Industrial production price index of the supplier sector			•
Industrial production volume index of the supplier sector			•
Supplier total production value			•
Supplier cost of goods sold			•
Supplier EBIT			•
Supplier tangible fixed asset value			•
Supplier debts versus supplier value			•
Supplier number of employees			•
Supplier ROE			•
Supplier ROCE			•
Supplier ROA			•
Supplier inventory rotation			•
Supplier collection times			•
Supplier payment times			•

each input configuration (HIST, HIST+ERP, HIST+ERP+EXT), models were developed and tuned independently to accommodate input-specific characteristics that may affect optimal hyperparameter settings. The original dataset was split into a training set (January 2021 –

January 2023) and a test set (January 2023 – December 2023), as reported in Table 7. To tune hyperparameters, we further subdivided the training set into an internal training subset (80%) and validation subset (20%). This internal split was used exclusively for model selection and tuning. Hyperparameter optimization was performed using Bayesian optimization over an 8-hour search window per model-input combination. The search space for each model is reported in Table 9.

Final model evaluation was conducted on the untouched test set and model performance was assessed using the Symmetric Mean Absolute Percentage Error (SMAPE), calculated as follows:

$$SMAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|Y_t - \widehat{Y}_t|}{\frac{Y_t+\widehat{Y}_t}{2}} \tag{1}$$

Where Y_t was the true historical value of the metrics to predict at time t for a specific component, $\widehat{Y}_t$ was the value predicted, and N was the length of the test set.

For the prescriptive analytics module, the SSOA problem is formulated as a Mixed-Integer Linear Programming (MILP) model. The objective function minimizes the sum of purchasing costs and costs related to non-punctual deliveries, incorporating predicted early and late delivery days from suppliers. Constraints ensure supplier capacity is not exceeded, minimum order quantities are respected, and demand is fully satisfied across planning periods. This formulation supports robust, risk-informed order allocation under uncertainty, using forecasts from the predictive module. The full structure of the model, including variables and parameters, is detailed in Section 3.2.1 of Gabellini et al. (2025).

The efficiency of the SSOA decision-making model has been measured in economic terms considering the difference between the purchasing cost, delivery delay cost in terms of shortage or inventory cost and the overall cost compared with those produced by perfect decision makers according to equations reported in Gabellini et al. (2025).

All the experiments were conducted on a Dell Latitude 5540, equipped with a 13th Gen Intel Core i7-1355U processor running at 1700 MHz, featuring 10 cores and 12 logical processors. The system was powered by 16 GB of installed RAM, with around 4.46 GB of physical memory available during testing. Virtual memory was also utilized, with 22.4 GB available and 6.75 GB allocated for paging. The operating system used was Microsoft Windows 11 Pro, version 10.0.22631, running in UEFI mode with secure boot enabled. The hardware configuration also included features like Kernel DMA protection and virtualization-based security, ensuring a secure and reliable environment for running experiments.

3.3.2. Socio-technical validation

On the other hand, considering the sociotechnical side, an experimental design has been proposed to assess how the IDT can improve operational efficiency in SCRM by aiding human decision-making and enhancing information retrieval. This approach emphasizes integrating both technological and human factors in evaluating the IDT. Specifically, the experiments compared the time required to complete tasks related to SC performance monitoring, risk analysis, risk prediction, and decision-making when using the IDT versus conventional tools typically used in industry, such as Excel spreadsheets. The experiment involved two groups of professionals with experience in SCRM. Participants were randomly assigned to one of the two groups to ensure that any observed outcome differences were attributable to the tools used rather than individual skill levels. Each group was tasked with completing the same tasks using the developed IDT and traditional practices relying on adopting Excel spreadsheet, ERP extractions and web searches, alternating between the two tools to assess their relative effectiveness comprehensively. The tasks were designed to simulate typical activities within SCRM, such as monitoring SC performance, forecasting future outcomes, and making decisions based on identified risks. A summary of the tasks performed is presented in Table 10.

To ensure reliability and minimize task- or user-related biases, each participant was assigned tasks in a randomized order, and time tracking was automated via logging software that recorded start and end timestamps for each task. Furthermore, to reduce variability due to participant familiarity with either tool, participants were given a short, standardized training session prior to the experiments, and all instructions were provided in written form to ensure consistency. The experimental environment was kept consistent, including computer hardware, software configuration, and network conditions.

The time each participant took to complete the tasks was carefully tracked. Each participant started the tasks at designated times, and completion times were recorded immediately after finishing the task. A statistical analysis was conducted on the time data collected from the experiment, focusing on comparing the mean task completion times between the two groups. The analysis aimed to determine whether the SCRM-IDT significantly reduced the time required to perform the tasks compared to the traditional manual practices developed relying on excel spreadsheets, ERP extractions and web searches.

An independent samples t-test was used to compare the mean

Table 9
Hyperparameter research space for the investigated models.

Model	Hyperparameter Name	Hyperparameter research space
ARIMA	P	[0-200]
	d	[0-2]
	q	[0-200]
CatBoost	Lags	[1:200]
	Iterations	[100:2000]
	Learning rate	[0.01:0.3]
	Depth	[3:10]
	L2_leaf_reg	[1:10]
	Loss function	RMSE
LSTM	Input chunk length	[1: 200]
	Hidden dim	[5:100]
	N rnn layers	[1:5]
	Dropout	[0.0:0.5]
	Training length	[12:72]
	N epochs	[1:100]
	Loss Function	RMSE

Table 10
SCRM tasks identified to evaluate the sociotechnical capability of the prototyped SCRM-IDT.

Task category	Task
Supply chain monitoring	Report the delivery punctuality, quality, and cost values for the last month, aggregated at the component, supplier, industrial sector, and country levels.
Supply chain monitoring	Report the values of delivery punctuality, quality, and cost over time, aggregated at the component, supplier, industrial sector, and country levels.
Risk monitoring	Report the geopolitical risks associated with the countries where the company's suppliers are located.
Risk monitoring	Report the macroeconomic risks associated with the sectors in which the company's suppliers operate.
Risk monitoring	Report the financial risks associated with the company's suppliers.
Risk monitoring	Report the raw material risks related to the main raw materials the company relies on.
Prediction generation	Generate predictions for each component for the next quarter regarding future delivery punctuality, quality, and cost.
Prediction generation	Aggregate all component predictions to generate supplier forecasts regarding delivery punctuality, quality, and cost for the next quarter.
Prediction generation	Aggregate all component predictions to generate country-level forecasts regarding delivery punctuality, quality, and cost for the next quarter.
Decision making	For a specific component subject to a multiple sourcing strategy, define the optimal order allocation strategy for the next quarter based on the generated forecasts and supplier capacity.

completion times for the two groups under the null hypothesis that no significant difference existed between the two tools in terms of time efficiency. Before conducting the t-test, the data were assessed to ensure compliance with the assumptions necessary for this analysis. The normality of task completion times was tested using the Shapiro-Wilk test, and Levene's test examined the homogeneity of variances.

4. Results

This Section initially presents the prototype of the SCRM-IDT developed starting from the framework presented in Fig. 2 according to the implementation details reported in Section 3.2. Following the evaluation procedure reported in Section 3.3, the results of its technical and sociotechnical evaluation have been reported. Specifically, Section 4.2 reports the proposed IDT's technical evaluation in predicting typical supply chain indicators exposed to risks and supporting the SSOA problem. On the other hand, Section 4.3 reports its sociotechnical effectiveness in improving the operational efficiency of solving typical SCRM-related tasks.

4.1. Intelligent Digital Twin prototype

Some illustrations of the prototype developed starting from the proposed framework respectively reporting its monitoring, predictive and prescriptive capabilities are reported in Figs. 3-6.

The developed prototype initially offers to the user the capability to navigate according to two different logics, as reported in Fig. 3. As a first logic, a decision-oriented logic has been proposed. The logic spans from monitoring the current SC status to predicting its future performance and concluding to supporting decisions. Conversely, as a second logic, a process-oriented logic has been selected to allow users to navigate, focusing on the process of interest between supply, production, inventory and demand processes.

Considering for example, the supply process, Fig. 4 reports the main views allowing the users to monitor the supply status and the evolution of the risk elements it is exposed to. Specifically, Fig. 4.a, provides geographical visualizations of supplier locations together with an indication of the supplier performance and of the sector and country risks they are exposed to. Moreover, univariate and bivariate visualizations of key SC performance indicators aggregated at different levels, such as country and supplier levels, have been proposed. These visualizations enabled users to identify SC issues and monitor performance metrics quickly. Additionally, a tabular (Fig. 4.b) and a time series view (Fig. 4.c) have been introduced. The tabular view allowed users to query and sort data by different levels of aggregation, enabling a more granular analysis of SC performance. Furthermore, the time series view enabled users to track the historical performance of specific entities and examine how risk-related metrics evolved, facilitating a deeper understanding of long-term trends.

Fig. 5 reports how the SCRM-IDT allows visualization of the generated supply-related predictions. According to the proposed framework, delivery punctuality, quality and cost represent the predicted metrics visualized according to tabular (Fig. 5.a) and time series (Fig. 5.b) views. The tabular view allowed users to quickly query specific SC entities and view their predicted future performance, while the time series view provided a more comprehensive visualization by showing both historical data and future predictions alongside the model's error margins. This feature was crucial for monitoring the accuracy of predictive models, allowing users to track when predictions might no longer be valid and need updating.

Lastly, Fig. 6 reports the decision-making interface proposed to users when solving the SSOA problem. According to Fig. 6.a, users are here supported in the identification of those requests for which multiple sourcing is present and according to Fig. 6.b, once they select a specific component, they receive information about suppliers' past and predicted performances considering risks, and are supported in understanding how much of the future order quantity to allocate over time to each supplier. To note that in this step, the decision-making process relies on inputs from various components of the IDT, including the historical performance recorded in the database and the generated predictions, but also requires user-provided data such as inventory shortage and holding costs and supplier capacity. The system was thus designed to support effective, data-driven decision-making, allowing users to optimize their SC operations and mitigate risks efficiently by integrating human and AI-generated knowledge.

In summary, the developed SCRM-IDT prototype integrated various open-source tools to create a comprehensive solution for managing SC risks. By incorporating advanced data visualization techniques, time series forecasting, and optimization models, the system was able to provide valuable insights into SC performance, predict future risks, and

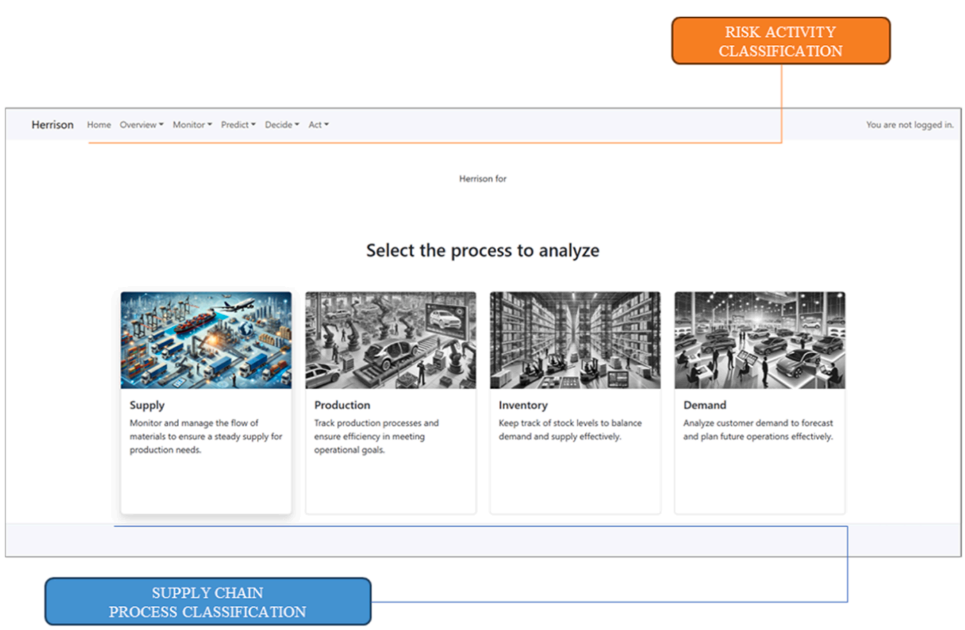

Fig. 3. Home page of the prototyped SCRM-IDT.

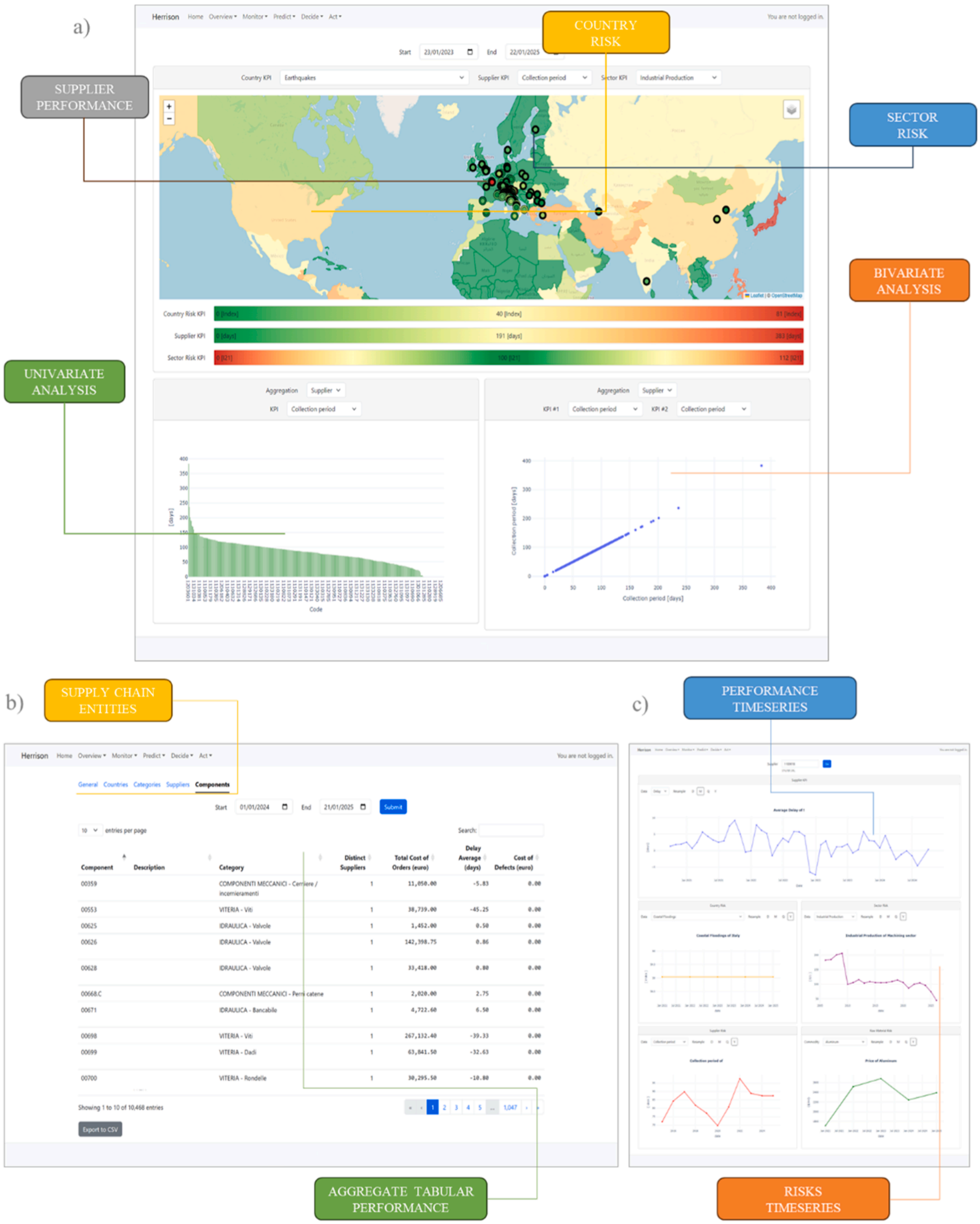

Fig. 4. Monitoring view of the supply process with descriptive statistics of the prototyped SCRM-IDT.

support informed decision-making. This integrated approach enables businesses to address both exogenous and endogenous SC risks, ultimately improving the resilience and efficiency of SC operations.

4.2. Technical evaluation results

The technical capability of the developed prototype in solving two relevant SCRM tasks is reported in Figs. 7 and 8, respectively.

Specifically, Fig. 7 reports the accuracy reached by the predictive models built within the prototyped version when forecasting supply metrics like supplier punctuality, quality and costs when considering different forecasting lengths depending on the model and data collection adopted.

According to the Figure, the predictive models within the proposed SCRM-IDT demonstrate varying accuracy levels, mostly depending on the forecasted metrics.

Pretty good predictive accuracy has been obtained when predicting supplier purchasing prices. Specifically, the best-performing combination is the ARIMA model relying only on the historical evolution of supplier price under both the short and long terms forecasting horizons, yielding respectively a median SMAPE of 0.01% and 0,03%, indicating an extremely accurate forecast. In contrast, the LSTM model relying on

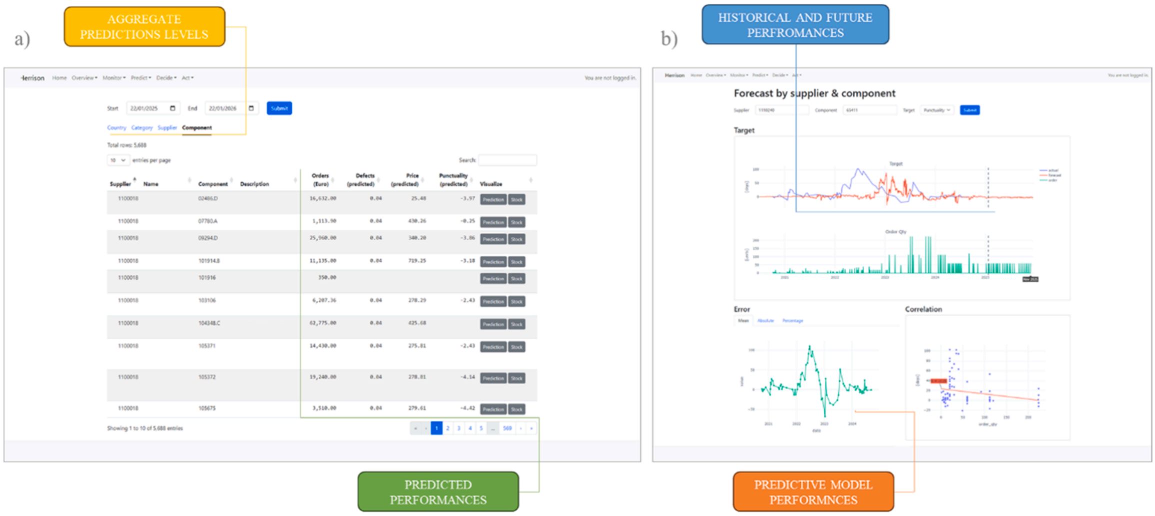

Fig. 5. Predictive views of the supply process of the prototyped SCRM-IDT.

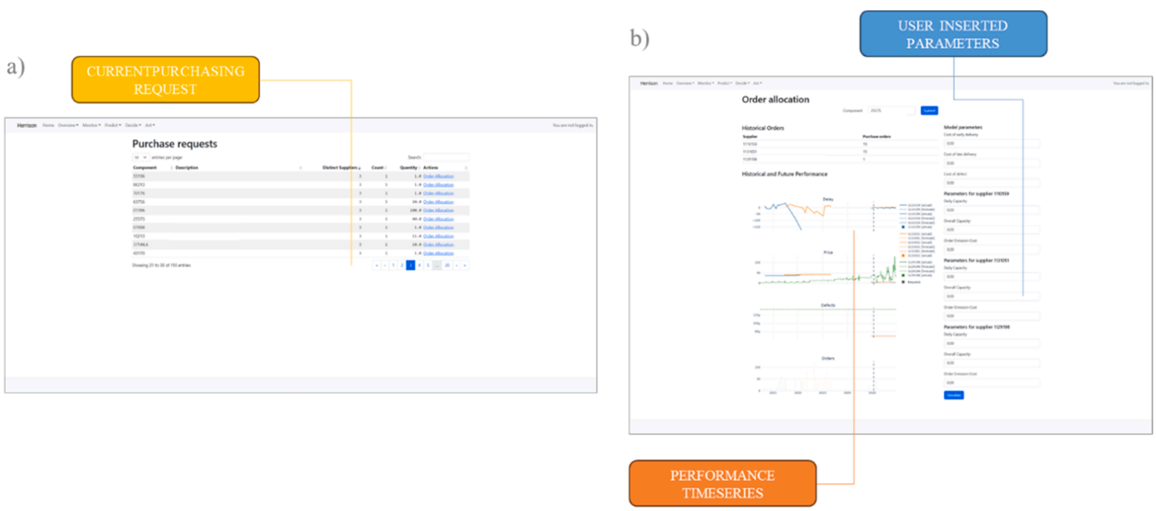

Fig. 6. Supplier selection and order allocation decision-making views of the prototyped SCRM-IDT.

historical data produced the worst performance for both forecasting horizons, with median SMAPE values of 7.9% and 16.6%.

Moderate predictive accuracy has been instead observed when forecasting supplier delivery punctuality, with the ARIMA model trained based on historical and ERP information performing best under short-term forecasting horizons, achieving a median SMAPE values of 117.4% and the LSTM model trained with both historical and ERP data performing better in long term forecast with a median SMAPE of 128.5%. CatBoost trained with historical and ERP input data instead reported the worst result in short terms forecast, producing median SMAPE values of 154.4%, while for long-term forecast, the worst accuracy has been reached by LSTM models trained only on historical data with a median SMAPE of 166.1%. However, for some components, accuracy errors up to 32.3% and 25.2% have been observed in some instances.

Lastly, not remarkable performances have been observed when forecasting supplier defects. Here, the CatBoost model trained with historical data, ERP data and data from external data provider reached only a median SMAPE value of 196.8% in the short-term forecast and 196.6% in the long-term forecast.

In conclusion, the results thus suggest the effectiveness of the proposed framework in supporting the development of an effective SCRM-IDT prototype obtaining state-of-the-art forecasts. Indeed, as the results suggest, any lack of remarkable performance should not be attributed to the prototype itself, but rather to the inherent complexity of the underlying process that generates the predicted metrics. Indeed, the comparison between the different forecasting technologies, input data, and forecasting horizons does not seem to be the primary factors driving performance. Instead, the nature of the forecasted metric plays a significant role in the accuracy of predictions, thus suggesting that the SCRM-IDT is effective in predicting supply chain metrics but that the complexity and predictability of the underlying examined process inherently influence the ease of prediction.

On the contrary, Fig. 8 illustrate the decision-making capability of the SSOA prescriptive module built within the proposed SCRM-IDT.

Indeed, the results presented in the Figure report the cost difference in terms of purchasing cost, delivery cost (attributable to holding or stockout costs arising from early or late supplier deliveries) and overall cost, between the decisions generated from the prescriptive model implemented in the SCRM-IDT and those generated from an idealized perfect decision-maker with perfect knowledge of the future. More details on the metrics computation can be found in Gabellini et al. (2025). These findings underscore the effectiveness of the proposed SCRM-IDT in supporting such decision-making processes. Notably, when examining the overall cost for each component, the prescriptive module implemented within the IDT demonstrated a cost difference with an

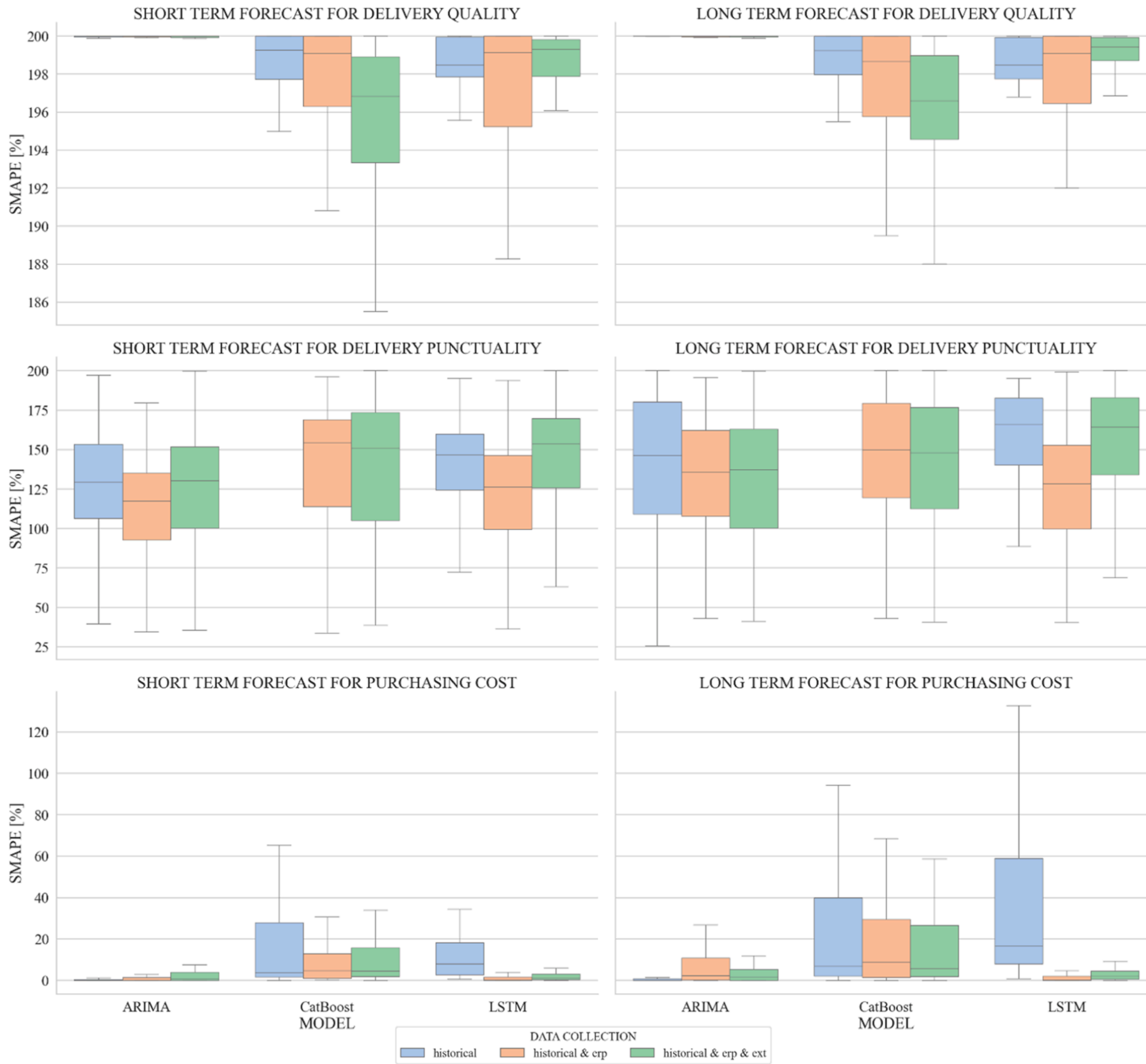

Fig. 7. Accuracy performance reached by the prototyped SCRM-IDT solving prediction tasks related to typical supply KPI.

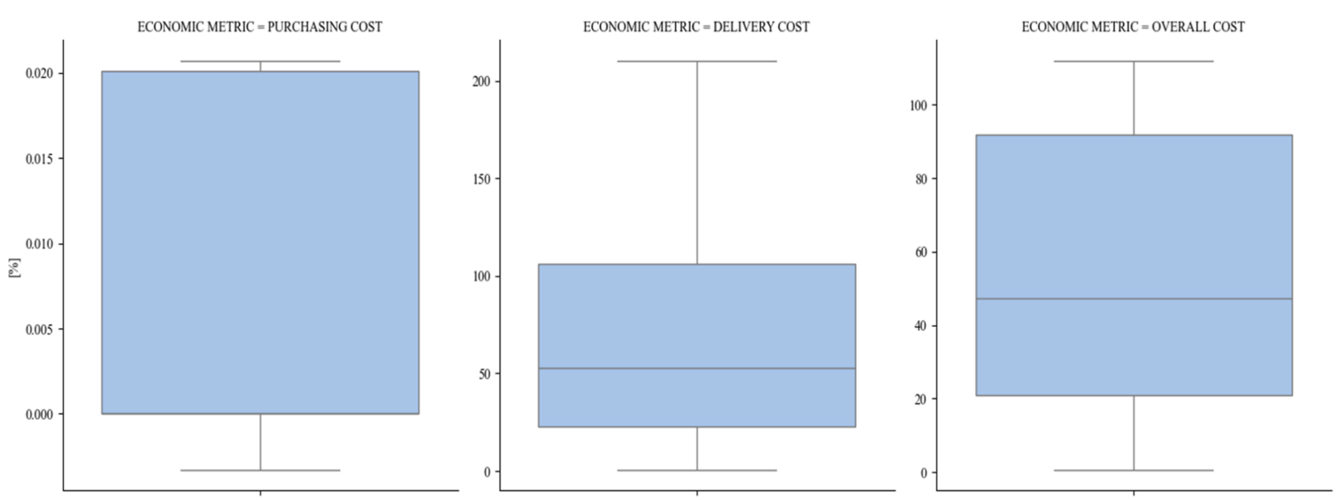

Fig. 8. Cost performances reached by the prototyped SCRM-IDT in solving SSOA tasks.

ideal decision maker of 47.4% for half of the considered decisions. As shown in the charts, these cost differences stem from the model's imperfect ability to predict supplier punctuality when allocating orders over time. In contrast, only minor differences were observed regarding the generated purchasing costs. The insights from Fig. 8 are consistent with those from Fig. 7, which indicate that while future purchasing costs can be predicted reasonably, supplier punctuality remains a source of significant uncertainty.

4.3. Sociotechnical evaluation results

In conclusion, the results related to the effectiveness of the proposed SCRM-IDT in supporting and increasing the efficiency of the typical SCRM are reported in Table 11. Specifically, the Table reports the time required to solve the tasks reported in Table 10 when relying on adopting the proposed SCRM-IDT and on standard procedures based on the adoption of Excel spreadsheets, ERP extractions and web search.

According to the Table, the results demonstrated a significant reduction in time across all task categories when relying on the SCRM-IDT. In performance monitoring, which required an average of 33,5 minutes with traditional tools, the time required to perform the tasks dropped to just 3,5 minutes using the IDT. Similarly, risk monitoring times decreased from 36,2 minutes to 3,1 minutes, and prediction generation times dropped from 57,5 minutes to 2,5 minutes. The most substantial improvement was observed in the decision-making task, where completion time was reduced from 242,5 minutes to 6,2 minutes. The results, analyzed through statistical testing, thus confirmed the significance of these time reductions. For performance monitoring, the average time reduction generated by adopting the SCRM-IDT has been 89.6%. Risk monitoring time decreased by 91.4%, and prediction generation saw a reduction of 95.7%. Lastly, decision-making had the most significant time savings, with a time reduction of 97.4%. The p-values for all tasks were less than 0.005, indicating that the observed time reductions were statistically significant.

The socio-technical investigation thus strongly suggested that the proposed framework allows SCRM-IDT to guarantee substantial improvements in operational efficiency and enable faster execution of supply chain management tasks, particularly in risk management and decision-making. The reductions in time across all task categories highlight the system's ability to streamline processes, providing users with quick access to critical information and effective decision support, which are crucial for managing SC risks in dynamic environments.

5. Discussion

This section is organized into three parts. Section 5.1 presents a detailed discussion of the empirical results obtained from the evaluation of the proposed SCRM-IDT prototype. Section 5.2 compares these findings with the existing literature, highlighting areas of agreement, divergence, and theoretical advancement. Finally, Section 5.3 outlines the theoretical contributions of the study, explaining how the proposed framework refines and extends current SCRM knowledge.

5.1. Discussion of empirical results

The results presented in the previous Section offer a comprehensive evaluation of the proposed framework to develop effective SCRM-IDTs in solving specific SCRM tasks and interacting seamlessly with human operators in day-to-day operations. This evaluation provides valuable insights into the system's technical proficiency and ability to improve operational efficiency.

Table 11
Statistical results of the comparison.

TASK	AVERAGE TIME WITH IDT [min]	AVERAGE TIME WITHOUT IDT [min]	DELTA	P-VALUE
Performance monitoring	33,5	3,5	89,6 %	< 0.005
Risk monitoring	36,2	3,1	91,4 %	< 0.005
Prediction generation	57,5	2,5	95,7 %	< 0.005
Decision making	242,5	6,2	97,4 %	< 0.005

The capability of the proposed framework to develop SCRM-IDT to generate effective predictions on future supply chain performance has been instead certified by the experiment reported in Section 4.2. Specifically, the results revealed that while the system performs well in generating forecasts, the performance of different forecasting models varies significantly depending on the metric being predicted. The analysis showed that more complex LSTM models do not always yield superior results. This observation suggests that, in some cases, simpler models, such as ARIMA, are more effective for certain types of predictions, especially when data is limited. Furthermore, including multiple risk indicators to support predictions does not always improve forecasting accuracy. While aggregating data from various risk sources is beneficial in the descriptive phase, it does not always enhance predictive outcomes. Therefore, managers developing SCRM-IDTs should consider both the availability of historical data and the complexity of the SC when selecting forecasting algorithms, as these factors significantly influence prediction quality.

An additional insight emerging from the analysis concerns the impact of input variability on predictive model performance. As shown in Table 6, the high standard deviations associated with input metrics such as delivery punctuality and quality suggest a wide range of supply behaviors. This variability inherently challenges the forecasting process. Although a formal sensitivity analysis was not conducted, the distribution of prediction errors reported in Fig. 7 allows us to qualitatively assess the relationship between input dispersion and forecasting performance. Specifically, metrics with greater inherent variability—such as punctuality and quality—exhibited broader SMAPE distributions across forecasting configurations, reflecting greater prediction uncertainty. In contrast, purchasing cost forecasts, derived from more stable data, showed narrower error bands and consistently lower SMAPE values. These patterns may indicate that input volatility significantly influences forecast reliability, reinforcing the importance of careful feature selection, robust preprocessing, and the potential benefits of data segmentation when dealing with highly variable supply chain behaviors.

Among the prediction tasks examined, supplier quality defects emerged as the most difficult to predict. This is primarily due to the inherently stochastic nature of quality issues, which are often influenced by unobservable or latent variables such as production shifts, human error, or batch-specific anomalies that are not typically captured in ERP systems or external datasets. As a result, even with enriched feature sets, the predictive signals are often weak or obscured by noise. To improve performance in this domain, future iterations of the model could benefit from incorporating more granular production process data (e.g., machine logs, operator data) or real-time quality monitoring systems, which would offer better visibility into the root causes of defects.

The results also emphasize the capability of the proposed framework to develop SCRM-IDT with a critical link between predictive accuracy and the quality of decision-making. As seen in the comparison of decision-making capabilities in Fig. 8, the quality of prescriptive recommendations heavily depends on the predictive models' accuracy. This insight highlights the importance of ensuring high-quality data and reliable predictive models before transitioning to prescriptive analytics. Managers should be aware that while significant improvements in decision-making can be achieved, some errors are inevitable, particularly when the underlying forecasts are uncertain. Thus, developing the prescriptive module should account for the inherent limitations in predictive accuracy to ensure that decisions remain robust even when facing imperfect forecasts.

Lastly, beyond the technical results, the sociotechnical results demonstrated the possibility of producing SCRM-IDT that positively impacts human-AI interactions. Indeed, as shown in Table 11, the obtained system enhances the capability to predict future events, optimize decision-making, and improve the operational efficiency of SCRM tasks. Time reductions in performance monitoring, risk monitoring, prediction generation, and decision-making were substantial, underscoring the efficiency gains provided by the system. These time savings enhance productivity and could potentially allow human operators to allocate more time to tasks that require strategic thinking, complex problem-solving, and domain-specific expertise—areas where human input remains crucial. However, while this implication is grounded in the observed time reductions, we acknowledge that no direct evidence (e.g., surveys or interviews) was collected to confirm a behavioral shift. Future research should explore user perceptions and behavioral adaptations in response to such systems, which would provide a more complete understanding of human-AI collaboration outcomes.

In conclusion, the prototype of the SCRM-IDT developed from the conceptual framework demonstrates the robustness and potential of the proposed framework to enhance both the effectiveness and efficiency of SCRM tasks.

5.2. Comparison of empirical findings with the existing literature

The results presented in this study both confirm and extend current research. Consistent with prior literature in demand forecasting (Elalem et al., 2023), our findings show that simpler models like ARIMA often outperform deep learning approaches such as LSTM also in supply forecasting when data is limited or noisy.

The difficulty encountered in predicting supplier quality defects reinforces findings by Kleindorfer & Saad, (2005) regarding the unpredictability of certain risk-related metrics. Our framework responds by embedding flexibility through human-in-the-loop decision support, thereby enhancing robustness—an area often underdeveloped in prior frameworks.

In the prescriptive domain, the results reported in Fig. 8 reinforce the idea reported in Murphy & Ehrendorfer, (1987) that even under imperfect forecasts, effective decisions can be reached—refining the assumptions of previous optimization models, which often presuppose high prediction accuracy.

Moreover, while Menon et al. (2023) highlight the potential of DTs to improve efficiency, this study provides empirical, statistically tested evidence of such gains. The significant reductions in time to complete SCRM tasks across all categories strengthen the sociotechnical dimension of IDT design and implementation.

Finally, compared to existing frameworks that often remain abstract or fragmented, the proposed layered structure explicitly connects data sources, predictive models, and decision outputs. Its top-down approach—starting from decision needs—offers a practical and integrative advancement, bridging the gap between conceptual frameworks and real-world application

5.3. Theoretical contributions

This study offers several theoretical contributions that enhance and extend current knowledge in SCRM. First, by proposing and validating a structured framework for the design of IDTs in SCRM, the study refines existing theory by specifying how risk management systems can transition from generic digital support tools to integrated, predictive, and prescriptive decision-support systems. While existing SCRM literature has extensively discussed the relevance of visibility, responsiveness, and risk anticipation, it has rarely provided operationalized pathways linking these objectives to specific data inputs, predictive requirements, and decision processes. The framework addresses this gap by offering a systematic mapping between the types of risks, the data needed to model them, and the decisions they inform—thereby expanding the theoretical foundation for digital risk mitigation.

Second, the study contributes to theory by empirically illustrating how different types of supply chain risks—such as cost volatility, delivery punctuality, and quality issues—differ in terms of predictability and decision impact. These findings nuance the existing theoretical understanding that all risks can be treated uniformly through analytics. Instead, the results emphasize that prediction quality depends not only on data availability and model sophistication but also on the stochastic nature of the risk itself. This insight refines theoretical assumptions around risk modeling and informs the design of differentiated risk mitigation strategies.

Third, the research provides theoretical clarity on the sociotechnical dimension of SCRM-IDT systems. By demonstrating significant efficiency gains and decision-time reductions when using the SCRM-IDT, the study supports emerging theory that digital twins are not only technical systems but also enablers of improved human decision-making. This reinforces and extends sociotechnical theory in SCRM by illustrating how intelligent systems can reallocate human effort from repetitive tasks to more strategic interventions.

In sum, the study enhances SCRM theory by operationalizing the design of intelligent systems that address specific risk-related decisions, expands theoretical insight into the variable predictability of supply chain risks, and refines our understanding of the human-machine interface in risk management practices.

6. Conclusions

This study proposed and validated a novel design framework for developing IDTs tailored to SCRM. The framework addresses an important gap in the existing literature by clearly defining which data should be collected, which predictive tasks must be performed, and which decision-making processes should be supported. To evaluate the framework's applicability and impact, a prototype was implemented in a real-world automotive case study, allowing for an empirical assessment of both its technical and socio-technical contributions.

The results confirmed the framework's ability to support two major SCRM tasks: predictive analytics and prescriptive decision-making. In terms of predictive capabilities, the SCRM-IDT delivered highly accurate forecasts for specific supply metrics, such as purchasing costs—achieving SMAPE values as low as 0.01%—while also highlighting the challenges in forecasting more volatile variables like quality defects. These findings demonstrate that increasing model complexity or input variety does not always improve predictive performance and emphasize the importance of careful feature selection. From a prescriptive standpoint, the IDT achieved decisions within 47.4% of the cost performance of a perfect-knowledge benchmark, illustrating its effectiveness in supporting cost-efficient decision-making under uncertainty. In addition, the SCRM-IDT demonstrated a 97.4% reduction in the time required for decision-making and between 89.6% and 95.7% for other SCRM tasks, with all time savings statistically significant ($p < 0.005$). These gains in operational efficiency underscore the system's practical value and its potential to relieve human managers from routine tasks, enabling them to focus on strategic oversight.

From a managerial and practical perspective, the study offers actionable guidance on how to develop SCRM-IDTs capable of enhancing both performance monitoring and decision-making under uncertainty. The prototype demonstrates how organizations can leverage real-time data, risk forecasting, and AI-driven recommendations to streamline operations and increase responsiveness. The substantial time savings observed free up managerial attention for higher-level strategic decision-making, thus reinforcing the complementary role of human expertise in AI-supported systems.

On the theoretical side, the study contributes to the SCRM literature by advancing the conceptual understanding of how IDTs can be designed to support risk-aware decision-making. Unlike existing frameworks, which often lack specificity or validation, this work offers a validated design structure that integrates risk factors, predictive accuracy, and decision-making quality. By empirically linking these dimensions, the study refines the theoretical foundation of SCRM digitalization, suggesting that effective IDT design must not only capture data complexity but also translate predictive insights into prescriptive value. This adds to the growing body of research on human-AI collaboration, digital supply chain resilience, and intelligent decision support.

Nevertheless, the study has several limitations. The framework was tested within a single industry setting, which may limit its generalizability. While the design principles are theoretically broad, future research should validate them across different industries and supply chain configurations.

Future studies could explore extending the framework in several directions. First, alternative forecasting methodologies—such as probabilistic or ensemble learning models—could be investigated to improve performance in highly uncertain domains. Second, multi-objective or stochastic optimization techniques could enhance the prescriptive module, offering better trade-off analysis under uncertainty. Finally, longitudinal or cross-sector validation efforts would strengthen the generalizability of the findings and support more universal adoption of IDT-based SCRM systems.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to improve writing quality. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

CRediT authorship contribution statement

Matteo Gabellini: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Alberto Regattieri:** Writing – review & editing, Writing – original draft, Resources, Project administration, Funding acquisition, Conceptualization. **Marco Bortolini:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Conceptualization. **Michele Ronchi:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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