International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(REVIEW ARTICLE)

Forecast accuracy as a driver of excess inventory reduction in ERP-centric supply networks

Pushpanjali Chauhan *

California State University, Fullerton and Fullerton, California.

International Journal of Science and Research Archive, 2026. 18(03), 1109-1120

Publication history: Received on 12 February 2026; revised on 17 March 2026; accepted on 20 March 2026

Article DOI: https://doi.org/10.30574/ijsra.2026.18.3.0574

Abstract

The other long-term structural inefficiency of the ERP-based supply networks despite the massive implementation of the advanced planning systems and analytics is the excessive inventory. Even though the accuracy of forecast has been a statistical aim, its practical importance has been anchored on how forecast indicators are transformed into replenishment decisions, safety stock computation and multi-echelon coordination models. The recent research suggests that the predictive improvement would not be commensurate savings in inventory especially when imbedded within mutually coherent systems of governance, the regular incentive plans and data structure. This review synthesizes theoretical and empirical evidence on how forecast accuracy influences excess inventory performance under the ERP based planning rationale. The discussion is related to the opinions of inventory control theory, organizational forecasting studies, digital transformation, and AI-based planning systems. These mediating processes are decision-translation fidelity, safety stock parameterization and information sharing across the nodes as one of the key determinants whether the improvement of the forecasts will result in reduced working capital and obsolescence risk. The last part of the review is the description of the future research agenda on the opportunities of AI integration and digital twins, sustainability indicators, and resilience modelling in the multi-echelon ERP contexts.

Keywords: AI-enabled demand planning; Digital supply networks; ERP systems; Forecast accuracy; Inventory governance; Multi-echelon supply chains; Safety stock; Working capital optimization

1. Introduction

Global supply networks operate in the context of volatile demand patterns, shorter product life cycles, omnichannel fulfilment requirements, and higher service-level expectations. Enterprise resource planning (ERP) systems serve as the central platform for transaction processing and planning, which is incorporated with the forecasting, procurement, production planning, inventory control, and financial management as a unit of decision support infrastructure [1], [2]. Although there is significant digitalization and sophisticated planning functionalities inherent in contemporary ERP systems, excess inventory remains a costly challenge across multiple industries, such as manufacturing, retail, pharmaceuticals, and renewable energy supply chains [3], [4].

Maintaining inventory beyond its required level is not a balance-sheet waste. It ties up working capital, compounding risk of obsolescence, higher warehouse cost, and handling cost and compounding environmental costs of overproduction and waste [5], [6]. The mistakes in forecasting can easily become an inventory waste and misplace capital in sectors such as renewable energy technologies where the components cost is high and both the demand and policy changes are affecting the demand [7]. Likewise, in AI-enabled hardware and semiconductor supply chains, the extremely high uncertainty in the predictions is caused by fast innovation cycles and demand peaks, which often lead to stockouts and backorders in turn [8]. These dynamics emphasize the fact that forecast accuracy is not a statistical

* Corresponding author: Pushpanjali Chauhan

performance indicator but a structure-based source of operational and financial performance in ERP-based supply networks.

The association between forecast accuracy and inventory performance is a subject of massive research in the classical operations management theory. The basic principles of inventory models indicate that safety stock is directly related to demand variability and forecast error variance [9], [10]. The literature on bullwhip effect also demonstrates how the variability of order moves upstream in the multi-echelon supply chains, growing the inaccurate forecasts and increasing inventory level in the nodes [11], [12]. To a large extent, however, the current literature considers forecasting and inventory control to be analytically distinct fields and tends to default upon either statistical measures of error (e.g., MAPE, RMSE) or optimal inventory policies under imposed demand distributions [13], [14]. The way forecast accuracy operationalizes in the ERP-driven context where the forecast signals are converted into replenishment decisions through the mediation of forecast planning logic, data latency, parameter governance and the system constraints have received limited attention.

There is further complexity created by the modern research environment. The emergence of machine learning-based forecasting models is associated with an increase in predictive performance in comparison with the conventional time-series methods [15], [16]. Meantime, the digital transformation initiatives have incorporated the advanced planning and scheduling (APS) modules, demand sensing tools, and real-time analytics in the ERP ecosystems [17]. However, greater statistical accuracy does not always translate into proportional reductions in excess inventory [18]. A lack of fit between the output of forecasts and ERP replenishment parameters, poor master data quality, and infrequent recalibration of parameters and lack of cross-functional governance can minimize or distort the inventory effect of forecasting improvements [19], [20]. Thus, the accuracy of the forecast cannot be examined as a predictive construct only, but should also be regarded as a systemic driver, intrinsic in the logic of the ERP and the organizational processes.

There are several significant gaps in research in this intersection. To start with, research studies in forecasting research and ERP centric inventory management do not adequately integrate particularly in the multi-echelon and globalized supply networks. Second, the performance evaluation systems are normally pegged on forecast error measures with no systematic relationship of the measures with downstream financial and operational measures such as excess inventory, fill rate, working capital turnover and trade-offs at the service level [21], [22]. Third, structural ERP designs, such as reorder point policies, lot-sizing rules, lead-time offsets and parameter update frequencies, which lead to the transformation of forecast signals to inventory decisions are hardly considered in the available literature [23]. Finally, the sustainability cost of excess inventory like carbon footprint and wastage of materials has not been studied adequately with regards to the forecast-based planning mechanisms [24].

Important gaps should be filled in these areas because the supply chain resilience, digitalization, and sustainability are converging as a strategic need of the moment. Correctness in prognostication is turning into an instrument of work quality, accounting and environmental responsibility. However, the scientific sources on the methodical synthesis of the role forecast accuracy has in the process of decreasing surplus inventory in ERP based supply chains are limited in quantity.

The proposed review is intended to provide an analytical and systematic discussion of theoretical, methodological and practical links of the correctness of the forecast and surplus inventory performance of the supply landscape based on the ERP. The review will (i) describe the conceptual bases of the forecast error and inventory dynamics relationship, (ii) overview how the ERP settings and the intercession of the planning logic can mediate the relationship, (iii) overview how the new forecasting technologies and their implications on inventory can be measured, and (iv) overview the research opportunities in the multi-echelon coordination, digital integration and sustainability. The rest of the paragraphs below will present synthesis of the existing models, empirical evidence, and system-level insights that come up with the conclusion of a research agenda of building academic studies and industrial practice.

2. Literature Review

Table 1 Summary of key studies linking forecast accuracy to excess inventory outcomes

Ref.	Focus	Findings (key results and conclusions)
[25]	Forecasting models evaluated *inside* an operational inventory-control setting (trade-off between inventory investment and customer service).	Shows that various forecasting models give different curves of inventory-service trade off on the basis of the same control logic, which means that the value of improved forecasting must be measured in terms of impacts on inventory, not just error measures [25].
[26]	Value of information sharing for inventory performance in supply chains (multi-stage effects).	Demonstrates that information about demand information sharing can reduce system-wide inventory and variability, although the magnitude of such reduction varies according to lead times, replenishment structure, and the entry point of information into the planning process that are directly relevant to ERP-centric visibility initiatives [26].
[27]	Forecasting and replenishment policy interactions as a driver of the bullwhip effect (control-theoretic analysis).	Measures the amplification of variability by the choice of forecasting parameters and the sequence of rules; points out that it is possible to reduce forecast-induced noise and to adjust replenishment parameters so as to reduce upstream inventory amplification and the resultant excess [27].
[28]	ERP/SCM/CRM implementations and firm performance (operational/financial outcomes).	Presents data that the use of enterprise systems can be linked to performance gains, although benefits depend on how they are executed and what other practices are implemented to support the argument that the gains in accuracy of forecasts must be converted to ERP governance and process congruence to limit needless inventory accumulation [28].
[29]	Intermittent/slow-moving demand: forecasting method selection linked to stock-control performance.	Discovers that there is a wide variation in the results of intermittent-demand estimators (stock-control measures such as service levels and inventory) which strengthens the argument that accuracy improvements need to be measured under the inventory policy adopted in replenishment [29].
[30]	Causal (exogenous-variable) forecasting embedded in safety stock planning.	Demonstrates how regression/causal model forecast error may be used as safety stock; better inventory decisions made when demand varies with drivers like price, weather, or promotions - popular with ERP demand planning [30].
[31]	Two-stage supply chain: forecast accuracy vs inventory performance, including information sharing.	Examines the relationship between forecast accuracy and the result of inventory and the value of forecast information exchange between retailer and manufacturer; the results indicate that better forecasts and sharing can lead to better inventory performance, although the impact varies with structure and parameters [31].
[32]	Forecast selection/combination (statistical + expert) evaluated by inventory outcomes.	Presents empirical data showing that both forecast accuracy and inventory performance can be enhanced by the use of selection/combination approaches, and hybrid workflows are frequently adopted around ERP demand planning and S&OP processes [32].
[33]	Safety stock calculation when demand is forecasted (correlated forecast errors over lead time).	Treats traditional methods of safety stocks as biased, since forecast errors in any lead time interval are correlated; offers corrected forms which have significant effects on reorder levels and can reduce systematic under/overstocking [33].
[34]	Conditional relationship: forecast accuracy vs inventory performance under periodic review and varying costs/lead times/service targets.	Concludes that value of increased forecast accuracy is conditional on inventory policy parameters and cost structure; most accurate method may not reduce total cost within certain settings which is important in the ERP environment where the policy settings are the intermediary of forecast to inventory translation [34].

3. Methodology

This diagram formalizes the core mechanism that has been highlighted in the literature: forecast quality influences inventory performance, once it has been transformed using (i) ERP data quality and integration, and (ii) the parameterized planning logic which determines which reorder quantities, MRP signals and buffers to compute. Practical and scientific works demonstrate that evaluation of forecasts within ERP systems may not coincide with statistical perfection due to cost-based regulated forecast error and policy contests that decide whether an error is a superfluous inventory or forfeited sales [35]. Structural barriers (such as data quality limitations e.g. inaccurate lead times, item masters and transactional inconsistencies) have, again and again, been found to result in a failure of planning systems to transform better forecast signals into better inventory performance [36] and more general evidence suggests that the structure of forecasting (process discipline, information sources and cross-functional integration) can drive better results than better forecast accuracy alone can [37].

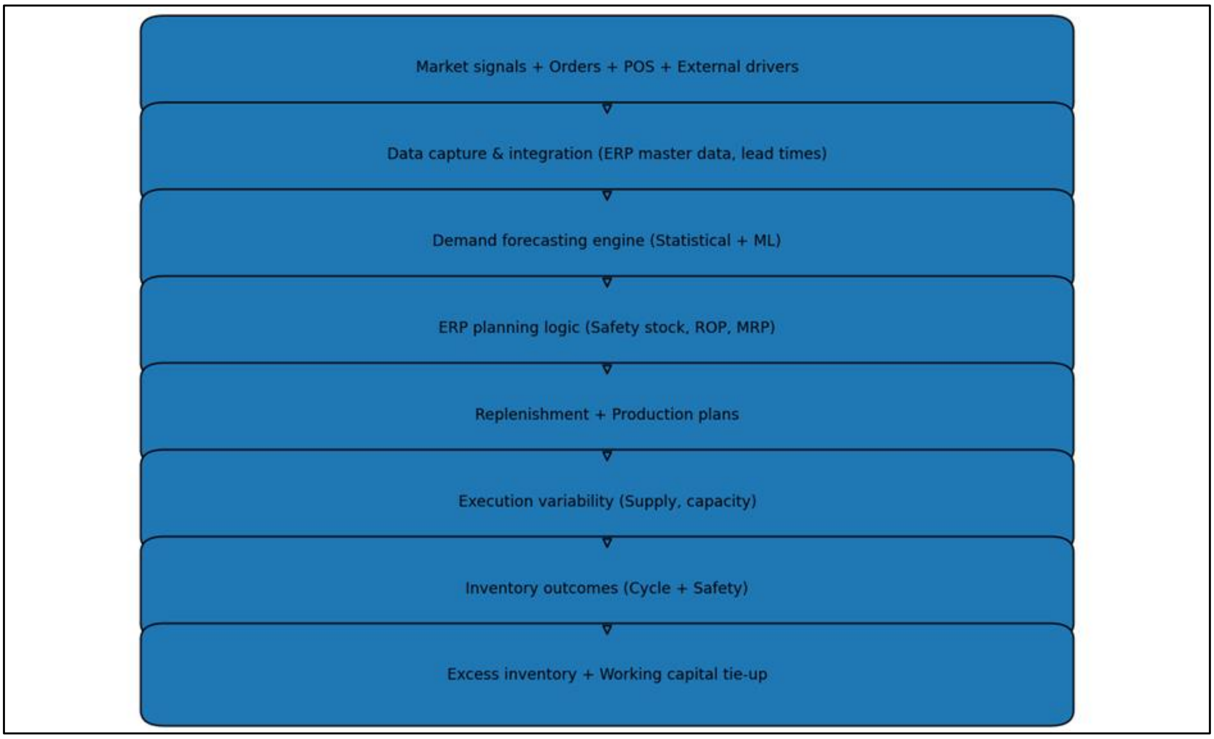

Figure 1 ERP-centric “forecast-to-excess-inventory” conversion pathway (end-to-end)

This governance loop demonstrates that predictive measures of accuracy can be employed as a managerial control and learning tool, however practical issues of controllability and goal congruence (such as target achievement will create bias leading to more inventory) exist [38]. Research on forecast bias and organizational incentives indicates that better forecast structure can minimize error and positive bias and is related to decrease in inventory, but this is contingent on incentive and accountability design [39]. The loop thus considers forecast accuracy an operating capacity that should be measured, rewarded and owned by parameters to minimize surplus inventory instead of taking it as a discrete analytics upgrade [38], [39].

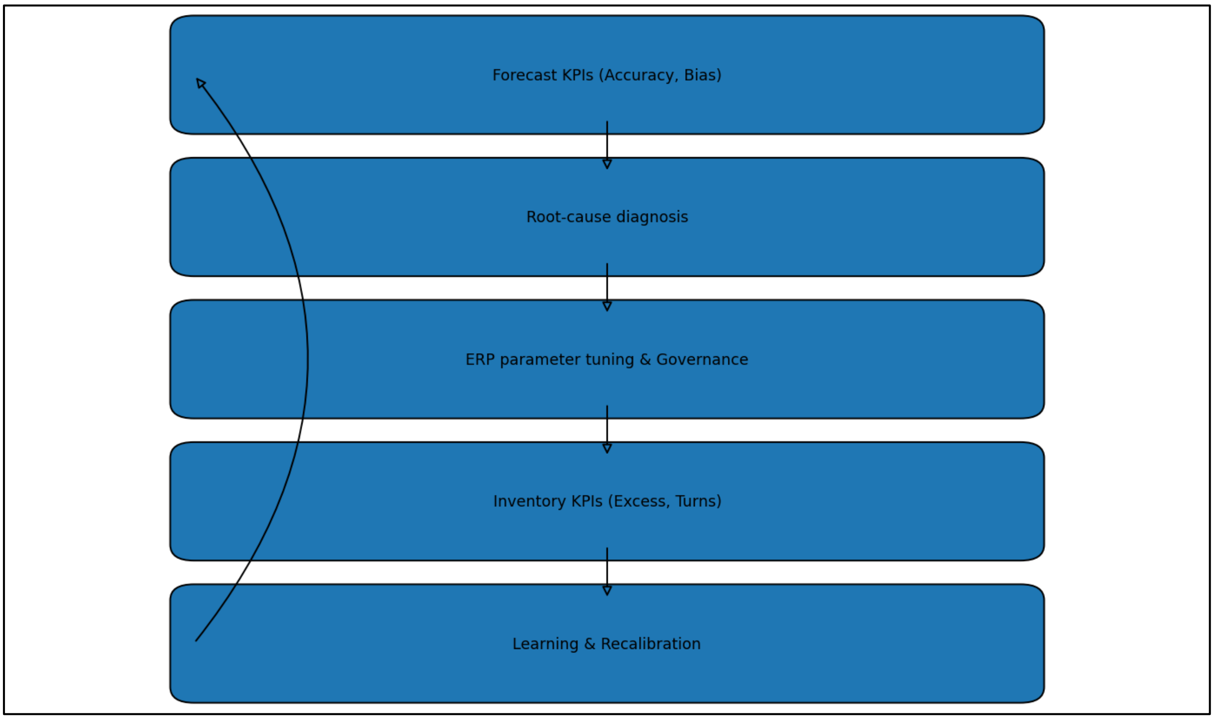

Figure 2 Closed-loop governance model for inventory reduction in ERP-centric networks

The studies on forecast error in supply chain reveal that inventory effect of forecasting is mediated by the replenishment structure and echelons sharing forecast information. With forecast information sharing, the same statistical forecast error can give significantly different inventory results with respect to how recovery nodes interpret demand and fix buffers [40]. This also justifies the necessity of ERP-centric models that explicitly embrace the information pathway (what is shared, to what level, and as often) instead of viewing forecast accuracy as a node-local characteristic.

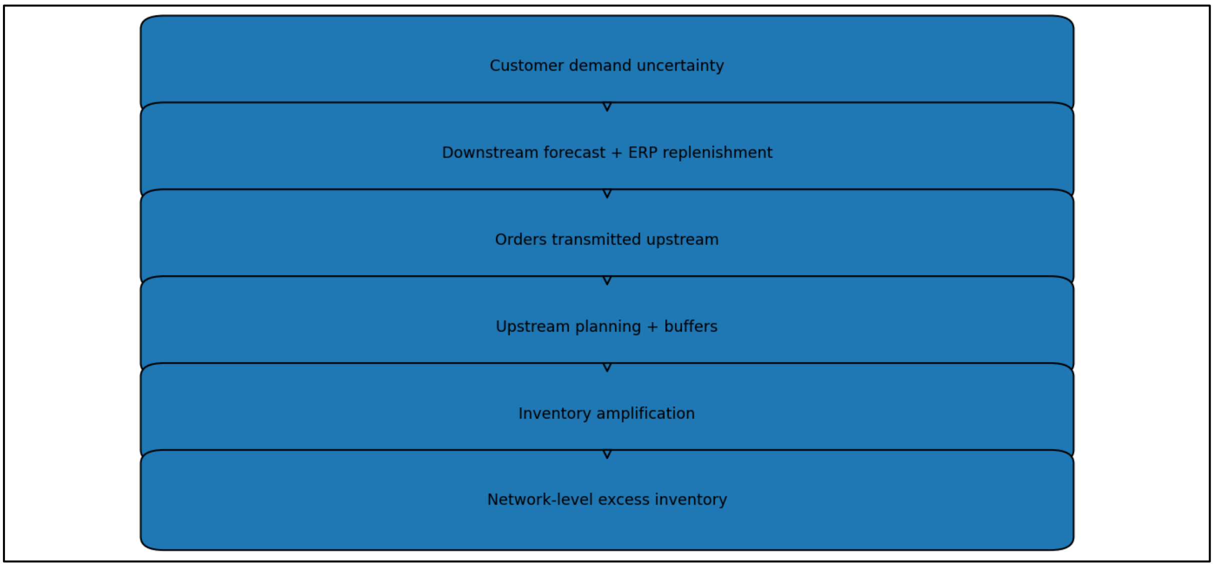

Figure 3 Multi-echelon propagation of forecast error under ERP planning and information sharing

Hypothesized theoretical framework: The proposed theoretical framework argues that reductions in excess inventory in ERP-based supply chains are driven not by forecast accuracy alone, but by the fidelity with which forecast signals are translated into replenishment, production, and procurement decisions within ERP logic.

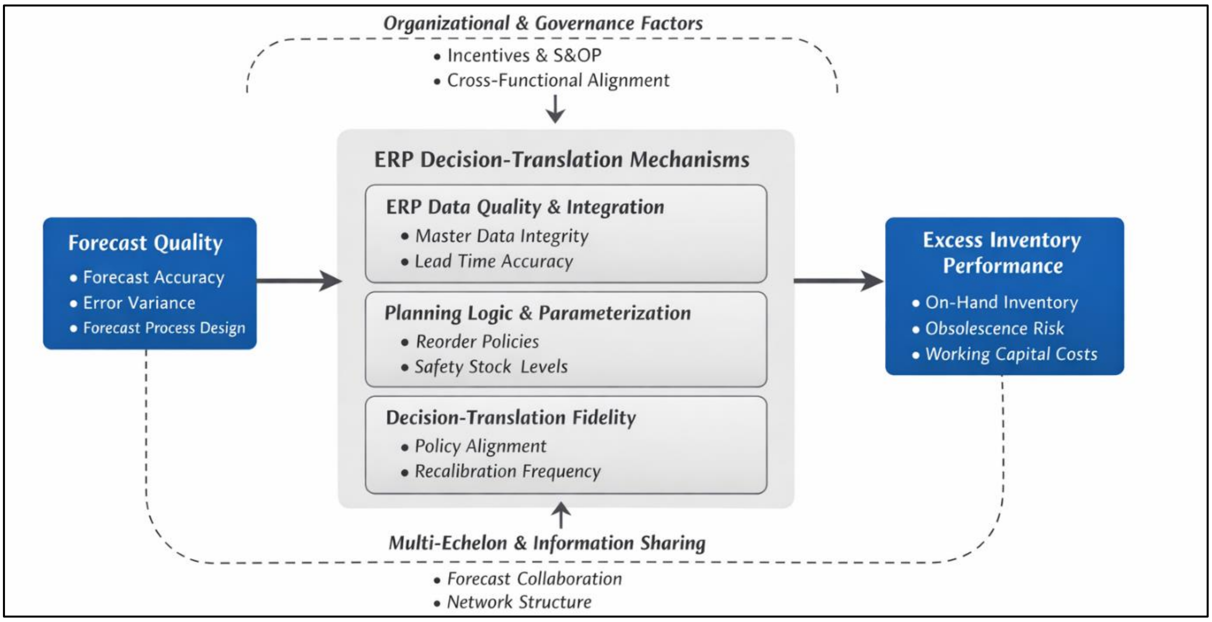

Figure 4 Constructs and causal structure (theoretical model)

3.1. Mechanistic interpretation supported by prior evidence:

Quality of forecast - inventory performance is mediated by policy. Experience in evaluating forecasts in operational control situations has shown that the optimal prediction by any statistical criterion is not required to reduce inventory cost or stock-out; since the inventory policy is an asymmetric transformer of error (excess stock is an over-forecast, lost service is an under-forecast) [35].

Decision-translation fidelity functions as a key mediating mechanism. The research on ERP implementation has consistently reported data quality as a requirement in its search to achieve successful planning performance; poor planning performance often results from poor-quality master and transactional data [36]. There is also complementary evidence to the fact that forecasting process design (information sources, structure and cross-functional implementation) affect operational performance, whereby the results of inventory are determined by how the process of forecasting is integrated into management processes, rather than simply by the choice of models [37].

Incentives and bias are direct influences on excess inventory. Indications of organizational forecasting environments reveal that positive forecast bias may amplify inventory; disaggregation and structural modifications can decrease bias, error, and nevertheless, incentive structures can perpetuate bias in high-risk items that organizations are most eager to avoid being kept in stock [39]. Empirical studies related to this indicate that forecast accuracy indicators as a results-control mechanism can be effective at improving the quality of planning, although this results in unwanted behavior unless applied in an interactive manner and in conjunction with the context [38].

The effect of inventory of a particular forecast error is modified by multi-echelon effects and information sharing. Error in the forecasts acts in concert with the flow of information: in terms of sharing forecast information, upstream inventory and system dynamics relate not just to the pathways of information transfer and interpretation of the flow of forecasts and replenishment cues but also to the accuracy of information available downstream [40].

AI/advanced methods cannot work without organizational integration. Recent studies on the supply chain note that the adoption and value creation of AI-enhanced forecasting is contingent on the state of the organization (process integration, governance, and change management), which supports the role of the mediator and not a direct accuracy - inventory benefit [41].

The location of inventory is determined by the network design decisions. Empirical evidence on the location of the multi-echelon inventory buffers demonstrates that the decisions of uncertainty management and the location of buffers (which can be realized using ERP/APS) decide where inventory is located and how much should be located, that the improvement of the forecast can also cause the change in the location of inventory but not its reduction unless it is optimized on a network-wide level [42].

The way this model can be employed in the review. The diagrams and model offer a principled prism to cluster the portions of the review around (i) the methodology of forecasting and assessment in alignment with the inventory cost, (ii) ERP translation mechanisms (parameters, master data, governance), (iii) organizational causes of the bias and process quality, (iv) multi-echelon information propagation and (v) prerequisite conditions of digital/AI integration needed to reduce excess inventory.

4. Discussion

A simulation experiment was developed to illustrate the proposition that forecast accuracy brings value only when converted into better inventory results in the ERP planning logic, which aligns with the accuracy-implication view [44] and the corresponding warnings about the understanding of forecast error measurements [43]. The experiment assumes 60 synthetic SKUs observed 104 weekly periods that contain structural properties that are characteristic of ERP-driven demand environment, including seasonality, trend, uplift in promotions and intermittent demand shocks. The train-test structure was implemented where the initial Weeks 1–78 were used in the model initiation and estimation of forecast error and Weeks 79-104 was to be used in performance evaluation. Three forecasting methods were considered including a Naive approach (last observation taken forward) Simple Exponential Smoothing (SES) and a regularized regression model (Ridge-ML) with lagged demand, rolling averages, promotional predictors, and seasonal characteristics. The embedded forecasts were in a weekly periodic review, order-up-to (base-stock) inventory policy with a fixed lead time. One-step-ahead forecasts-together with a safety stock value proportional to the rolling standard deviation of the recent forecast errors, reflecting standard error-based buffering practice in the presence of uncertainty [46], [47]. The performance was measured during the test horizon in terms of fill rate, mean on-hand inventory, mean excess inventory (mean excess inventory, which is operationally defined as on-hand inventory exceeding forecasted near-term demand), and a mean weekly cost proxy (sum of holding and shortage penalties). This design ensures that forecasting methods are evaluated based on their inventory and cost implications rather than purely statistical accuracy [43], [44], and is conceptually aligned with network-level safety stock placement principles [45].

Table 2 Experimental results (test horizon averages across 60 SKUs)

Forecasting approach	Mean fill rate	Mean on-hand inventory	Mean excess inventory	Mean weekly cost	Excess reduction vs naive (%)	On-hand reduction vs naive (%)	Cost reduction vs naive (%)
Naive	0.9456	143.9109	7.9490	212.5469	0.0000	0.0000	0.0000
Ridge(ML)	0.9369	108.9238	1.6160	187.1853	79.6704	24.3116	11.9322
SES	0.9402	120.4907	2.8935	194.6963	63.5993	16.2741	8.3984

Ridge (ML) yields the greatest reduction in mean excess inventory (79.7%) and mean on-hand inventory (24.3%) relative to the Naive method. It also lowers the mean weekly cost by 11.9% under the simulated ERP policy. SES also reduces excess inventory (63.6%) and on-hand inventory (16.3%). Interestingly, the optimal inventory result is not manifested solely in the form of service levels (service and fill rate discrepancies are significantly minor), corroborating that inventory and cost results should be the evaluation instrument in a situation where forecasting is used as an input to ERP planning [44]. This is logically consistent with safety stock reasoning: the smaller and less predictable forecast errors the smaller the variability buffer, and less systematic over-ordering is avoided [46], [47]. The use of network level inventory implications also correlates with strategic buffering knowledge in multistage environments [45].

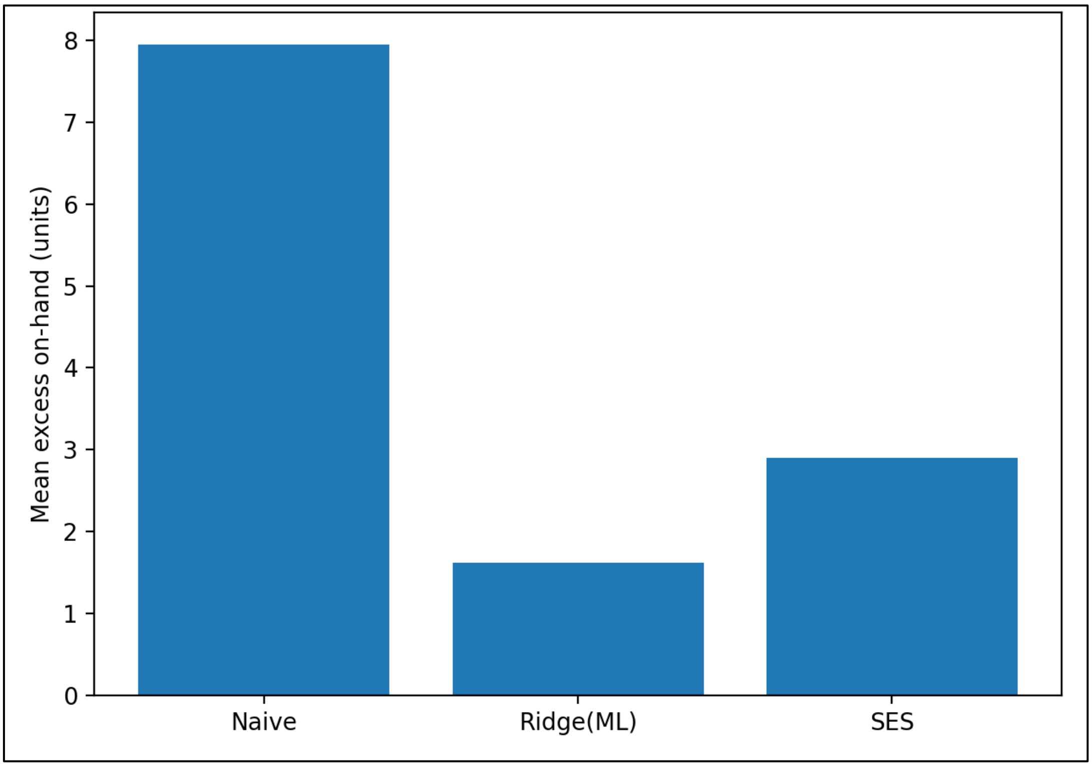

Figure 5 Mean excess inventory by forecasting approach

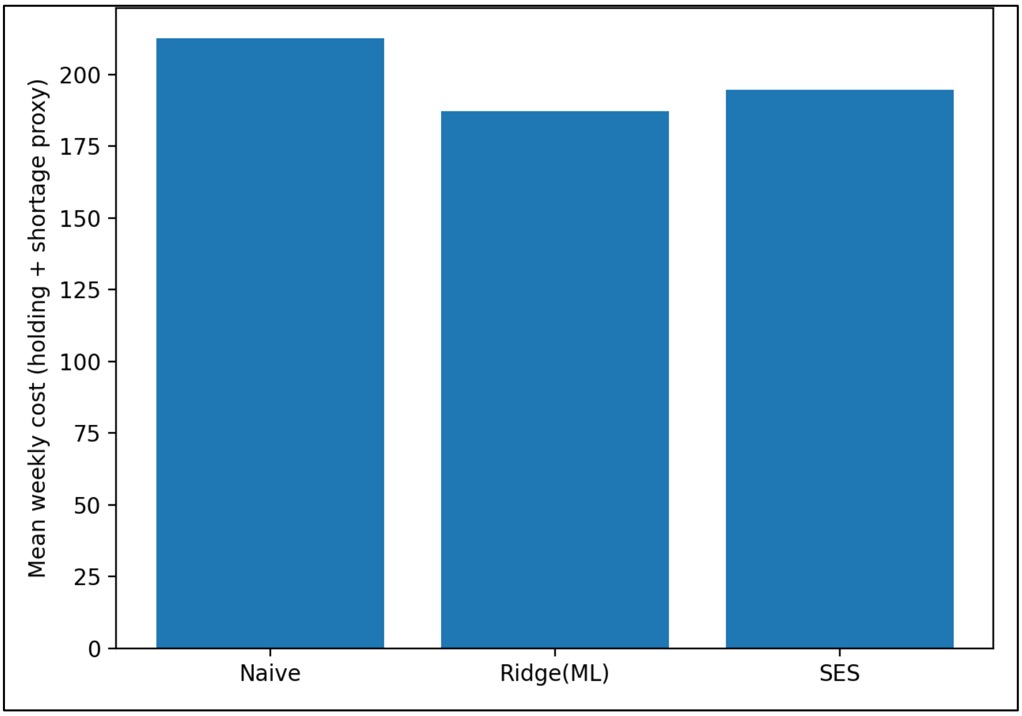

Figure 6 Mean weekly total cost by forecasting approach

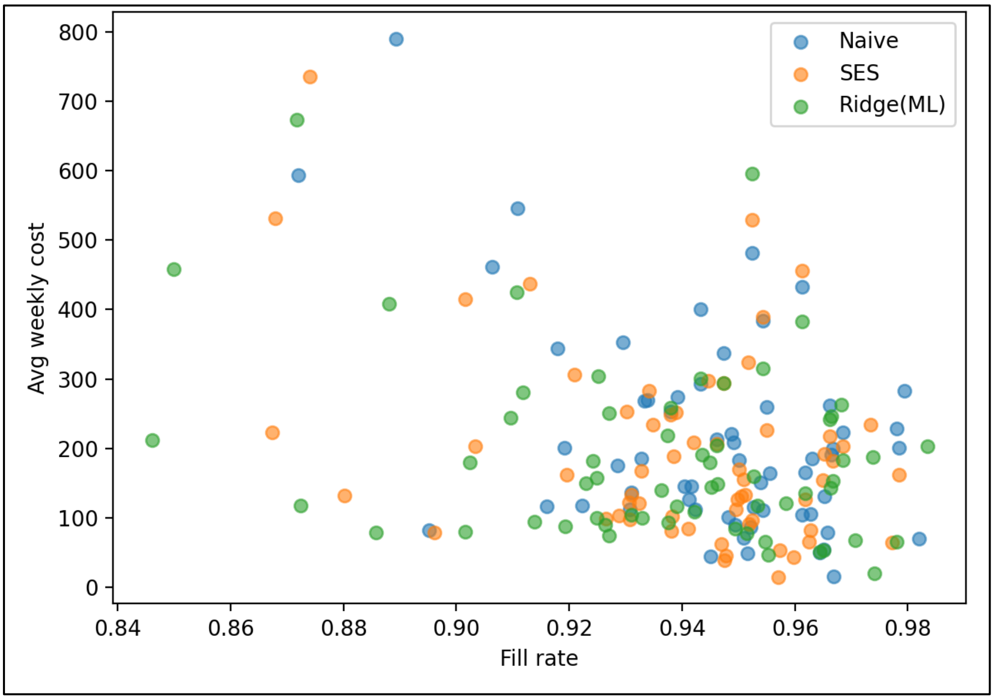

Figure 7 SKU-level cost vs fill rate trade-off

4.1. Future Directions

4.1.1. Artificial Intelligence-Based Prognostication and inventory translation trustworthiness.

The last developments of artificial intelligence and machine learning have shown better predictive performance in complex demand settings [55]. Nevertheless, there is a need to do a study to measure the interaction of AI-based models with the ERP parameterization and safety stock rules. Comparative study needs to be carried out on whether incremental accuracy changes of deep learning or hybrid models are reflected in nonlinear reductions in inventory in the face of various service-level targets. The model interpretability and trust in future work should also be studied, especially in the high-value or regulated industries.

4.1.2. Real-Time Buffer Optimization and Digital twins.

Digital twin technologies provide the opportunity to simulate the planning environment that is based on ERP under dynamic uncertainty. Combined with real-time data streams, digital twins, and multi-echelon data placement of safety stocks would facilitate a combination of adaptive buffers optimization that is no longer reliant on the fixed parameter settings [52]. Operational control systems would be connected to forecasting research through empirical validation of such architectures.

4.1.3. Incentives, Behavioral Dimensions, and Forecast Bias.

According to behavioral forecasting literature, systematic bias persistence and implications are central to inventory results [51]. Future research ought to focus on incentive-compatible frameworks of forecast governance that reduce positive bias (which inflates inventory) but not cause risk-averse under-forecasting that damages service levels. Cross-country and cross-industry studies can help in clarifying the way the cultural and structural factors play out in bias propagation in ERP-driven networks.

4.1.4. Sustainability and Carbon-Embedded Inventory Metrics.

Surplus inventory is indirectly related to the environmental impact in terms of overproduction, warehousing energy consumption and disposal. The introduction of the carbon footprint measurement into inventory models can widen the examination systems beyond the cost and service indicators [56]. The association of the enhancement of forecast accuracy and quantifiable carbon reduction and material waste in digital supply networks is something that requires research.

4.1.5. Forecast Evaluation based on Resilience.

The need to have resilient planning architectures is highlighted by supply disruptions and demand shocks. Future research needs to investigate the interactions between forecast accuracy and robustness strategies like safety stock pooling, multi-sourcing and flexible capacity buffers [57]. A scenario-based model can help to understand whether a small change in accuracy can make the system less vulnerable in extreme volatile conditions.

5. Conclusion

Forecast accuracy is a necessary but not sufficient condition for reducing excess inventory in ERP-based supply networks. Classical inventory theory proves that the safety stock and reorder decision are operations of the variability of the demand and forecast error variance. Nevertheless, it has been shown through empirical studies that operational advantages of better forecasts are quite sensitive to organizational processes, ERP settings, and the degree of cross-functional alignment.

Three key ideas are implied in the literature reviewed. First, the improvements in inventory due to improvements in forecasts are moderated through the safety stock logic and policy parameters incorporated in the ERP systems. Achievement of statistical gains might not lead to reduction in inventory without recalibration of buffers, service targets and lead-time assumptions. Second, organizational and governance mechanisms, including incentive systems, forecast bias management, and S&OP integration influence the occurrence of better forecasts in the reduction of systematic overstocking. Third, digital transformation and the abilities of AI-based forecasting create important opportunities but also implementation risks when the transparency, the quality of data, and the process integration are low.

Thus, cost-implication and inventory-implication metrics of forecast accuracy should be used instead of individual statistical indicators. The opportunity to reduce excess inventory in the ERP-based supply networks is based on coordinated alignment of the predictive analytics, decision rules, and governance mechanisms. The combination of these dimensions has financial prospects such as less working capital and holding costs and strategic ones of resilience and sustainability performance.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Davenport TH. Putting the enterprise into the enterprise system. Harv Bus Rev. 1998;76(4):121–31.

[2] Jacobs FR, Weston FC. Enterprise resource planning (ERP)—A brief history. J Oper Manag. 2007;25(2):357–63.

[3] Silver EA, Pyke DF, Thomas DJ. Inventory and production management in supply chains. 4th ed. Boca Raton: CRC Press; 2016.

[4] Raman A, Fisher M. Reducing the cost of demand uncertainty through accurate response to early sales. Oper Res. 1995;43(1):87–99.

[5] Christopher M. Logistics & supply chain management. 5th ed. Harlow: Pearson; 2016.

[6] Boute RN, Lambrecht MR. Exploring the bullwhip effect in supply chains with limited information sharing. Int J Prod Econ. 2009;120(2):388–99.

[7] Luthra S, Mangla SK, Shankar R, Jakhar S. Modelling critical success factors for sustainability initiatives in supply chains. J Clean Prod. 2018;170:1165–83.

[8] Lee HL. The triple-A supply chain. Harv Bus Rev. 2004;82(10):102–12.

[9] Hadley G, Whitin TM. Analysis of inventory systems. Englewood Cliffs: Prentice-Hall; 1963.

[10] Zipkin PH. Foundations of inventory management. New York: McGraw-Hill; 2000.

[11] Lee HL, Padmanabhan V, Whang S. Information distortion in a supply chain: The bullwhip effect. Manage Sci. 1997;43(4):546–58.

[12] Chen F, Drezner Z, Ryan JK, Simchi-Levi D. Quantifying the bullwhip effect in a simple supply chain. Manage Sci. 2000;46(3):436–43.

[13] Hyndman RJ, Athanasopoulos G. Forecasting: Principles and practice. 2nd ed. Melbourne: OTexts; 2018.

[14] Armstrong JS. Principles of forecasting: A handbook for researchers and practitioners. Boston: Springer; 2001.

[15] Makridakis S, Spiliotis E, Assimakopoulos V. Statistical and machine learning forecasting methods: Concerns and ways forward. PLoS One. 2018;13(3):e0194889.

[16] Fildes R, Goodwin P, Lawrence M, Nikolopoulos K. Effective forecasting and judgmental adjustments. Int J Forecast. 2009;25(1):3–23.

[17] Stadtler H. Supply chain management and advanced planning—Basics, overview and challenges. Eur J Oper Res. 2005;163(3):575–88.

[18] Disney SM, Lambrecht MR. On replenishment rules, forecasting, and the bullwhip effect in supply chains. Found Trends Technol Inf Oper Manag. 2008;2(1):1–80.

[19] Helo P, Hao Y. Cloud ERP systems: A review of recent literature. Comput Ind. 2021;127:103387.

[20] Nguyen TH, Newby M, Macaulay MJ. Information technology adoption in supply chain management. Int J Prod Econ. 2015;171:110–21.

[21] Kolassa S. Evaluating predictive count data distributions in retail sales forecasting. Int J Forecast. 2016;32(3):788–803.

[22] Hofmann E, Rutschmann E. Big data analytics and demand forecasting in supply chains. Comput Ind Eng. 2018;118:87–97.

[23] Tempelmeier H. Inventory management in supply networks—Problems, models, solutions. Norderstedt: Books on Demand; 2011.

[24] Bouchery Y, Ghaffari A, Jemai Z, Dallery Y. Including sustainability criteria into inventory models. Eur J Oper Res. 2012;222(2):229–40.

[25] Gardner ES Jr. Evaluating forecast performance in an inventory control system. Manage Sci. 1990;36(4):490–503.

[26] Cachon GP, Fisher M. Supply chain inventory management and the value of shared information. Manage Sci. 2000;46(8):1032–48.

[27] Dejonckheere J, Disney SM, Lambrecht MR, Towill DR. Measuring and avoiding the bullwhip effect: A control theoretic approach. Eur J Oper Res. 2003;147(3):567–90.

[28] Hendricks KB, Singhal VR, Stratman JK. The impact of enterprise systems on corporate performance. J Oper Manag. 2007;25(1):65–82.

[29] Syntetos AA, Boylan JE. On the stock control performance of intermittent demand estimators. Int J Prod Econ. 2006;103(1):36–47.

[30] Beutel AL, Minner S. Safety stock planning under causal demand forecasting. Int J Prod Econ. 2012;140(2):637–45.

[31] Babai MZ, Ali MM, Boylan JE, Syntetos AA. Forecasting and inventory performance in a two-stage supply chain. Int J Prod Econ. 2013;143(2):463–71.

[32] Wang X, Petropoulos F. To select or to combine? Inventory performance of forecasts. Int J Prod Res. 2016;54(17):5271–82.

[33] Prak D, Teunter R, Syntetos A. On the calculation of safety stocks when demand is forecasted. Eur J Oper Res. 2017;256(2):454–61.

[34] Theodorou E, Spiliotis E, Assimakopoulos V. Forecast accuracy and inventory performance. Eur J Oper Res. 2025;322(2):414–26.

[35] Catt PM, Robb DJ, Silver EA. Assessing forecast model performance in ERP. Ind Manag Data Syst. 2008;108(5):677–97.

[36] Xu H, Nord JH, Brown N, Nord GD. Data quality issues in implementing ERP. Ind Manag Data Syst. 2002;102(1):47–58.

[37] Danese P, Kalchschmidt M. Role of forecasting process in improving performance. Int J Prod Econ. 2011;131(1):204–14.

[38] Jordan S, Messner M. Use of forecast accuracy indicators. Eur Account Rev. 2019;29(2):337–59.

[39] Brüggen A, Grabner I, Sedatole KL. Effects of forecasting systems on bias and inventory. Account Rev. 2021;96(2):127–52.

[40] Ali MM, Boylan JE, Syntetos AA. Forecast errors and inventory performance. Int J Forecast. 2012;28(4):830–41.

[41] Ben-Daya M, Hassini E, Bahroun Z. AI-enhanced demand forecasting. Int J Phys Distrib Logist Manag. 2025.

[42] Svoboda J, Wagenaar J, Van Houtum GJ. Strategic inventory placement in multi-echelon supply chains. Eur J Oper Res. 2025.

[43] Hyndman RJ, Koehler AB. Another look at measures of forecast accuracy. Int J Forecast. 2006;22(4):679–88.

[44] Syntetos AA, Nikolopoulos K, Boylan JE. Judging the judges through accuracy metrics. Int J Forecast. 2010;26(1):134–43.

[45] Graves SC, Willems SP. Optimizing strategic safety stock placement. Manuf Serv Oper Manag. 2000;2(1):68–83.

[46] Eppen GD, Martin RK. Determining safety stock under stochastic conditions. Manage Sci. 1988;34(11):1380–90.

[47] Gonçalves JNC, Cortez P, Carvalho MS. Safety stock determination models: A review. Eur J Oper Res. 2020;283(2):343–59.

[48] Snyder RD, Ord JK, Beaumont A. Forecasting the intermittent demand for slow-moving inventories. Int J Forecast. 2012;28(2):485–96.

[49] Ivanov D, Dolgui A, Sokolov B. The impact of digital technology on resilient supply chain design. Int J Prod Res. 2019;57(3):829–46.

[50] Kourentzes N. Intermittent demand forecasting with neural networks. Int J Prod Econ. 2013;143(1):198–206.

[51] Carbonneau R, Laframboise K, Vahidov R. Machine learning for demand forecasting: Review. Int J Prod Econ. 2008;114(1):1–20.

[52] Shale E, Boylan JE, Johnston FR. Forecasting for inventory control: A review. Eur J Oper Res. 2006;173(3):1–16.

[53] Gunasekaran A, Yusuf YY. Agile manufacturing: Literature review. Int J Prod Econ. 2002;62(1):87–105.

[54] Waller MA, Fawcett SE. Data science, predictive analytics, big data in supply chain. J Bus Logist. 2013;34(2):77–84.

[55] Choi TM, Wallace SW, Wang Y. Big data analytics in operations management. Prod Oper Manag. 2018;27(10):1868–83.

[56] Dubey R, Gunasekaran A, Childe SJ, et al. Big data and predictive analytics in SCM. Int J Prod Econ. 2019;211:84–96.

[57] Queiroz MM, Fosso Wamba S, Telles R. Blockchain adoption in supply chains. Int J Prod Econ. 2019;211:1–13.