

Forecast Bias Control In High-Mix, Low-Volume Data Center Rack Supply Chains For AI Infrastructure

Varun Uppalapati*

*Nanyang Technological University, Singapore Email ID: varunuppalapati@gmail.com

Abstract

The intensive expansion in the artificial intelligence (AI) workload has resulted in the unprecedented need of the purpose-specific, high-performance racks of data centers, which has radically transformed the configuration of the supporting supply chains. The supply chains are of the high-mix, low-volume (HMLV) type such as high-level product customization, long-component lead time, low-density demand data, and very high capital intensity. Forecast bias - constant over estimation or under estimation of the demand has a great threat to capacity planning, inventory management and decisions on investments in such environments. Bias, unlike random forecast error, builds up over the years, and may result in continued misallocation of resources, stagnant capital, or sluggish infrastructure implementation. The review is a synthesis of the studies based on the forecasting theory, behavioral operations management, and supply chain coordination to investigate the origins of forecast bias and the mechanisms that can be used to manage the forecast bias in HMLV situations. The paper identifies bias drivers as behavioral, organizational and structural, and assesses statistical, judgmental, process-based and contractual bias management techniques. Specific consideration is drawn to the use of the methods in AI data center rack supply chains where the impact of biased forecasts is magnified by the rapid change of technologies and power and cooling limits. The review points to the fact that purely analytical solutions have their limitations and should be replaced with integrated solutions that incorporate structured judgment, cross-functional governance, and incentive alignment. Citing the best practices and uncovering the most critical knowledge gaps in the literature review, the present paper offers a basis to practitioners and researchers wanting to enhance the predictability of forecasts in complex AI infrastructure supply chains.

Keywords: Forecast bias, High-mix low-volume supply chains, AI data center infrastructure, Demand forecasting, Supply chain planning.

1. Introduction

The recent growth in the workloads of artificial intelligence (AI) has fundamentally altered the design and functionality of current data centers. In contrast to conventional enterprise computing, AI infrastructure can be configured for such highly specialised hardware as graphics processing units (GPUs) or other sophisticated networking devices, high-density power and cooling. These elements are being incorporated more in specialized data center racks that should comply with stringent performance, energy efficiency, and deployment schedules. Consequently, the supply chains of AI data center racks are strongly defined by the great variety of products, small volumes of production, and high-level complexity of configuration, which puts them squarely in the high-mix, low-volume (HMLV) manufacturing systems category [1].

Demand in HMLV supply chains is by nature quite challenging to forecast because of little previous data, dynamic customer needs, and constant changes in engineering. These issues are compounded in the AI infrastructure context by a rapidly evolving technology, long lead times on components, and the high competition between them over a limited number of

resources like GPUs and advanced semiconductors. In these conditions, the damage of forecast bias, the consistent overestimation or underestimation of demand, may be worse than random forecast error, because it results in long-run mis-allocation of capacity, too much inventory, or miss-met demand [2].

Previous studies have indicated that forecast bias is usually not only due to statistical constraint but also due to behavioral and organizational, such as optimism bias, incentive misalignment and the manipulation of forecasts by managers to serve their strategies [3]. These problems are especially severe in the capital-intensive supply chains, where the functions of sales, engineering, and operations have to coordinate in a high level of uncertainty and with long-term planning. Biased predictions in AI data center rack supply chains may lead to the premature investment in capacity, excessive order quantities of scarce parts, or the deferral of the essential infrastructure deployments with high financial and strategic implications.

The issue of forecast bias has been heavily researched in conventional manufacturing and retail settings, and the suggested ways to address it include both statistical methods of bias correction to the approach to reducing bias based on organizational frameworks, including Sales and Operations Planning (S&OP) and cross-functional consensus forecasting [4]. Nevertheless, much of the available literature is on large volume or comparatively stable product environments. Little has been synthesized on the effectiveness or ineffectiveness of these bias control techniques applied to the management of HMLV systems with extreme customisation, sparse demand signals, and short technology cycles, in the case of an AI infrastructure supply chain.

This is the gap that the review paper covers, as it will systematically analyze the causes of forecast bias and how the mechanisms related to bias control can be effective in HMLV data center rack supply chains to support AI infrastructure. The paper seeks to create a systematic knowledge on how forecast bias could be detected, eliminated and managed in this new and strategically important field by incorporating the lessons of the forecasting theory, behavioral operations management and supply chain coordination. The results are to be used by the researchers to continue to apply a forecasting theory to complex industry environments and practitioners tasked with planning and implementing AI infrastructure supply chains in high uncertainty environments [5].

2. High-Mix, Low-Volume Data Center Rack Supply Chains for AI Infrastructure

The large number of different configurations of products, the comparatively small quantities of the production, and the high complexity of operations characterizing high-mix, low-volume (HMLV) supply chains. The systems are contrasted with the traditional high-volume manufacturing setting where a standardized product and predictable demand trends allow the scale to be efficient. Previous studies have indicated that HMLV supply chains demand radically different approaches to planning, sourcing and coordination because of higher levels of uncertainty and fewer carries of using inventory pools [7].

The extreme manifestation of the HMLV paradigm is the AI data center rack supply chains. In contrast to traditional server racks, AI racks are usually project-defined, and their specifications can vary in terms of the type of GPUs, the number of accelerators, the memory architecture, the network topology, the power and cooling specifications. Such a high level of customization leaves the application of traditional make-to-stock strategies challenging and drives the firms towards assemble-to-order and engineer-to-order operating models. The product-supply chain framework proposed by Fisher implies that this type of innovative and

fast changing products needs responsive, rather than efficiency-driven supply chains, which also makes it harder to make any demand forecast and capacity planning decisions [7].

Strategic exploitation of modular product structures is one of the major structural attributes of HMLV supply chains. Modularity enables the firms to integrate standardized components with customized ones, which decrease complexity in the process of maintaining flexibility. Studies on modularity and commonality have shown that properly designed modular systems are able to alleviate some of the cost and responsiveness problems that are related to a high variety of products [8]. Modularity in AI data center racks is shown through the standard rack enclosures, power distribution units, and cooling subsystems, but compute and networking modules are very configurable. Nevertheless, despite modularity, the usefulness of pure reactive planning methods is constrained by the long lead times of key parts (like GPUs and high-end semiconductors).

One of the most common ideas that are suggested to address uncertainty in an HMLV environment is postponement strategies. The firms can minimize the chances of obsolescence and forecast bias through postponing final configuration decisions until more information on demand is available. The literature about postponement points out its usefulness in a high uncertainty of demand environment with short product life cycles, which are very close to AI infrastructure markets [9]. However, the possibility of delay in AI rack supply chains is limited by the early orders, which need to be made on limited elements and upstream forecasts are especially fragile to bias.

The other distinguishing feature of HMLV AI rack supply chains is the requirement of agility. Agile supply chains lay stress on quick response, inter-departmental coordination and tight cooperation between suppliers. Empirical research has demonstrated that agility correlates positively with performance in volatile and uncertain markets but easily at the expense of complex planning and decision making based on judgment [10]. Such circumstances predispose the systematic forecast bias particularly where organisational incentive inclines towards aggressive growth assumptions.

Lastly, the location of the decoupling point, the point where demand is no longer forecast-driven, but order-driven is also a very important factor in HMLV supply chain design. Studies of decoupling points have indicated that product structure and planning logic may not be in line and thus may lead to increased forecast bias and inventory risk [11]. In AI data center rack supply chains, long component lead times cause the decoupling points to push upstream, exposing them to biased forecasts and further motivating the establishment of a consistent bias control mechanism (Figure 1).



Figure 1. The major causes of Forecast Bias in High-mix, Low-volume (HMLV) Supply Chains.

This number shows the key behavioral, organizational, and structural causes of predictive bias in HMLV settings.

3. Complex and HMLV Supply Chain Forecast Bias

Forecast bias is a systematic and directional error in the forecast that does not equal a random error and causes systematic overestimation or underestimation. Contrary to the forecast accuracy measures which reflect the dispersion around the true demand, the use of bias reflects the problems of structural issues in the forecasting process and choice behavior. Forecast bias has been demonstrated to be more harmful than forecast variance in complex chains of supply chain especially involving high uncertainty and having long planning horizons [12].

Behavioral decision-making is considered one of the most researched sources of forecast bias. Studies in behavioral operations management indicate that forecasters often have an optimism bias, anchoring and overconfidence which makes them make inflated demand forecasts even when historical data is pointing to the contrary. Such tendencies are particularly strong when the forecasts are applied not merely to the planning but also to the performance measures, acquisition of resources or signaling of strategies [13]. Forecasters in HMLV settings are more biased because they are left more to judgement, and the historical data available to guide their decisions is sparse and noisy.

The structure and incentive systems of an organization are also highly important in determining forecast bias. It has been estimated in the research that the act of sale, marketing, and operations under a misaligned incentive can be found to deliberately, or more subconsciously compute a forecast to be biased to meet the local goals. An example is that sales teams might forecast extra capacity or budget whereas the operations might forecast less so that they will have fewer risks. The end result of such strategic action is biased consensus forecasts which do not reflect the actual demand in a systematic way [14]. Their dynamic is especially bad in AI data center rack supply chains, where capital investments and extended lead times exaggerate the impact of biased inputs. The phenomenon of forecast bias is also directly associated with the bullwhip effect, which causes minor changes in downstream demand signals to cause significant variability in the upstream. Although the bullwhip effect is commonly believed to be related to demand variability, the empirical data shows that biased forecasting is a significant cause of instability in upstream supply chains, especially with low-volume and project-based supply chains [15]. Biased predictions of the demand on rack level may be spread over the AI infrastructure supply chains to suppliers of components, and cause either shortage or surpluses of GPUs, power electronics, and cooling devices. The second structural cause of forecast bias in HMLV systems is the combination of long lead time and short life cycle of products. Forecasters are inclined to overestimate future growth and underestimate future downside when they have to make decisions about the procurement of components whose performance parameters are changing rapidly. This asymmetry has been observed in the technology-intensive sectors, where forecast bias has been reinforced by stories of exponential growth of demand, and competitive urgency [16]. Such stories are stereotypical in AI data center rack supply chains, which only deepens the presence of optimistic bias. The literature indicates that forecast bias in supply chains of HMLV is not only a technical forecasting issue but a systemic issue, which is based upon human behavior, motivation by organization and structural limitation. It is key to know these

sources to assess the bias control mechanisms because pure statistical solutions somehow cannot be effective without other organizational and process-level solutions (Table 1).

Table 1. Sources of Forecast Bias in High-Mix, Low-Volume (HMLV) Supply Chains

Source of Forecast Bias	Description	Relevance to AI Data Center Rack Supply Chains
Optimism bias	Systematic tendency to overestimate demand growth and adoption rates	Leads to overcommitment of GPU capacity, power infrastructure, and rack-level investments
Strategic bias	Intentional distortion of forecasts to secure resources or budget	Sales or program teams may inflate AI rack demand to reserve scarce components
Judgmental bias	Overreliance on managerial intuition due to sparse historical data	Common in new AI configurations where historical demand data are limited or nonexistent
Incentive misalignment	Conflicting objectives across sales, engineering, and operations	Results in biased consensus forecasts that reflect local objectives rather than true demand
Long lead-time distortion	Early forecasts required for components with long procurement cycles	Bias introduced at early planning stages propagates through the entire supply chain
Technology-driven narratives	Assumptions of exponential AI growth without downside consideration	Reinforces persistent overforecasting in AI infrastructure planning

4. Forecast Bias Control Methods in HMLV Supply Chains

Due to structural and behavioral origins of forecast bias, scholars have stressed that bias management would be best achieved through a set of analytical, organizational, and contractual instruments as opposed to application of a single forecasting methodology. The bias control methods in the HMLV supply chains where sparse data and high uncertainty restrict the efficacy of sheer statistical models should directly involve human judgment, as well as the design of the system [17].

4.1 The control of statistical and analytical bias used in the study

A single type of bias control procedures dwells on ex post statistical adjustment of foretelling. The techniques entail quantifying historical bias and refining future forecasts on the basis of it, commonly by means of additive or multiplicative correction factors. It has also been demonstrated through empirical research that basic bias-correcting rules can greatly enhance the performance of forecasts, especially in contexts that have systematic patterns of over or undercuring forecasts [18]. Nevertheless, this effectiveness is based on how stable

bias is in the long run, a situation that is not necessarily always true in fast developing AI infrastructure markets.

Further sophisticated methods of analysis include probabilistic prediction and Bayesian updating to directly consider uncertainty and insufficient data. Bayesian techniques can remove overreacting to momentary signals and extreme forecasts because of a combination of previous beliefs and new information. It has been proposed that this type of approach is especially useful in a low-volume environment because time-series-based techniques are ineffective in these cases, as there is a lack of data [19]. However, these procedures continue to be dependent on the quality of the preliminary assumptions and can implicitly integrate biased priors when organizational motivations are not harmonized.

4.2 Structured Override and Judgmental forecast

Judgmental forecasting cannot be avoided in HMLV environments particularly in case of new product or configuration. Instead of removing judgment, the literature goes on to promote structured judgmental processes that restrain prejudices. Some of the ways through which optimism bias can be minimized and in which transparency can be enhanced include structured analogies, scenario planning, and a written record of forecast assumptions [17]. Notably, research shows that unstructured managerial overrides are likely to deteriorate forecast performance, whereas structured and responsible modifications may be value-adding. The combination of judgment and the supply chain models of analytics specifically applies to AI data center rack supply chains, where qualitative data on customer roadmap, technology transitions, and regulatory constraints can be in place before quantitative demand indicators. Nevertheless, as configured to happen in the absence of formal controls, these qualitative inputs can systematically bias forecasts in the positive and support biasing more than reducing it.

4.3 Controls based on Organization and Process

In addition to technical approaches, organizational processes are very important in regulating forecast bias. Sales and Operations Planning (S&OP) and its more recent variation, Integrated Business Planning (IBP) are widely mentioned as processes that have been used to align forecasts between functions and to minimize strategic distortion. Empirical data indicate that in cross-functional consensus there is better forecast credibility and less bias when the decision rights and accountability is well established [20]. On the other hand, bias may be institutionalized through poorly executed consensus processes whereby skewed inputs are averaged. Another important factor is process maturity. Studies have shown that any organization that has well defined forecasting responsibilities, performance measurement methods, as well as feedback loops can easily remove bias in the long term [18]. Such discipline can be difficult but necessary in HMLV AI rack supply chains where the time to plan is frequently reduced to respond to market pressure (Figure 2).



Figure 2. AI Data Center Rack Supply Chain Forecast Bias Control Framework.

This figure provides some of the crucial analytical, organizational and contractual strategies employed to alleviate forecast bias of AI data center rack supply chains.

4.4 Mechanisms of Contractual and Incentive Alignment

Lastly, the management of forecast bias is not limited to the firm only but to relationships with the supply chain. Contractual incentives like capacity reservation agreements, information-sharing contracts and risk-sharing arrangements would minimize incentives to forecast inflation. Supply chain contracting theory proposes that the less the downstream firms have to bear the cost of the forecast error, the less they are inclined to provide biased forecasts [21]. They are especially applicable to AI infrastructure supply chains, where upstream suppliers have severe capacity constraints and invest at severe levels of customer predictions.

All in all, as the literature demonstrates, efficient forecast bias management in HMLV supply chains involves an equal balance of techniques. Analytical corrections are capable of dealing with quantifiable bias, but in the long term, the solution lies in organizational discipline and incentive alignment, which is particularly important in AI data center rack supply chains with high uncertainty and strategic rivalry.

5. Forecast Bias Control on Supply Chains in AI Data Centres Racks

The application of forecast bias control techniques to AI data center rack supply chains has its own set of challenges that cannot be compared to the normal manufacturing or retailing setup. AI data centers are made to support large-scale machine learning workloads requiring extreme power density, power consumption, and advanced cooling solutions. Consequently, rack-level infrastructure is fully integrated with facility-level design choices, which lead to the long planning horizons and reduced flexibility after commitments are undertaken. These traits contribute greatly to the exorbitant nature of biased predictions wherein the fault in the planning at the initial stages spreads to various levels of the supply chain. The critical nature of power and thermal limits is one of the characteristic features of AI data center rack supply chains. In contrast to the traditional IT infrastructure, AI racks are usually larger in terms of traditional power density limits, necessitating specialized power allocation, liquid cooling, and retrofit of the facility itself. The literature on warehouse-scale and hyperscale data centers notes that decisions related to infrastructure are often committed many years

prior to the factual occurrence of the workload demand [22]. As a result, an over-built infrastructure and stranded capital can be the result of forecast bias, especially systematic over-estimation of AI workload growth, whereas loss of revenue opportunities and massive deployment delays are possible because of underestimation.

The intensive development of the AI hardware also makes predicting more complex. The short cycles of evolution of GPU architectures, interconnect technologies, and accelerator designs make products have a shorter life time and have a higher chance of becoming obsolete.

The more recent case is the growth in NVIDIA GPU demand due to the recent accelerating use of generative AI in 2023–2024. The introduction of big language models greatly spurred the demands of NVIDIA A100 and H100 GPUs, causing acute shortages of supply, long lead times and allocations among hyperscalers and AI startups. Large cloud providers had to rewrite plans to increase infrastructure, postpone deployments and get long-term supply contracts. Simultaneously, smaller companies could not find enough compute capacity, which pushed up the cost of adding rental prices to GPU instances. This supply-demand mismatch identifies the role of fast hardware cycles and supply concentration in increasing forecasting risks in AI infrastructure supply chains. The empirical research on power-conscious as well as performance-oriented data center design points out that hardware-related decisions are frequently taken in the conditions of considerable uncertainty about the nature of future workloads [23]. In these situations, biased predictions may cause not only volume decisions to be biased, but also the choice of technology, which may lock the firms in less optimum configurations.

Under such circumstances, scenario-based planning and rolling forecasts have become some of the most important bias mitigation strategies in AI infrastructure supply chains. Instead of using a single-point forecast, companies continue to use rolling planning cycles, whereby demand expectations are updated when new information is available. The quality of rolling forecasts however is subject to whether the organization is capable of making objective adjustments of assumptions. Rolling forecasts can easily provide a continued positive or negative view instead of rectifying it unless specific controls on bias are in place.

Simulation based planning tools like digital twins provide more opportunities in reducing forecast bias in AI rack supply chains. Digital twins combine real-time operational data and simulation models to assess how various demand conditions affect the capacity, inventory, and the level of service. The recent supply chain research indicates that digital twins can enhance visibility and allow making decisions under uncertainty more balanced, especially in complex and capital-intensive systems [24]. Stress testing of forecasts across various scenarios can help firms to detect implicit bias and estimate downside risks and commit resources.

Another important enabler of bias control is the data integration throughout the supply chain. The supply chains of AI infrastructure produce high data volumes in the design tools, procurement systems, and monitoring platforms of operation. The literature on data-driven supply chain management indicates that better data sharing and analytics can decrease the use of subjective judgment and reveal systematic distortion in predictions [25]. Nevertheless, the abundance of data does not negate the problem of bias; organization and rules of decision-making are necessary to make sure that insights are interpreted in a similar way and implemented accordingly.

On the whole, forecast bias control in AI data center rack supply chains need a hybrid methodology which involves the integration of analytical tools, iterative planning process,

and organizational discipline. Although improved technologies like digital twins and real-time analytics can make the processes more transparent, their success will be determined by the readiness of the decision-makers to test assumptions and align incentives across the functions and supply chain partners (Table 2) (Figure 3).

Table 2. Comparison of Forecast Bias Control Techniques for AI Data Center Rack Supply Chains

Bias Control Technique	Primary Strength	Key Limitation in AI Rack Context
Statistical bias adjustment	Simple implementation; corrects persistent historical bias	Assumes bias stability, which may not hold in fast-evolving AI markets
Bayesian and probabilistic forecasting	Explicitly incorporates uncertainty and limited data	Sensitive to prior assumptions, which may embed organizational bias
Structured judgmental forecasting	Improves transparency and reduces unstructured overrides	Requires strong governance and disciplined execution
Sales and Operations Planning (S&OP)	Enhances cross-functional alignment and accountability	Can institutionalize bias if inputs are strategically distorted
Rolling forecasts	Allows demand updates as new information emerges	May reinforce initial bias without explicit correction mechanisms
Digital twins and simulation	Stress-tests forecasts under multiple scenarios	High implementation complexity and data integration requirements
Contractual risk-sharing	Aligns incentives across supply chain partners	Difficult to design and negotiate in rapidly changing AI ecosystems

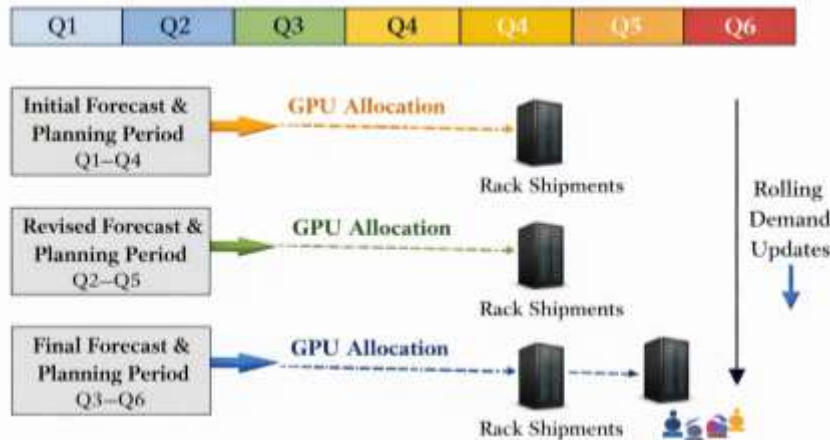


Figure 3. Rolling Forecast and Capacity Committee Process of AI Data Center Rack Supply Chains.

This value can be used to show a rolling forecast model where the cuts of the demand of AI data centers racks are updated at each new planning horizon.

6. Managerial Implications Research Gaps

The results of the forecast bias literature have a number of key managerial implications to the firms that are operating AI data center rack supply chains. To begin with, managers ought to note that forecast bias is not just a technical issue in forecasting but a systemic issue that occurs due to organizational incentives, decision rights and structural constraints. The supply chain leaders will have to supplement the analytical forecasting tools with governance mechanisms that enhance accountability and transparency within the sales, engineering, and operations functions [26].

Second, cross-functional integration is sufficiently an important enabler of bias management in HMLV settings. Empirical literature reveals that the closer the demand planning, procurement, and production functions are coordinated, the better quality of information and the lower the risk of the distortion of strategic forecasts [27]. In AI rack supply chains, where initial demand indications tend to be unclear and qualitative, a systematic partnership is needed to make sure that optimistic assumptions do not become entrenched in long-term capacity choices.

Third, it is important that managers consider the location of buffers, e.g. inventory, capacity, or time, with respect to designing AI infrastructure supply chains. Operational management studies have indicated that the use of improper buffering strategies may exaggerate the effects of biased forecasts particularly where the variability is motivated by judgmental decisions as opposed to stochastic demand [28]. Since AI infrastructure has long lead times and is highly capital-intensive, wherever possible firms should prefer flexible capacity and modular design to ensure exposure to forecast bias is limited.

Although the interest in forecast bias has increased, there are still a number of gaps in research. Very little empirical work has been done on the performance of bias control mechanisms in project-based, technology-intensive supply chains like AI data center racks. The majority of the studies that are already available are based on consumer goods or conventional manufacturing settings, which constrain their generalization. Moreover, although the use of machine learning and advanced analytics in forecasting is becoming more and more popular, research on the interaction between algorithmic forecasts and human bias in HMLV is scanty. In future studies, hybrid human-algorithm forecasting systems, incentive-sensitive forecasting models, and longitudinal case studies of AI infrastructure supply chains should be investigated to gain a more accurate idea of how forecast bias changes and can be successfully reduced with time [29].

7. Conclusion

The problem of forecast bias is a major issue that is not given the necessary attention in high-mix, low-volume data center rack supply chains to support AI infrastructure. This review shows that it is not just the limitations of the data that lead to bias but also the human judgment or incentives of an organization and structural limitations like long lead times and rapid change of technology. When statistical bias correction and advanced analytics are used alone, they are not effective enough, although they provide useful tools. Good bias

management necessitates a comprehensive strategy that incorporates both analytic and systematic judgement, multi-functional coordination and incentive-congruity relationship of the supply chain. The cost of biased forecasts is especially high in the context of AI infrastructure where initial planning decisions have a long-term financial and operational impact. Future studies ought to be conducted on empirical research of AI supply chains, hybrid human-algorithm forecasting systems, and governance mechanisms that clearly consider bias. The gaps are critical to overcome by addressing to enhance the robustness of planning in more sophisticated and capital-imposing supply chains.

References

- [1] Sanchis Llopis, Juan A., Juan A. Mañez, and Andrés Mauricio Gómez-Sánchez. 2024. "The Dynamic Links between Product and Process Innovations and Productivity for Colombian Manufacturing." *Applied Economic Analysis* 32 (94): 62–82.
- [2] Pasumarthi, Rekha, Shariq Mohammed, Vishnu Laxman, V. Krishnamoorthy, S. Durga, and Sampath Boopathi. 2024. "Digital Transformation in Developing Economies: Forecasting Trends, Impact, and Challenges in Industry 5.0." In *Advances in Human Resources Management and Organizational Development*, 47–68. IGI Global.
- [3] De Cremer, David, and Devesh Narayanan. 2023. "How AI Tools Can-and Cannot-Help Organizations Become More Ethical." *Frontiers in Artificial Intelligence* 6 (June): 1093712.
- [4] Bhalla, Swapnil, Erlend Alfnes, Hans-Henrik Hvolby, and Olumide Oluyisola. 2023. "Sales and Operations Planning for Delivery Date Setting in Engineer-to-Order Manufacturing: A Research Synthesis and Framework." *International Journal of Production Research* 61 (21): 7302–32.
- [5] Syntetos, A. A., Boylan, J. E., & Croston, J. D. (2005). On the categorization of demand patterns. *Journal of the Operational Research Society*, 56(5), 495–503.
- [6] Sanders, N. R., & Manrodt, K. B. (2003). Forecasting practices in U.S. corporations: Survey results. *Interfaces*, 33(2), 64–85.
- [7] Burke, Haydn, Abraham Zhang, and Jason X. Wang. 2021. "Integrating Product Design and Supply Chain Management for a Circular Economy." *Production Planning & Control*, October, 1–17.
- [8] Fixson, S. K. (2005). Modularity and commonality research: Past developments and future opportunities. *Concurrent Engineering: Research and Applications*, 13(2), 85–111.
- [9] Prataviera, Lorenzo Bruno, Amer Jazairy, and Ismail Abushaikh. 2024. "Navigating the Intersection between Postponement Strategies and Additive Manufacturing: Insights and Research Agenda." *International Journal of Production Research*, November, 1–23.
- [10] Gunasekaran, A., Yusuf, Y. Y., Adeleye, E. O., & Papadopoulos, T. (2017). Agile manufacturing practices: The role of big data and business analytics with multiple case studies. *International Journal of Production Economics*, 189, 1–13.
- [11] Melnyk, S. A., Narasimhan, R., & DeCampos, H. A. (2014). Supply chain design: Issues, challenges, frameworks and solutions. *International Journal of Production Research*, 52(7), 1887–1896.
- [12] Makridakis, S., & Taleb, N. N. (2009). Decision making and planning under low levels of predictability. *International Journal of Forecasting*, 25(4), 716–733.
- [13] Murdoch, Alexander Ivon King, Jordan Blum, Jie Chen, Dean Baziotis-Kalfas, Angelie Dao, Kevin Bai, Marina Bekheet, et al. 2023. "Determinants of Clinical Decision Making under Uncertainty in Dentistry: A Scoping Review." *Diagnostics (Basel, Switzerland)* 13 (6): 1076.

- [14] Fildes, R., Goodwin, P., Lawrence, M., & Nikolopoulos, K. (2009). Effective forecasting and judgmental adjustments: An empirical evaluation and strategies for improvement. *International Journal of Forecasting*, 25(1), 3–23.
- [15] Wu, Lin, Miao Wang, Ajay Kumar, and Tsan-Ming Choi. 2024. “Mitigating the Bullwhip Effect through Supply Chain ESG Transparency: Roles of Digitalization and Signal Strength.” *International Journal of Operations & Production Management* 44 (9): 1707–31.
- [16] Lovallo, D., & Kahneman, D. (2003). Delusions of success: How optimism undermines executives’ decisions. *Harvard Business Review*, 81(7), 56–63.
- [17] Akram, Muhammad, Naila Ramzan, and Muhammet Deveci. 2023. “Linguistic Pythagorean Fuzzy CRITIC-EDAS Method for Multiple-Attribute Group Decision Analysis.” *Engineering Applications of Artificial Intelligence* 119 (105777): 105777.
- [18] Qiao, Xiujie, Tian Peng, Na Sun, Chu Zhang, Qianlong Liu, Yue Zhang, Yuhang Wang, and Muhammad Shahzad Nazir. 2023. “Metaheuristic Evolutionary Deep Learning Model Based on Temporal Convolutional Network, Improved Aquila Optimizer and Random Forest for Rainfall-Runoff Simulation and Multi-Step Runoff Prediction.” *Expert Systems With Applications* 229 (120616): 120616.
- [19] Ord, J. K., Fildes, R., & Kourentzes, N. (2017). *Principles of business forecasting*. Wessex Press Publishing, London, UK.
- [20] Thomé, A. M. T., Scavarda, L. F., Fernández, N. S., & Scavarda, A. J. (2012). Sales and operations planning: A research synthesis. *International Journal of Production Economics*, 138(1), 1–13.
- [21] Song, Ju Myung, Tawei Wang, Ju-Chun Yen, and Yu-Hung Chen. 2024. “Does Cybersecurity Maturity Level Assurance Improve Cybersecurity Risk Management in Supply Chains?” *International Journal of Accounting Information Systems* 54 (100695): 100695.
- [22] Barroso, L. A., & Hölzle, U. (2007). The case for energy-proportional computing. *Computer*, 40(12), 33–37.
- [23] Patterson, M. K. (2008). The effect of data center temperature on energy efficiency. *Proceedings of the 11th Intersociety Conference on Thermal and Thermomechanical Phenomena in Electronic Systems*, 1167–1174.
- [24] Ivanov, D., Dolgui, A., Das, A., & Sokolov, B. (2019). Digital supply chain twins: Managing the ripple effect, resilience, and disruption risks by data-driven optimization, simulation, and visibility. *International Journal of Production Research*, 57(24), 8291–8310.
- [25] Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. *Journal of Business Logistics*, 34(2), 77–84.
- [26] Chopra, S., & Meindl, P. (2016). *Supply chain management: Strategy, planning, and operation* (6th ed.). Pearson Education, Boston, MA.
- [27] Flynn, B. B., Huo, B., & Zhao, X. (2010). The impact of supply chain integration on performance: A contingency and configuration approach. *Journal of Operations Management*, 28(1), 58–71.
- [28] Hopp, W. J., & Spearman, M. L. (2008). *Factory physics* (3rd ed.). McGraw-Hill/Irwin, New York, NY.
- [29] Chen, F., Drezner, Z., Ryan, J. K., & Simchi-Levi, D. (2000). Quantifying the bullwhip effect in a simple supply chain: The impact of forecasting, lead times, and information. *Management Science*, 46(3), 436–443.