Advancing ERP Systems from Reporting to Predictive Decision Support in Supply Chain Planning

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***Abstract*—** The traditional Enterprise Resource Planning (ERP) systems have been used as back office transactional systems and reporting infrastructures to supply chain planning. Nevertheless, environmental volatility, the pressure of digital transformation, and the spread of artificial intelligence (AI) technologies have increased the pace of the move to descriptive reporting to predictive and prescriptive decision support. Present-day studies show that analytics-empowered supply chain functions provide a great contribution to responsiveness, resilience, and operational performance in case of effective information systems and data governance systems. Simultaneously, a new set of paradigms including digital twins, real-time integration of IoT, and explainable AI are redefining the architectural and managerial underpinnings of the intelligent enterprise systems. This review focuses on how ERP systems have evolved into forecasting and decision-support engines in the supply chain planning function of the ERP systems. Critical architectural enablers, governance frameworks, analytical models, and empirically obtained performance results were examined. The review found that there were still research gaps associated with integration complexity, model transparency, cross-enterprise data interoperability, and sustainability-oriented planning optimization. The future of research is focused on the autonomous planning systems, AI-human collaboration frameworks, resilience-by-design architecture, and sustainability-based ERP ecosystems. The results locate predictive ERP systems as strategic supporting platforms of intelligent, adaptive, and accountable supply chain management.

***Index Terms* -** Enterprise Resource Planning; Predictive Analytics; Supply Chain Planning; Artificial Intelligence; Digital Twin; Decision Support Systems; Industry 4.0; Resilient Supply Chains; Sustainable Operations

I. INTRODUCTION

Enterprise Resource Planning (ERP) systems have evolved from transactional record-keeping systems into enterprise-wide information systems, which helps to support major business processes, such as procurement, production, inventory, distribution, and finance. Originally intended to facilitate internal operations and enhance the consistency of data within the different departments, ERP systems served as a backbone to contemporary supply chain planning systems by facilitating centralized reporting, real-time visibility and coordination of geographically dispersed operations [1], [2]. Due to increasing complexity of global supply chains, their interconnectedness, and susceptibility to disruptions, the demand on ERP systems has changed their focus on the static reporting in favor of dynamic and data-driven decision support.

The growing instability of international markets, accelerated digitalization and exposure to geopolitical, environmental and demand side shocks have fundamentally shifted the priorities of supply chain management. Pandemic-related shutdowns, energy prices, shortages in semiconductor supplies and others have highlighted the shortcomings of traditional, reporting-based ERP systems that mostly offer descriptive analytics. The modern supply chains need predictive and prescriptive systems that have the potential to predict changes in demand, forecast risk, and optimize resource allocation in the uncertain conditions [3], [4]. This change is consistent with the overall developments in artificial intelligence (AI), machine learning (ML), big data analytics, and cloud computing, which are transforming enterprise decision-making paradigms by industry [5], [6].

The introduction of AI-driven predictive models integrated into ERP-based supply chain planning is a timely and essential research problem in the modern research environment. The use of AI technologies promotes high-level demand prediction, anomaly identification, and dynamic inventory optimization as well as scenario-based planning, which enables proactive rather than reactive decision-making [7]. The integration of ERP systems and advanced analytical platforms is also a larger result of intelligent enterprise systems and Industry 4.0 models, in which cyber-physical systems, IoT sensors, and digital twins create a continuous stream of data that can be exploited to make predictions [8], [9]. In this context, ERP systems are becoming increasingly important not only as operational databases but also as a platform of predictive decision support.

In spite of these technological findings, there are still a number of challenges and research gaps. To begin with, the legacy ERP systems tend not to be flexible and scalable to deploy the advanced AI and real-time analytics modules without substantial customization and cost [2], [10]. Second, data and information quality, interoperability and governance are still significant issues to dependable predictive modelling especially consolidating disparate data sources among suppliers, logistics companies and subsystems within an enterprise [11]. Third, the literature has not reached a general consensus on the standardized models of integrating predictive analytics into ERP-based supply chain planning processes. Most research is on individual forecasting or optimization methods, but does not consider how to integrate the system, adoption by individuals, explanations, and the willingness of organizations [12]. Also, there are issues of cybersecurity, algorithm bias, and the automation of ethical decisions, which add further complexity to predictive ERP settings [6].

Within the wider context of digital transformation and AI-powered enterprise systems, the development of ERP into a platform based on predictive decision support engines rather than a reporting-based one is a very important research paradigm. Not only does this shift help in improving operational efficiency and resilience but also helps in achieving sustainability goals by allowing improved demand planning, minimizing waste, establishing energy-saving logistics, and optimizing resources. Predictive ERP systems can be a source of data-driven strategic planning as companies seek to have resilient and sustainable supply chains.

This review aims at critically analysing how ERP systems have changed since being considered as traditional reporting tools into predictive decision support platforms in supply chain planning. The review is the summary of the prevailing literature on the ERP architecture, advanced analytics integration, AI-based forecasting, and intelligent planning structures. It recognizes technical, organizational and governance issues and points to the new models and best practices that can be used to instantiate predictive capabilities into ERP settings. The following sections present a systematic discussion of (i) historical evolution of ERP in the supply chain management, (ii) integration of AI and predictive analytics into the supply chain planning systems, (iii) architecture and data related issues, (iv) evaluation systems and performance measures, and (v) future research directions towards entirely autonomous and robust supply chain planning systems.

II. LITERATURE REVIEW

The following table summarizes influential work underpinning the shift from ERP-centric reporting to the predictive decision support in supply chain planning, across the foundations of ERP, embedded BI/analytics, data quality, BDPA capability building, and AI-enabled risk-aware planning [13]-[22].

Table 1. Key findings and summaries

Focus	Findings (key results and conclusions)	Ref.
ERP research landscape and limitations relevant to decision support	Consolidated ERP research themes and highlighted persistent constraints in leveraging ERP data for higher-level planning and decision support, motivating complementary analytics and decision-support layers beyond core transaction processing [13].	[13]
ERP as an integration backbone for analytical work	Found that ERP implementations often leave core management control and advanced analytical techniques outside the ERP core, implying that predictive decision support typically requires additional systems, data pipelines, and governance beyond standard ERP deployment [14].	[14]
Tactical/strategic planning augmentation via APS connected to enterprise systems	Demonstrated how Advanced Planning Systems (APS) support tactical/strategic planning use cases through structured planning models and integration with enterprise data, while noting implementation and organizational challenges that affect realized planning benefits [15].	[15]
BI/analytics as a bridge from reporting to performance outcomes	Provided empirical evidence that BI-enabled process performance relates to organizational performance, supporting the view that analytics capabilities layered on enterprise systems can create measurable value beyond descriptive reporting [16].	[16]
Evolution of BI&A and implications for enterprise decision support	Positioned BI&A as an evolving discipline (from structured BI to big data and emerging analytics paradigms), establishing the conceptual basis for embedding predictive analytics into enterprise platforms for decision-making impact [17].	[17]
Predictive analytics and data science as a supply chain transformation lever	Framed predictive analytics and big data as transformative for supply chain design/management and emphasized the need for domain-grounded analytics capability (skills, governance, and problem framing) to translate predictions into decisions [18].	[18]
Data quality as a prerequisite for predictive supply chain decisions	Established that predictive insights are only as reliable as underlying data, and proposed monitoring/control approaches for supply chain data quality—directly relevant to ERP-driven pipelines feeding predictive planning models [19].	[19]
BDPA for supply chain decision-making (editorial framing and agenda)	Synthesized why BDPA matters for supply chains and articulated research directions centred on how predictive analytics can improve visibility, decision speed, and performance when operationalized in real settings [20].	[20]
BDPA assimilation and performance impacts	Showed that BDPA value depends on assimilation (e.g., acceptance → routinization → assimilation) and enabling resources (connectivity, information sharing, management commitment), clarifying organizational mechanisms needed to operationalize predictive ERP decision support [21].	[21]
AI for supply chain risk management and decision support under uncertainty	Mapped AI methods to risk tasks (identification, assessment, response) and identified under-explored areas (data-driven adaptation, integration, and decision operationalization), strengthening the case for predictive, risk-aware ERP decision support [22].	[22]

III. METHODOLOGY

The block diagram illustrates the functional development of descriptive reporting to predictive/prescriptive decision support, which aligns with dimensions of ERP success (information quality, system quality, net benefits) in the established IS success theory [23].

Figure 1. From ERP reporting to predictive decision support in supply chain planning

This diagram shows the information-to-decision flow and the management criteria that identify whether prediction models are reliable and can work in practice. Reliable predictive planning requires data quality dimensions (e.g., completeness, timeliness, interpretability), whereas business analytics capability (people-process-technology) clarifies the difference in performance results observed in comparable data environments across the organizations [24] and [25].

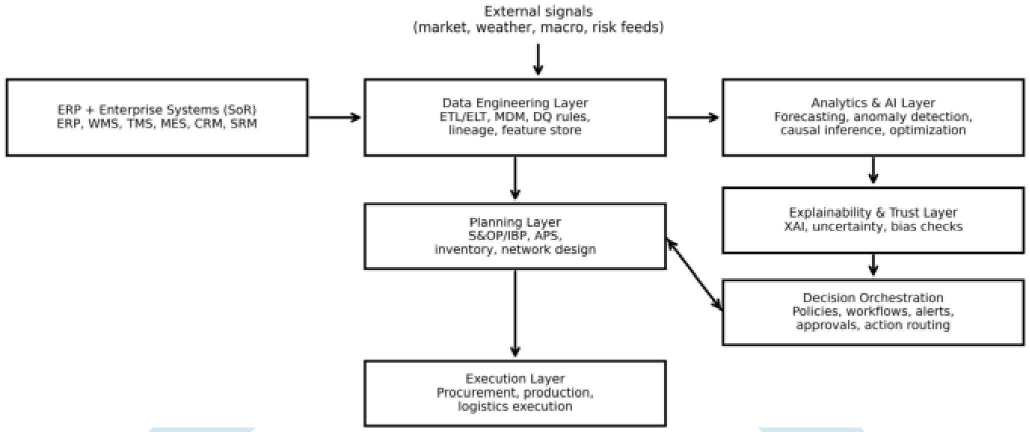

Figure 2. Reference architecture for predictive ERP-enabled supply chain planning.

SoR = System of Record; MDM = Master Data Management; DQ = Data Quality; APS = Advanced Planning Systems; S&OP/IBP = Sales and Operations Planning / Integrated Business Planning.

This theoretical framework explains the effects of ERP-based predictive decision support in generating planning and supply chain effects. It is a combination of (i) IS success logic (quality - use - net benefits) [23], (ii) underlying information-fitness-to-use data-quality theory, (iii) business analytics capability, an organizational enablement of value-creation, (iv) explainable AI, a trust and adoption mechanism of high-stakes planning decisions [26], and (v) twin thinking, a mechanism of scenario assessment and resilience-oriented decision-making [27]. The model identifies S&OP/IBP as the management process in which prediction is transformed into cross-functional plans and performance improvements [28].

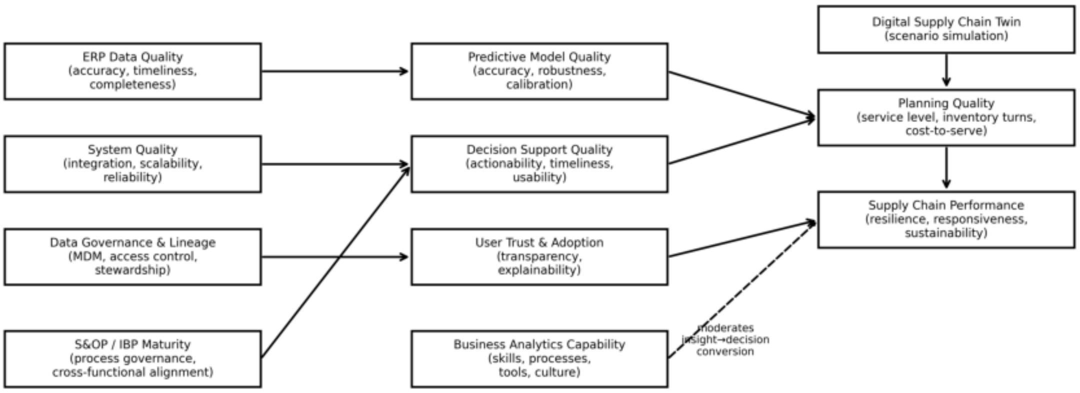

Figure 3. Proposed theoretical model for advancing ERP to predictive decision support

- ERP data quality [A] influences predictive model data quality [D]. ERP master and transactional data related to the fitness-for-use of predictive planning performance limits the timeliness, completeness, and interpretability of performances and weak data quality amplifies the error and instability of the model in the results of planning [24].
- System quality [B] - decision support quality [E]. Reliable, scalable and integrated enterprise platforms enhance the availability and usefulness of decision support artifacts (alerts, what-if outputs, recommended actions), which is in accordance with the theory of IS success that associates system and information quality with successful application and net benefits [23].
- E – Decision support quality [E]; H – planning quality [H] and I- supply chain performance [I]. As the operationalization of predictive outputs occurs in the form of planning workflows (setting inventory, replenishment policy, capacity allocation) decision support is something that contributes to quantifiable analytic planning performance. IS success logic considers these operational benefits as net benefits due to a quality of systems and information used [23].
- Explainability and trust [F] as an adoption mechanism. The decisions of supply chain planning may be high impact (service, cost, risk). Explainable AI enhances human cognition of model reasoning and uncertainty, promotes responsibility and use in decision making [27].
- As a moderating variable, business analytics capability [G]. The skills, processes, and governance, as well as enabling technologies, are examples of organizational capabilities in analytics that enhance conversion of predictions into decisions and benefits, which explain why the same technologies produce different outcomes in different settings [25].
- Digital supply chain twin mechanism [J] and S&OP/IBP embedding [K]. Simulation-based resiliency-oriented planning Scenario simulation and digital-twin-based decision support can enhance resiliency-oriented planning by being able to evaluate response strategies under disruption quickly, whereas mature S&OP/IBP can bridge the gap between predictive and executable plans [26], [28].

IV. DISCUSSION

A common statistical finding through the literature on ERP-supply-chain analytics is that value can be realised when ERP data (transactions, master data, and execution signals) is transformed into predictive and decision-oriented capabilities (forecasting, risk prediction, inventory and replenishment optimization, and exception-based planning), as opposed to just serving a descriptive reporting purpose. Repeated cross-sectional analytics research indicates statistically significant correlations between analytical capabilities and supply chain performance, the strength of which correlates with factors of information-system support and quality/accuracy of the data [32], [30]. Case and benchmark studies have provided complementary findings on the operational benefits, which are measurable in the form of improved service levels, lower logistics or inventory costs, and quantified benefits in forecast accuracy when the predictive models are incorporated into the planning processes (demand planning, safety stock and exception management) [29], [36], [37].

Table 2. Quantitative outcomes reported in key empirical / case / benchmarking studies

Ref.	**Evidence type + context**	**Predictive / decision-support focus**	**Key reported results (metrics)**
[29]	Industrial FMCG case study	Demand planning intervention; improved forecasting and planning execution	Customer service level increased from 86% to 95% and logistics cost reduced from 7.8% to 6.0% of sales; A-class item error reduced (reported drop of 4.9 percentage points to 16.1%) and overall MAPE reported as 14.71% after the intervention [29].
[30]	Survey + PLS-SEM (organizational sample)	Advanced analytics (AA) → operational performance (OP), moderated by data accuracy	Moderation effect reported ($\beta = 0.21$, $p = 0.01$) for AA×data-accuracy → OP; AA → OP ($\beta = 0.12$, $p = 0.04$); when mediator included, AA → OP becomes non-significant ($\beta = 0.02$, $p = 0.37$) suggesting mediated impact via data-related mechanisms [30].
[31]	Survey + PLS-SEM (supply chain analytics capability)	Supply chain analytics (SCA) effects on operational performance via supply chain process capability	Reported standardized paths: SCA → process capability ($\beta = 0.45$) and process capability → operational performance ($\beta = 0.42$); a smaller direct SCA → performance path ($\beta = 0.15$) is also reported, supporting partial mediation [31].
[32]	Cross-sectional global survey (SCOR-aligned analytics) + SEM	Business analytics across Plan/Source/Make/Deliver and SC performance; moderation by IS support/BPO	Reported explained variance increases as model richness increases: baseline analytics-to-performance model $R^2 = 0.667$, adding BPO and IS support $R^2 = 0.6925$, and including moderators $R^2 = 0.7231$ (strong explanatory power for performance variability) [32].
[33]	Controlled model comparison (forecasting experiments)	Machine-learning demand forecasting vs traditional approaches	Average error reductions reported versus benchmark: 6.70%, 3.11%, and 10% improvements in the reported comparisons (study reports quantitative error reductions across evaluated cases) [33].
[34]	Retail forecasting benchmark study (multi-channel retail)	ML regressors and a hybrid RF–XGBoost–LR model	Reported R^2 values: RF 0.9351, XGBoost 0.9547, GB 0.9116, AdaBoost 0.9308, ANN 0.3958, Hybrid 0.9551—hybrid best overall by R^2 [34].
[35]	Benchmarking study (M5 dataset)	Comparison of ML/forecasting approaches (K-fold setting)	Reported K-fold RMSE values (lower is better): RF 3.03, ARIMA–NN 3.07, ETS 3.05, LSTM 2.68, BiLSTM 2.63 [35].
[36]	Industrial case study + simulation (inventory policy)	Safety-stock optimization using hybrid strategies	Across unit-shortage-cost scenarios, the best hybrid method yields ~27–30% lower total inventory cost than the company's existing method; also reported large reductions vs alternatives (e.g., up to 87% lower than TOC replenishment under one scenario) while targeting minimum 99% service level [36].
[37]	Applied empirical modeling (retail SCM; ML + risk prediction)	XGBoost forecasting + RNN-based risk tasks; sustainability-aware evaluation	Reported forecast metrics for XGBoost: MAE = 0.1571, MAPE = 0.48%; RNN tasks report F1 ≈ 98% (fraud and late delivery prediction); also reports 18% MAE and 22% RMSE reductions vs an ARIMA benchmark [37].
[38]	Systematic survey (open-access, journal)	Predictive big data analytics for SCM demand forecasting (taxonomy + gaps)	Identifies and categorizes 64 research papers (2005–2019) on predictive analytics for demand forecasting and highlights under-studied contexts such as closed-loop supply chains; supports evidence-based gap framing for ERP→predictive decision support integration [38].

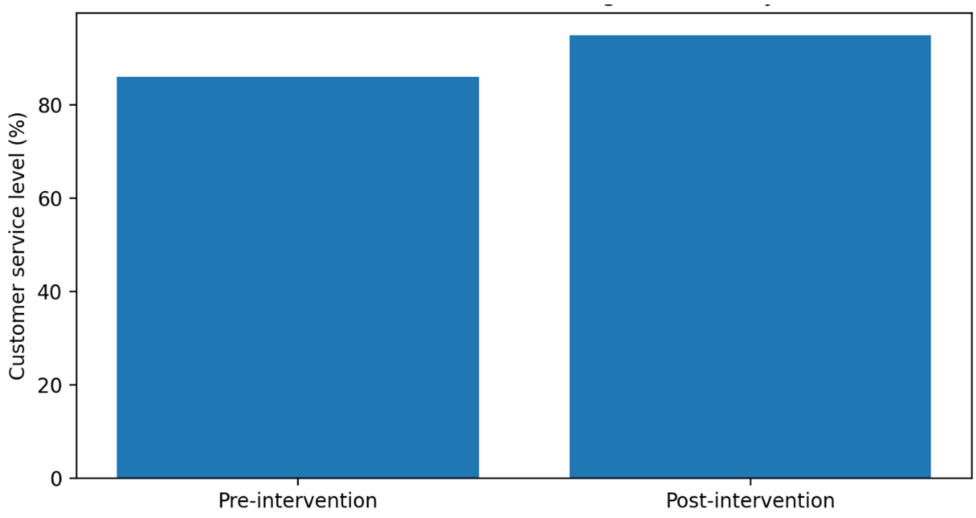

Figure 4. Customer service level change

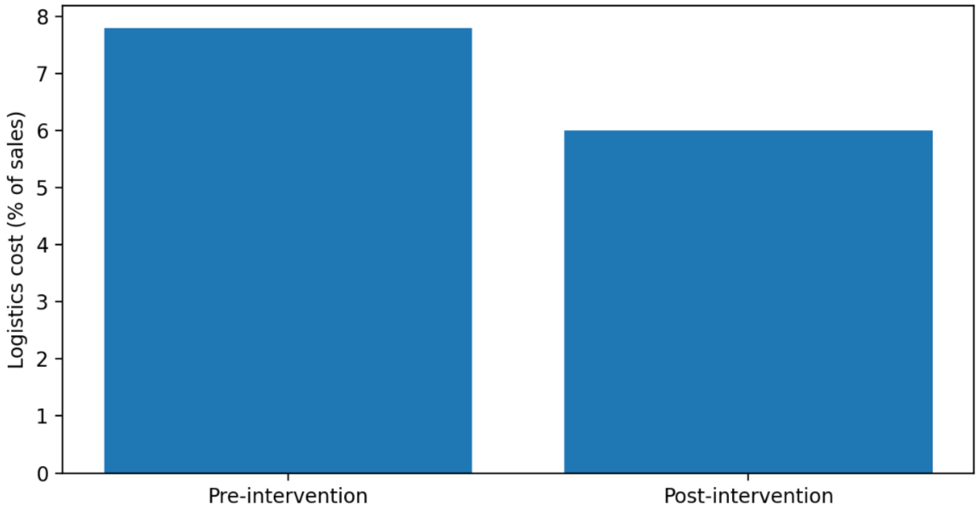

Figure 5. Logistics cost change

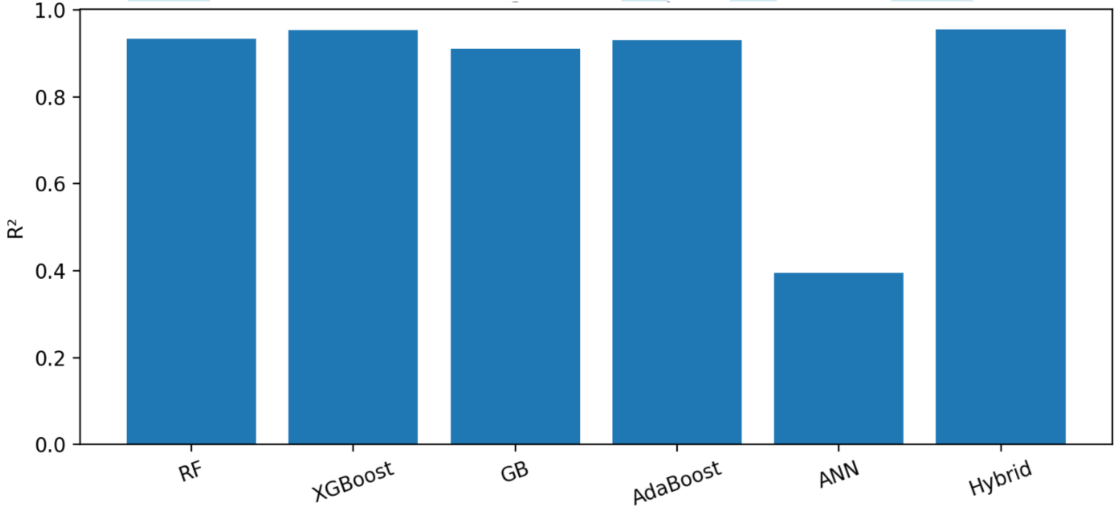

Figure 6. Forecasting model comparison (R²)

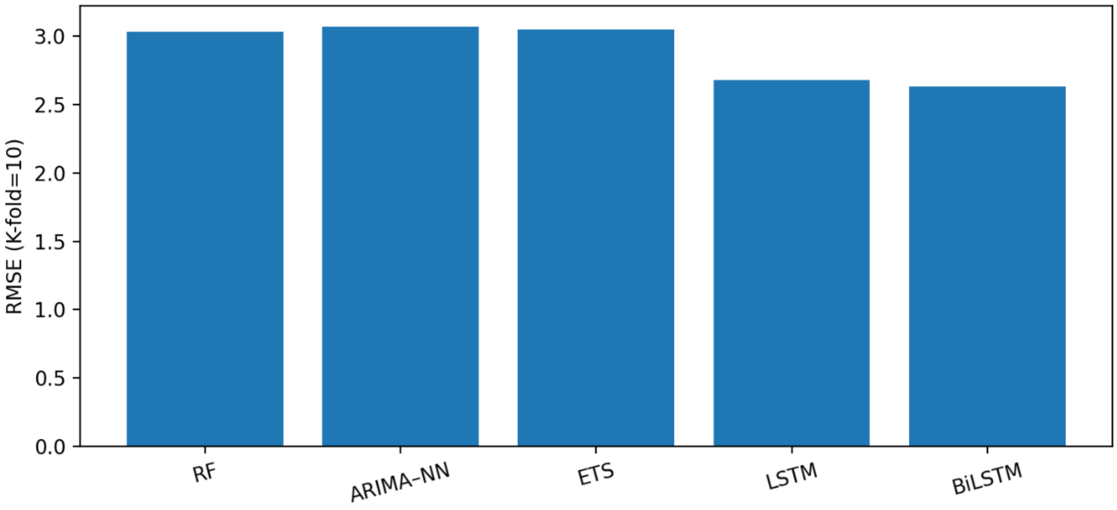

Figure 7. M5 dataset RMSE comparison (K-fold)

The empirical works agree on two implementation-critical mechanisms to be used to take ERP to the next level of prediction based decision support on the supply chain planning. First, the analytical capability should be operationalized in the form of planning decisions rather than dashboards: cross-sectional studies of SEM reveals extensive explanatory power of analytics constructs to performance, and it goes up in case of the inclusion of moderators; that is, increasing the R^2 to 0.7231 (with the incorporation of IS support and process orientation) [32]. Second, there is no option of data accuracy or data-to-decision pathways: evidence shows that the performance advantage of advanced analytics is practically conditioned by both data-accuracy interactions (e.g. moderation = 0.21, $p = 0.01$) and the mediated effects that can make direct analytics-to-performance links insignificant when the mechanisms are modelled explicitly [30]. On the planning-method level, standard comparisons and benchmarks have continuously indicated that ML and hybrid algorithms may perform better on classical accuracy measures (e.g., hybrid $R^2 = 0.9551$) [34], and deep recurrent algorithms may perform better on error measures in standard dataset (e.g., BiLSTM RMSE = 2.63) [35]. Incorporated into actual planning and inventory policy procedures case evidence reports quantifiable business outcomes of service-level increases of cost-reduction amounts ranging into large total-inventory-cost-reductions under a variety of shortage-cost conditions and still achieve and sustain tight service-targets [29], [36]. Collectively, these findings explain why architecture-to-evidence (how ERP data is transformed into an effective predictive sign), model-to-workflow binding (how prediction prompts actionable planning responses), and governance-to-auditability (how the accuracy, drift, and accountability are controlled) [32], [30], [38] should be reviewed.

V. FUTURE DIRECTIONS

5.1 Autonomous and Self-Optimizing Planning Systems

Future studies in the field of AI-based supply chains indicate a transition to autonomous versions of planning systems, which can autonomously change the parameters of inventory, replenishment, and sourcing decisions depending on the ongoing data streams [39]. Future development ought to consider reinforcement learning-based ERP extensions while maintaining governance and oversight structures by dynamically re-setting the parameters of planning.

5.2 Integration of Digital Twins within ERP Architectures

Digital twins provide simulation-based planning, which empowers resilience and scenario assessment [41]. Nevertheless, little research covers the interoperability of seamless ERP–digital twin integration, synchronization of the data in real time and scalable architecture design. In the future, research in hybrid ERP-twin frameworks that would facilitate cross-enterprise and multi-echelon simulation needs to be carried out.

5.3 Responsible and Explainable AI in Supply Chain Decision Support

With predictive models gaining more and more control over the process of procurement, production, and logistics, the issue of transparency grows essential. Explainable AI models increase interpretation and reduce the risks of bias when using algorithms [42]. Further studies ought to establish explainability modules that can be compatible with ERP to give the planners and the regulators traceable decision rationale.

5.4 Embedded ERP Planning of Sustainability

Supply chains play an important role in meeting the goals of sustainability, such as emissions reduction and transitions to the circular economy. Although digital transformation is beneficial to sustainability performance [40], predictive ERP models do not often include environmental metrics in the optimization goals. Future studies ought to come up with multi-objective decision-support ERP models with cost, service level, carbon emission, and resource efficiency.

5.5 Cross Enterprise Data Governance, Interoperability

Predictive planning is becoming more dependent on common data between suppliers, logistics and customers. One of the greatest impediments to cross-organizational predictive analytics is interoperability issues. The studies ought to deal with federal models of data governance, use of blockchain to enable traceability and standard data schema to facilitate secure collaboration without infringing on competitive limits.

5.6 Human-AI Partnership in the workflow Planning

The predictive ERP systems should not substitute managerial judgment but supplement it. Exploring the system of human-AI collaboration, i.e., algorithms produce proposals, and planners confirm or modify them, can boost trust and optimize the quality of decisions. The acceptance and use of behavioural and cognitive load as well as performance implications of AI-augmented planning should be investigated through empirical research.

VI. CONCLUSION

The redesign of the ERP systems as the reporting-oriented platforms into the forecasting decision-support infrastructures is a radical paradigm shift in supply chain planning. Conventional ERP systems were mostly built in such a way that they guaranteed uniformity of data, interoperability and consistent reporting. Although these functions cannot be ignored, the modern supply chain needs anticipatory functions that can predict the variability of demand, determine risks of disruption and optimise the decisions on inventory, production and distribution dynamically.

Empirical studies have always indicated that with the adoption of analytics capability, operational performance and supply chain effectiveness are greatly improved when coupled with enterprise systems [39]. Nevertheless, adoption of technology is not sufficient to achieve better results. The maturity of digital transformation, governance, and process alignment are some of the critical mediating factors that help in the translation of analytical insights into actionable planning activities [40].

The development of digital supply chain twins also expands the ERP capabilities by allowing them to simulate scenarios, stress-test, and make decisions with uncertainty-based information [41]. The digital representations enable the planning teams to assess the alternative sourcing, capacity allocation and distribution plans in near real-time, enhancing the resilience to systemic disruption. Moreover, AI-based automation should be accompanied by transparency and explainability solutions to make sure that there is trust, accountability, and regulatory adherence in high-stakes planning decisions [42].

There is an uneven pace of migration to predictive ERP systems, even across industries in spite of significant advances. The complexity of the integration, limitations of the legacy systems, data silos, and the lack of cross-functional analytics also persist in limiting the complete benefits of predictive planning. Moreover, the aspects of sustainability, such as optimization of carbon footprint, resource efficiency, or cyclic supply chains, are not yet systematically enshrined in the ERP-based decision-support systems.

To move ERP system to intelligent planning ecosystems, the development of architecture design, analytics integration, governance, and human-machine collaboration models should be coordinated. The data indicates that predictive ERP systems are not only technological upgrades but strategic platforms that have the potential to facilitate adaptive, resilient and sustainable operational systems within the supply chains.

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