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REVIEW ARTICLE

The Role of Big Data Analytics and Artificial Intelligence in Strengthening Integrated Business Planning: A Sales and Operations Planning Case Study

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ABSTRACT

Integrated business planning (IBP) depends upon timely information, reliable forecasting and agreement among different functions. However, many sales and operations planning (S&OP) processes continue to operate through fragmented information and periodic managerial judgement. This study aims to investigate how big data analytics (BDA), artificial intelligence (AI) and related decision-support capabilities can strengthen the IBP process through a PRISMA-informed systematic review that was conducted by using a manually developed dataset for the period 2016–2026. Twenty-four structured searches through the Crossref DOI registry were followed by verification using exact titles, DOIs, Semantic Scholar and publisher pages. From 1,440 returned records, 932 unique records were screened and 120 candidates were coded, producing 70 primary studies, 16 background reviews and 34 excluded records. Descriptive mapping, multi-label coding and thematic synthesis were applied through a 47-field extraction matrix, and the findings show that machine learning and deep learning represented the largest primary category with 24 studies, whereas S&OP and demand planning each contained 23 studies. Analytics has a significant role in forecast accuracy, planning speed, evaluation of scenarios, integration and resilience. However, its value depends upon data quality, organisational capability, cross-functional coordination and the trust of managers. Only three studies explicitly considered explainability and ten discussed human judgement, which reflects an important governance gap. Therefore, an evidence-based S&OP case synthesis and an augmented IBP control wheel are proposed. The framework considers AI as a governed planning partner rather than an autonomous replacement of planners. Since full texts were not systematically retrieved for all records, the findings support systematic mapping and cautious thematic interpretation instead of statistical meta-analysis.

1. Introduction

Integrated business planning is developed to connect commercial priorities, operational limitations and financial consequences within one recurring process of decision-making. In practice, S&OP commonly performs this operating function by reconciling the choices of demand, supply, inventory, capacity and product portfolio. The present challenge is informational as well as procedural because planners are required to combine internal transaction data with market information, customer signals and risk indicators, while maintaining a decision rhythm that senior managers can understand and follow. According to Schlegel et al. (2021), BDA capability can expand the information-processing capacity of an organisation and consequently enable a more efficient and effective S&OP process. This argument places analytics in a central position within IBP; however, it does not establish that a greater volume of data will automatically develop integration.

The S&OP literature consistently explains coordination as a socio-technical problem in which information sharing creates benefits when the information is suitable for the planning context and is incorporated within appropriate mechanisms of collaboration (Kaipia et al., 2017). Similarly, Swaim et al. (2016) identify organisational antecedents behind an effective S&OP process, while Seeling et al. (2022) show the importance of finance participation when operational plans are converted into economic consequences. More recently, Goh and Eldridge (2024) connected S&OP culture with performance through different mechanisms of coordination. From the above findings, an algorithm may improve forecasting but still fail to strengthen IBP when functions do not share common definitions, incentives and rights of decision-making.

BDA and AI have widened the possible design of the planning process because predictive models can identify nonlinear patterns of demand, prescriptive approaches can compare plans under constraints, simulation can reveal different trade-offs and explainable interfaces can support managers in challenging a recommendation. Supply-chain studies have established a relationship between analytics capability, organisational performance and dynamic capability (Gunasekaran et al., 2017; Wamba et al., 2017). At the level of planning activities, Xu et al. (2023) found that the relevance of BDA differs across tasks, although it may improve accuracy, response time and flexibility. However, adoption is still constrained by data integration, available skills, interpretability and organisational readiness (Kache & Seuring, 2017; Raut et al., 2021).

The developing literature on AI introduces a further tension within this relationship nexus, as Jazairy et al. (2025) found that the adoption of AI in S&OP creates different paradoxes that need active managerial attention instead of a simple implementation of technology. Automation can increase planning speed but may reduce the perceived level of control, while augmentation may improve managerial insight while increasing dependency on specialised knowledge. Explainable AI therefore has relevance for decision support in the supply chain (Olan et al., 2024), whereas predictive-risk studies show a continuing trade-off between interpretability and model performance (Baryannis et al., 2019). Due to these aspects, a review integrating forecasting, planning, organisational capability and human governance is required.

Previous review studies have examined S&OP theory, information technology, predictive demand analytics and applications of AI in supply chains (Kreuter et al., 2022; Nicolas et al., 2021; Seyedan & Mafakheri, 2020; Toorajipour et al., 2021); unfortunately, the evidence remains distributed among different levels of planning. This study addresses the above fragmentation through four research questions, where RQ1 asks: Which BDA, AI, machine-learning and decision-support capabilities are applied within IBP, S&OP and linked planning sub-processes? RQ2 asks: How do these capabilities influence forecasting, balancing, scenario planning, integration, decision quality and performance? RQ3 asks: Which technological, data, organisational, governance and human conditions enable or constrain analytics-supported planning? Finally, RQ4 asks: What evidence-based framework can guide implementation and the design of an organisational S&OP case study? Therefore, the paper contributes a transparent evidence map, a synthesis oriented towards the case and a governed control framework for analytics-enabled IBP.

2. Materials and Methods

2.1 Review design and scope

The review followed the evidence-informed management-review logic developed by Tranfield et al. (2003), while PRISMA 2020 principles were used to document study identification, screening and final inclusion (Page et al., 2021). Systematic mapping was selected because the candidate papers applied heterogeneous methods, organisational contexts and outcome measures. The unit of analysis was a peer-reviewed journal article or conference paper published in English during 2016–2026. For inclusion, a study had to investigate IBP, S&OP or a clearly related planning sub-process and apply BDA, AI, machine learning, predictive or prescriptive analytics, simulation, optimisation, digital-twin logic, advanced planning systems or a relevant information-processing capability. Review articles were maintained separately for conceptual framing and refinement of the search, but they did not enter the primary-study count.

2.2 Manual search and dataset construction

The dataset was manually constructed instead of being imported as an unchecked bibliographic collection, and on 10 July 2026, twenty-four Boolean search routes were conducted through the accessible Crossref DOI registry. Planning expressions such as “sales and operations planning”, “integrated business planning”, “demand planning”, “supply-chain planning”, “scenario planning”, “production planning” and “inventory planning” were combined with technological expressions, including “analytics”, “big data”, “artificial intelligence”, “machine learning”, “predictive analytics”, “prescriptive analytics”, “digital twin”, “advanced planning systems” and “decision support”. The applied filters focused on journal records published during 2016–2026 and relevance to the English language.

Every search route returned 60 records for the manual screening of titles and metadata, resulting in 1,440 search-route records. Matching by DOI and normalised title removed 508 duplicated routes and produced 932 unique records. The reviewers then examined the titles, publication outlets, DOI identities and available abstracts. A relevance pre-screen excluded 812 records without a relationship between analytics and IBP, S&OP or a linked planning decision. The remaining 120 candidates were recorded individually within the verified matrix, while high-relevance seed papers were checked through exact DOI, backward and forward citation tracing, Semantic Scholar metadata and accessible pages of publishers. Crossref served as the main index of bibliographic identity, while publisher pages were preferred for final publication details.

For every search route, the workbook retained the search ID, exact query, filters, returned number, source URL and notes concerning access. Scopus, Web of Science and Google Scholar were not accessed directly. Therefore, the method does not claim searches or database exports from these sources. This distinction has methodological importance because several accessible indexes supported the verification process, although the reproducible identification number remains based on the records returned through Crossref. Manual dataset development also allowed ambiguous papers, reviews and adjacent supply-chain studies to be classified explicitly instead of being removed without explanation.

Table 1.
Eligibility and classification rules

Criterion	Included / retained	Excluded / separated
Planning relevance	IBP, S&OP or a directly linked demand, supply, production, inventory, capacity or scenario decision	Generic AI/SCM without a planning connection
Technology	BDA, AI, ML/DL, predictive/prescriptive analytics, simulation, optimisation or decision-support capability	No qualifying analytics or information-processing element
Publication	Peer-reviewed journal or conference record; English; 2016–2026	Non-peer-reviewed, outside boundary or unclear venue
Identity	Verified title, outlet and DOI/URL where available	Unverifiable or conflicting bibliographic identity
Evidence class	Empirical, technical, modelling or directly relevant case study	Review/conceptual synthesis retained as background only

2.3 Screening, quality appraisal and extraction

The inclusion criteria required a verified bibliographic identity, direct relevance to planning, a qualifying analytics or information-processing capability, an eligible publication type and compliance with the language and date boundaries. Duplicate records, non-peer-reviewed materials, general AI or supply-chain articles without planning relevance, sales analytics without an operational relationship and records that could not be verified were excluded. Following verification and quality screening, 70 papers entered the primary synthesis, 16 review or conceptual papers were retained as background evidence and 34 records were excluded.

A 47-field matrix was used to extract bibliographic information, planning domain, category of analytics, specific technique, research design, data source, modality, sample or organisational context, planning target, outcomes, metrics, model, explainability, theory, findings, IBP implications, business relevance, enablers, barriers, limitations and suggestions for future research. Multi-label coding was permitted because one paper could integrate machine learning, prediction and optimisation. Quality was provisionally scored from 0 to 12 across six criteria worth two points each: bibliographic identity, alignment with the topic, clarity of method, clarity of data or context, clarity of findings and quality of source. These scores were applied for sensitivity awareness rather than exclusion through an arbitrary threshold.

2.4 Analysis procedure

The analysis was completed through four stages: first, descriptive frequencies were calculated for publication year, outlet, planning domain, primary analytics category, research approach and data type. Second, cross-tabulation established the relationship between primary technology categories and different planning domains, while third, thematic synthesis organised the extracted outcomes into forecasting, planning effectiveness, integration, decision quality, inventory or service, agility, resilience and business performance. The iterative coding procedure followed thematic-analysis principles through which codes are compared and refined into explanatory themes (Braun & Clarke, 2006). Finally, the published S&OP case evidence was triangulated to construct a case-study pathway beginning with fragmented data and progressing towards governed augmentation of decisions.

No pooled effect size was estimated in this study because the definitions of outcomes, samples, metrics and validation periods were highly different, while all 70 primary records retained at least one flag for manual full-text checking. Therefore, exact model metrics, sample features, limitations and theoretical statements were applied only when accessible full text or publisher materials allowed verification. In the remaining cases, category-level patterns and cautious implications are reported, and this process preserves the methodological difference between a systematic evidence map and a statistical meta-analysis.

3. Results

3.1 Study selection and evidence profile

Figure 1 presents the flow of the review process and shows that the final evidence base contained 70 primary journal articles. Publication activity increased during the later part of the reviewed period, as 32 studies were indexed during 2024–2026 and 14 of these appeared in 2025. Production Planning & Control and IFAC-PapersOnLine were identified as the most frequent publication outlets, with five studies in each outlet. All reported frequencies follow the year field in the workbook, which retains online-first information when it was provided by the registry.

The quality audit found 31 records with a score of 12/12 and 14 records scoring 11/12, while one record scored 10, one scored 9, thirteen scored 6, nine scored 5 and one record scored 4. The lower values mainly resulted from missing abstract details or unclear descriptions of methods within the accessible metadata rather than confirmed methodological weakness. From these results, the evidence profile is bibliographically strong, although extraction at the individual-study level remains uneven; the principal characteristics are reported in Table 2.

Figure 1. PRISMA-informed selection funnel for the manually constructed dataset.

Table 2.
Profile of the 70 primary studies

Dimension	Largest categories	n	% of 70
Planning domain	S&OP	23	32.9
Planning domain	Demand planning and forecasting	23	32.9

Dimension	Largest categories	n	% of 70
Primary technology	Machine learning/deep learning	24	34.3
Primary technology	Big data analytics	13	18.6
Research method	Machine-learning modelling (multi-label)	27	38.6
Research method	Case study (multi-label)	12	17.1
Human governance	Human/managerial judgement discussed	10	14.3
Human governance	Explainability explicitly addressed	3	4.3

3.2 RQ1: Analytics capabilities across planning domains

Machine learning and deep learning represented the largest primary category, containing 24 of the 70 studies or 34.3%. BDA was identified in 13 primary studies, AI in six, prescriptive analytics or optimisation in four, planning technology in four, predictive analytics in three and simulation in one study. Fifteen papers primarily examined general planning or information-processing capability. When the multi-label coding was considered, machine learning or deep learning appeared in 27 studies, predictive analytics in 27, planning or decision-support technology in 20 and prescriptive analytics or optimisation in 12. Therefore, the findings show a diversified technological base with a clear concentration around learning and prediction.

The distribution was highly concentrated according to the planning task, as S&OP and demand planning each contained 23 studies, while only two papers were directly coded under IBP. Figure 2 indicates that machine learning is mainly concentrated within demand planning, whereas the general information-processing capability is dominant in S&OP studies. This finding reflects two different traditions of research because algorithmic papers generally optimise one planning input, while organisational papers investigate the coordination process through which different inputs are developed into an agreed plan.

Demand-forecasting studies applied conventional machine learning, neural networks, recurrent and long short-term memory structures, ensemble methods and external data enrichment, while Zhu et al. (2021) demonstrated the importance of combining supply-chain information with machine learning in the pharmaceutical sector. Similarly, Yani and Aamer (2023) investigated forecasting accuracy through a pharmaceutical case, whereas Feizabadi (2022) connected machine-learning forecasting with supply-chain performance. El Filali et al. (2022) compared an optimised LSTM technique with statistical and neural alternatives by using actual pharmaceutical sales history. Together with the broader reviews (Douaioui et al., 2024; Seyedan & Mafakheri, 2020), these findings show that the selection of a model depends upon the data structure, forecast horizon and business environment.

Prescriptive research extended the forecasting process towards decisions under different constraints, as Wery et al. (2018) developed a simulation-optimisation framework for S&OP within a co-production setting, while Lim et al. (2017) applied simulation-optimisation to automotive build-to-order planning with distant sourcing. Dinis et al. (2020) established a connection between predictive analytics and capacity planning, while Garre et al. (2020) used machine learning to support production planning under uncertainty concerning waste, and Lauer et al. (2019) examined plan instability in semiconductor master-production planning. From the above studies, a progression can be identified from predicting what may happen towards selecting the most appropriate plan under existing constraints.

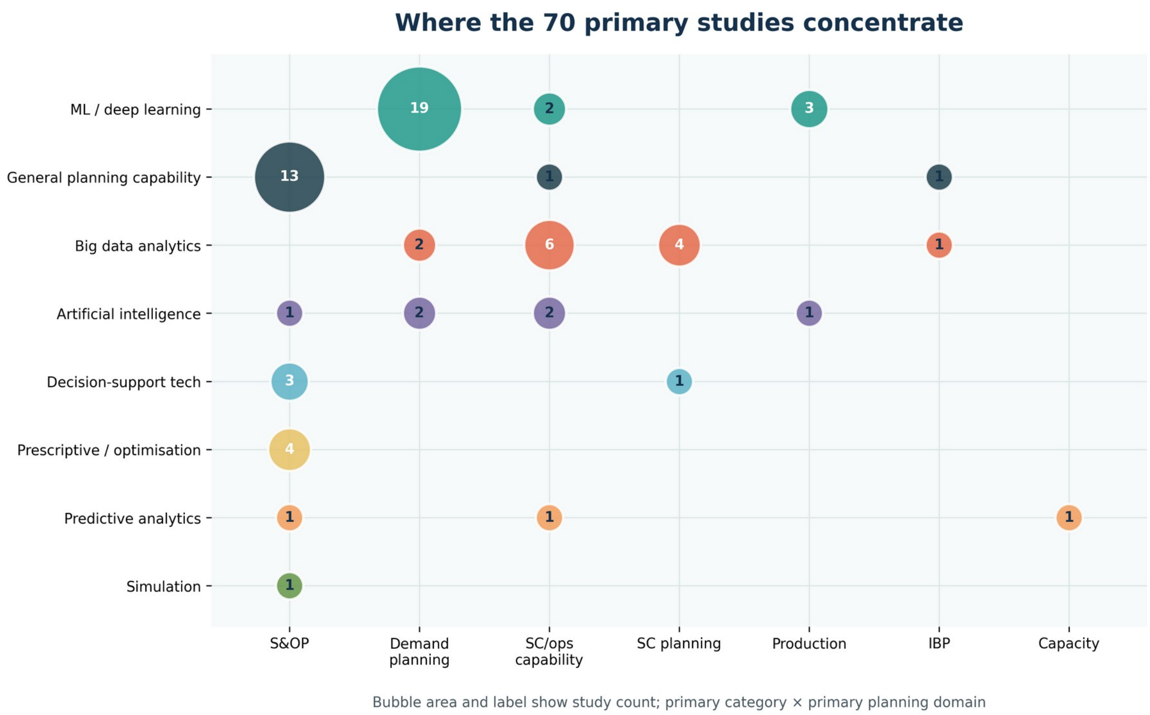

Figure 2. Evidence landscape by primary analytics category and planning domain.

Table 3.
Analytics capability portfolio and planning contribution

Capability	Primary n	Dominant use	Representative evidence
ML/deep learning	24	Demand sensing and forecasting	Zhu et al. (2021); Yani & Aamer (2023)
Big data analytics	13	Data integration, planning visibility and capability	Schlegel et al. (2021); Xu et al. (2023)
Artificial intelligence	6	Augmented decisions, adoption and resilience	Jazairy et al. (2025); Belhadi et al. (2024)
Prescriptive/ optimisation	4	Constrained plan and scenario selection	Lim et al. (2017); Wery et al. (2018)
Predictive analytics	3	Capacity, risk and demand signals	Dinis et al. (2020); Baryannis et al. (2019)
Planning capability/technology	19	Information processing and coordination	Kaipia et al. (2017); Nicolas et al. (2021)

3.3 RQ2: Effects on planning and performance

The coded language concerning outcomes was considerably broad, as business or operational performance appeared in 31 papers, planning effectiveness in 25, decision quality in 17, cross-functional or data integration in 14, inventory or service outcomes in 13, resilience in seven, agility or flexibility in six and forecast accuracy in six studies. These values are non-exclusive because one study could report several outcomes, and therefore the frequencies indicate the general direction of the literature but cannot establish one common causal effect.

At the predictive level, analytics converts different signals into a more responsive view of demand, and Xu et al. (2023) found that BDA may improve planning accuracy, response time and flexibility, although its level of relevance varies among planning activities. Improved forecasting has importance for IBP because it influences capacity, purchasing, inventory and financial projection; however, a reduction in forecast error does not automatically generate a better integrated plan. Planners must still determine the acceptable level of uncertainty and decide how the associated risk should be shared among different functions.

At the level of the process, the findings emphasise coordination and the availability of information, while the embedded case of Schlegel et al. (2021) shows that tangible, human and intangible BDA capabilities should develop in sequence for supporting IBP. Kaipia et al. (2017) found that the benefits of information sharing are contextual rather than universal, while participation of finance creates another control dimension by connecting operating assumptions with their value implications (Seeling et al., 2022). Thus, analytics can strengthen IBP when it establishes a shared and challengeable representation of demand, supply and financial exposure.

At the enterprise level, BDA capability has a relationship with performance through complementary organisational capabilities instead of technology by itself (Gunasekaran et al., 2017; Wamba et al., 2017). Similarly, Ma and Chang (2024) consider integration and agility as important mechanisms within digital transformation of the supply chain. AI-oriented resilience research indicates that analytical innovation can support performance under changing conditions (Belhadi et al., 2024), while digital-twin logic contributes to the analysis of disruption and planning for recovery (Ivanov & Dolgui, 2021). Therefore, the common implication is that the value of analytics is influenced by the organisational capacity to convert insight into action.

3.4 RQ3: Enablers, barriers and the human-governance gap

Nineteen studies explicitly identified data integration, analytics capability, collaboration or organisational readiness as important enablers of implementation, whereas thirty studies identified uncertainty, adoption tension, problems with data, interpretability or organisational barriers. Raut et al. (2021) demonstrate why implementation challenges require separate consideration from the performance of a model. According to Xu and Pero (2023), adoption of BDA in supply-chain planning requires the orchestration of resources. This means that data assets, analytical knowledge and planning routines need to be configured together as one capability system.

Human governance was not strongly visible within the reviewed literature. Fifty-seven studies did not report human judgement in their accessible metadata, ten discussed managerial judgement and only three papers explicitly investigated explainability or interpretability. This represents a significant gap because S&OP is dependent upon negotiation, accountability and the management of exceptions. Olan et al. (2024) argue for explainable AI capability within supply-chain decision support, whereas Baryannis et al. (2019) demonstrate the relationship between predictive performance and interpretability. Therefore, the review considers human-in-the-loop design as a requirement of control rather than a preference relating only to the user interface.

Jazairy et al. (2025) provide the most direct warning concerning S&OP, as their interview findings identify paradoxes in the adoption of AI and suggest that an organisation should maintain a balance between automation and augmentation. Similarly, Fries et al. (2025) place the role of workers at the centre of AI-supported production planning, and these results challenge the assumption that greater planning maturity is demonstrated through the removal of human involvement. A more appropriate indicator is whether overrides remain transparent, explanations are recorded, model drift is monitored and the owners of decisions remain accountable.

3.5 RQ4: Published S&OP case synthesis

The case-study component is an analytical reconstruction based on published evidence and does not represent a newly observed organisation. It uses the multinational agrochemical case reported by Schlegel et al. (2021) as the central IBP example and triangulates this case with published S&OP evidence relating to information sharing, finance participation, organisational culture, maturity and AI adoption. Through this approach, an organisation is not invented, while the reviewed findings can still provide a foundation for designing a future field case.

The reconstructed case begins from fragmented operational and market information, after which a governed layer of data develops shared definitions, access arrangements and data lineage. Descriptive analytics provides visibility, predictive approaches generate demand and risk signals, while prescriptive or simulation models compare responses that are operationally feasible. However, cross-functional review remains the stage where assumptions are challenged and financial consequences are reconciled, while Seeling et al. (2022) confirm that finance performs a substantive function within this integration. The executive S&OP decision therefore accepts, changes or rejects the analytical recommendation and records the reason for this decision.

The outcomes of execution provide information for the following cycle, where forecast value added, service, inventory, utilisation of capacity, margin exposure, performance of overrides and model drift become important learning indicators. Wu et al. (2025) show the importance of adjustment mechanisms within the S&OP process, while Pacheco et al. (2025) connect maturity with integration across global food networks. Figure 3 presents the proposed control wheel for capturing this closed-loop process, and the design differs from a linear implementation of technology because every planning cycle returns evidence towards data governance, model calibration and decision practice.

Table 4.
Evidence-based S&OP case reconstruction

Case condition	Analytics contribution	Managerial control	Evidence anchor
Fragmented data and definitions	Integrated, governed planning data product	Ownership, lineage and common definitions	Schlegel et al. (2021); Kaipia et al. (2017)
Uncertain demand and constraints	Predictive signals and feasible scenarios	Baseline comparison and confidence review	Zhu et al. (2021); Wery et al. (2018)
Functional plan conflict	Shared assumptions and economic exposure	Cross-functional challenge with finance	Seeling et al. (2022); Goh & Eldridge (2024)
AI adoption tension	Automation for scale; augmentation for exceptions	Explainability, override rationale and escalation	Jazairy et al. (2025); Olan et al. (2024)
Execution learning gap	Outcome, drift and forecast-value-added feedback	Review decision and model performance together	Wu et al. (2025); Pacheco et al. (2025)

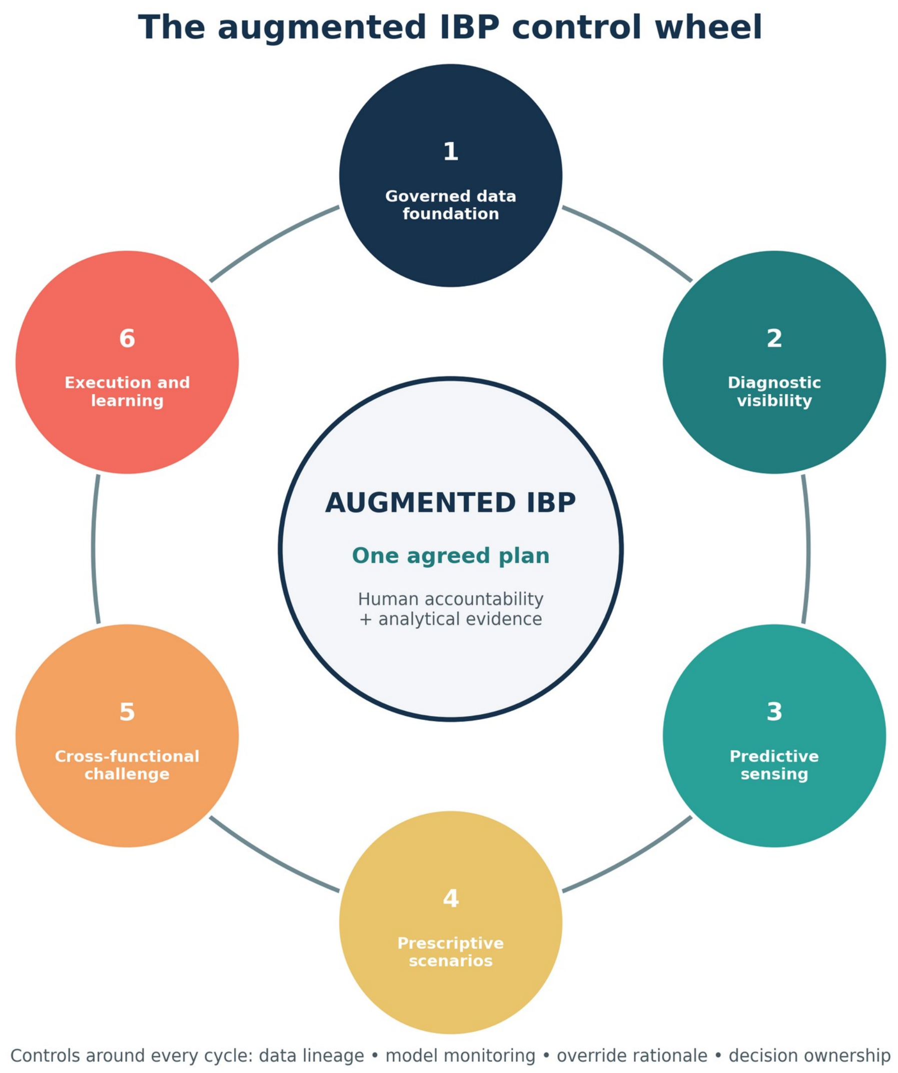

Figure 3. Augmented IBP control wheel linking analytical capability with accountable S&OP decisions.

4. Discussion

4.1 Interpretation and theoretical contribution

The review findings reveal a structural division within the literature because algorithmic studies are developed strongly in demand forecasting but remain comparatively limited in end-to-end governance of IBP. In contrast, S&OP studies provide rich evidence concerning coordination and information processing but are generally less specific regarding AI models. This article contributes by connecting the two research streams, where predictive accuracy becomes an input for integration, while coordination provides the mechanism that transforms analytical output into an accountable decision at the enterprise level.

Organisational information-processing theory provides the strongest direct explanation of the identified relationship because uncertainty increases the requirements for processing information, while BDA can expand the available processing capacity (Schlegel et al., 2021). However, this review adds a governance condition because processing capacity creates value when the information is trusted, relevant and included within clear decision rights. Resource orchestration contributes the implementation logic, as dispersed data, people and technological tools must be configured and utilised together (Xu & Pero, 2023). Finally, dynamic-capability research explains how organisations sense environmental change, choose a response and reconfigure the plan (Wamba et al., 2017).

The evidence further supports an augmentation perspective in which automated forecasting is suitable for recognising patterns at a large scale, whereas managers continue to be responsible for structural changes, strategic trade-offs and decisions that are ethically or commercially sensitive. The paradox findings reported by Jazairy et al. (2025) show that gains and tensions can occur at the same time, and therefore explainability, governance of overrides and auditability should be considered as boundary conditions for stronger IBP instead of optional additions following model deployment.

4.2 Managerial implications

Managers should begin from a decision and control problem rather than from a collection of available algorithms. An appropriate sequence is to identify the planning decision, determine its owner and time horizon, define the minimum trusted data product, develop a transparent baseline and then examine whether analytics improves that particular decision. Advanced models can be justified when they create reliable value after considering data latency, maintenance cost and explainability. Nicolas et al. (2021) similarly demonstrate that technology and analytics should be understood within the complete S&OP process instead of being treated as isolated applications.

The control wheel proposes six important managerial disciplines, beginning with a governed data foundation developed through shared definitions for product, customer, calendar and capacity. Second, diagnostic visibility should be created for demand, constraints and assumptions, while third, predictive sensing should be applied to selected areas of uncertainty. Fourth, optimisation, simulation or scenario methods should compare the feasible courses of action, while fifth, a cross-functional challenge should be conducted by clearly identified decision owners. Finally, outcomes of execution and managerial overrides should be captured for continuous learning, and Table 5 shows that every discipline contains a business measure together with a governance measure.

A pilot application should be limited to one planning family, market or decision horizon. Its baseline should include forecast accuracy, bias, service, inventory, cycle time of planning and quality of manual overrides. Yani and Aamer (2023) show how machine learning can be evaluated against forecast accuracy in an actual supply-chain case; however, the evaluation of IBP should extend beyond forecasting error. Managers should also measure adoption, decision latency, closure of exceptions, financial reconciliation and learning after the decision, since a technically accurate model cannot be considered as an IBP success when planners regularly avoid using its recommendations.

Table 5.
Implementation controls for analytics-enabled IBP

Stage	Decision question	Analytics role	Human accountability	Example measure
Data foundation	Can functions trust the same inputs?	Integrate, clean and version data	Approve definitions and access	Completeness; latency; lineage
Visibility	Where is the current imbalance?	Diagnose demand, supply and financial exposure	Validate exceptions and assumptions	Bias; backlog; constraint age
Predictive sensing	What is likely to change?	Forecast demand, risk and capacity	Review uncertainty and structural breaks	Error; calibration; drift
Prescriptive scenarios	Which feasible response is preferred?	Optimise or simulate alternatives	Set constraints and trade-offs	Service; inventory; margin

Stage	Decision question	Analytics role	Human accountability	Example measure
Challenge and decision	What plan will the business own?	Present evidence and sensitivity	Accept, modify or reject with rationale	Decision time; override value
Execution learning	What happened and what changes next?	Compare plan, outcome and model behaviour	Close actions and update policy	Forecast value added; action closure

4.3 Research agenda

Future studies should move from isolated comparisons of models towards longitudinal evaluation within organisations, where multi-cycle field studies can examine the relationship among model recommendations, managerial overrides and final outcomes. Comparative case evidence is also required across different levels of planning maturity, industry volatility and data availability, while Vlachos and Reddy (2025) identify a broad agenda for machine-learning research within supply chains. However, the present review narrows this agenda towards IBP by giving priority to ownership of decisions, process fit and consequences across organisational functions.

Explainability requires direct empirical testing: future research should compare explanation formats, planner trust, quality of overrides and decision speed instead of assuming that a greater amount of explanation will always produce better results. Studies should also evaluate the performance of human-AI teams against human-only and model-only conditions; unfortunately, the present evidence base provides limited explicit observation of these mechanisms (Baryannis et al., 2019; Olan et al., 2024).

Finally, common definitions of outcomes are required: forecast error, service, inventory, cost, margin, resilience and cycle time should have a documented causal relationship. Comparable reporting may eventually allow a statistical meta-analysis. Until such evidence is available, strong claims concerning average performance effects remain premature, although individual modelling papers and case studies provide promising results (El Filali et al., 2022; Garre et al., 2020; Zhu et al., 2021).

4.4 Limitations

This review contains four limitations: first, study identification depended upon accessible Crossref searches and supplementary verification rather than direct exports from Scopus, Web of Science or Google Scholar. Second, the estimated search results within Crossref were extremely broad; therefore, the reproducible count is based on the 1,440 records actually returned through the 24 search routes. Third, full texts were not systematically obtained for each primary paper, and 70 records continue to contain manual flags relating to methods, metrics, limitations or theory. Finally, the primary categories simplify papers that apply multiple technologies, and although the multi-label matrix and transparent appendix reduce this loss of information, coder judgement cannot be fully removed.

5. Conclusions

BDA and AI can strengthen IBP by increasing the speed, range and analytical depth of decisions within S&OP. The evidence map of 70 studies shows a strong concentration on machine-learning demand forecasting and a complementary organisational literature regarding information sharing, coordination and capability. From the above findings, the value pathway begins with governed data and moves through predictive sensing, feasible scenarios, cross-functional challenge, accountable choice and learning from execution; however, it does not create a direct relationship from model accuracy towards performance at the enterprise level.

The principal weakness of the evidence is related to governance because explainability and human judgement were explicitly observed in only a small proportion of the coded papers. The proposed augmented IBP control wheel responds to this gap by including human accountability, recording of overrides and feedback within the operating design. For researchers, the main priority is longitudinal and comparative evaluation through common outcomes of planning and business performance, while for managers, the priority is a bounded and measurable pilot supported by trusted information and clearly established decision rights. Therefore, AI should be treated as a governed planning partner whose recommendations can be challenged, traced and continuously improved.

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Appendix A. Included-study register

The register provides traceability for all 70 primary records. Year values reproduce the verified workbook field; some records use online-first metadata. Detailed metrics and limitations remain subject to manual full-text audit.

ID	Author–year	Study title	Planning domain	Primary category	DOI
R001	Schlegel et al. (2020)	Enabling integrated business planning through big data analytics: a case study on sales and operations planning	Integrated business planning (IBP)	Big data analytics	10.1108/ijpdlm-05-2019-0156
R002	Jazairy et al. (2024)	Impact pathways: walking a tightrope—unveiling the paradoxes of adopting artificial intelligence (AI) in sales and operations planning	Sales and operations planning (S&OP)	Artificial intelligence	10.1108/ijopm-07-2024-0582
R003	Wu et al. (2025)	Exploring adjustment mechanisms in the sales and operations planning process: an industrial case study	Sales and operations planning (S&OP)	Planning/decision-support technology	10.1108/ijopm-05-2024-0378
R004	Pacheco et al. (2025)	Enhancing sales and operations planning maturity: an integrative model for food supply chains in global networks	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1108/bpmj-01-2024-0021
R005	Goh et al. (2022)	Sales and operations planning culture and supply chain performance: the mediating effects of five coordination mechanisms	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1080/09537287.2022.2069058
R006	Tchokogué et al. (2022)	Learning from sales and operations planning process implementation at ASTRO Inc.	Sales and operations planning (S&OP)	Planning/decision-support technology	10.1108/bpmj-10-2020-0459
R007	Seeling et al. (2022)	The role of finance in the sales and operations planning process: a multiple case study	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1108/bpmj-07-2021-0447
R008	Swaim et al. (2016)	Antecedents to effective sales and operations planning	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1108/imds-11-2015-0461
R009	Fatemi-Anaraki et al. (2025)	Capacity representation in sales and operations planning: Aggregation through projection	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1080/24725854.2025.2477690
R010	Seeling et al. (2021)	Sales and operations planning: learnings from 15 Brazilian companies	Sales and operations planning (S&OP)	General planning/information-processing capability	10.14488/bjopm.2021.019
R011	Löffel et al. (2026)	Decision support for sales and operations planning under asymmetric power: A case study from the agrochemical industry	Sales and operations planning (S&OP)	Prescriptive analytics/optimisation	10.1177/10591478261457704
R012	Alfnes et al. (2025)	Case analysis of sales and operations planning (S&OP) systems in uncertain engineer-to-order (ETO) equipment production	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1016/j.ifacol.2025.09.352
R013	Santos et al. (2020)	A System Dynamics Model for Sales and Operations Planning	Sales and operations planning (S&OP)	Simulation/system dynamics	10.4018/ijsda.2020010101
R014	Kaipia et al. (2017)	Information sharing for sales and operations planning: Contextualized solutions and mechanisms	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1016/j.jom.2017.04.001
R019	Willms et al. (2019)	Emerging trends from advanced planning to integrated business planning	Integrated business planning (IBP)	General planning/information-processing capability	10.1016/j.ifacol.2019.11.602
R020	Wery et al. (2018)	Simulation-optimisation based framework for Sales and Operations Planning taking into account new products opportunities in a co-production context	Sales and operations planning (S&OP)	Prescriptive analytics/optimisation	10.1016/j.compind.2017.10.002

ID	Author–year	Study title	Planning domain	Primary category	DOI
R021	FAKHRY et al. (2022)	Making Decisions in Highly Uncertain and Opportunistic Environments: Towards a Decision Support System for Sales and Operations Planning	Sales and operations planning (S&OP)	Planning/decision-support technology	10.1016/ j.ifacol.2022.09.371
R022	Lim et al. (2017)	A simulation-optimization approach for sales and operations planning in build-to-order industries with distant sourcing: Focus on the automotive industry	Sales and operations planning (S&OP)	Prescriptive analytics/optimisation	10.1016/ j.cie.2016.12.002
R023	Shurrab et al. (2026)	An information-centric framework for sales and operations planning in engineer-to-order manufacturing: evidence from four industrial cases	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1080/09537287.2026.2668590
R024	Shurrab et al. (2026)	Adapting sales and operations planning to engineer-to-order complexity: a multifaceted information processing approach to managing uncertainty and equivocality	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1016/ j.ijpe.2026.110023
R025	Wu et al. (2024)	Global Sales and Operations Planning: exploring transitional pathway from a fit perspective	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1016/ j.procir.2024.10.228
R026	Fakhry et al. (2024)	A Financialized Model for a Risk-Focused Sales and Operations Planning	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1016/ j.ifacol.2024.09.118
R028	Xu et al. (2023)	A resource orchestration perspective of organizational big data analytics adoption: evidence from supply chain planning	Supply-chain planning	Big data analytics	10.1108/ijpdlm-04-2022-0118
R029	Yani et al. (2022)	Demand forecasting accuracy in the pharmaceutical supply chain: a machine learning approach	Demand planning and forecasting	Machine learning/deep learning	10.1108/ijphm-05-2021-0056
R030	Zhu et al. (2021)	Demand Forecasting with Supply-Chain Information and Machine Learning: Evidence in the Pharmaceutical Industry	Demand planning and forecasting	Machine learning/deep learning	10.1111/poms.13426
R031	Garre et al. (2020)	Application of Machine Learning to support production planning of a food industry in the context of waste generation under uncertainty	Production planning	Machine learning/deep learning	10.1016/ j.orp.2020.100147
R032	Feizabadi (2020)	Machine learning demand forecasting and supply chain performance	Demand planning and forecasting	Machine learning/deep learning	10.1080/13675567.2020.1803246
R033	Dinis et al. (2020)	ForeSim-BI: A predictive analytics decision support tool for capacity planning	Capacity planning	Predictive analytics	10.1016/ j.dss.2020.113266
R034	Lauer et al. (2019)	Application of machine learning on plan instability in master production planning of a semiconductor supply chain	Production planning	Machine learning/deep learning	10.1016/ j.ifacol.2019.11.369
R035	Stüve et al. (2025)	Supply chain planning in the food industry: mixed methods research on the adoption of advanced planning systems	Supply-chain planning	Planning/decision-support technology	10.1080/09537287.2025.2508719
R036	Hofmann et al. (2018)	Big data analytics and demand forecasting in supply chains: a conceptual analysis	Demand planning and forecasting	Big data analytics	10.1108/ijlm-04-2017-0088
R038	Fries et al. (2025)	Exploring AI Integration in SME Production Planning: Design Spaces and the Role of Workers	Production planning	Artificial intelligence	10.1007/s10606-025-09512-6
R040	Kache et al. (2017)	Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management	Supply-chain/operations planning capability	Big data analytics	10.1108/ijopm-02-2015-0078
R041	Ma et al. (2024)	How big data analytics and artificial intelligence facilitate digital supply chain transformation: the role of integration and agility	Supply-chain/operations planning capability	Big data analytics	10.1108/md-10-2023-1822

ID	Author–year	Study title	Planning domain	Primary category	DOI
R042	Prastuti et al. (2026)	A predictive analytics method for multiregional supply chain demand forecasting with spatial time series and machine learning	Demand planning and forecasting	Machine learning/deep learning	10.1016/ j.dajour.2026.100706
R043	Syberg et al. (2023)	Framework for predictive sales and demand planning in customer-oriented manufacturing systems using data enrichment and machine learning	Demand planning and forecasting	Machine learning/deep learning	10.1016/ j.procir.2023.09.133
R044	Xu et al. (2023)	Unfolding the link between big data analytics and supply chain planning	Supply-chain planning	Big data analytics	10.1016/ j.techfore.2023.12280 5
R045	He et al. (2020)	Internet-of-things enabled supply chain planning and coordination with big data services: Certain theoretic implications	Supply-chain planning	Big data analytics	10.1016/ j.jmse.2020.03.002
R046	Ooi et al. (2025)	Orchestrating agile omnichannel supply chain planning through big data analytics and end-to-end visibility	Supply-chain planning	Big data analytics	10.1016/ j.ajsl.2025.05.002
R047	Garred et al. (2026)	Automatic demand forecast model selection in supply chains: a forecast value-added analysis of selection strategies, machine learning, and hyperparameter optimisation	Demand planning and forecasting	Machine learning/deep learning	10.1080/00207543.20 26.2623194
R048	Olan et al. (2024)	Enabling explainable artificial intelligence capabilities in supply chain decision support making	Supply-chain/operations planning capability	Artificial intelligence	10.1080/09537287.20 24.2313514
R049	Gunasekaran et al. (2017)	Big data and predictive analytics for supply chain and organizational performance	Supply-chain/operations planning capability	Big data analytics	10.1016/ j.jbusres.2016.08.004
R050	Wamba et al. (2017)	Big data analytics and firm performance: Effects of dynamic capabilities	Supply-chain/operations planning capability	Big data analytics	10.1016/ j.jbusres.2016.08.009
R051	Wang et al. (2016)	Big data analytics in logistics and supply chain management: Certain investigations for research and applications	Supply-chain/operations planning capability	Big data analytics	10.1016/ j.ijpe.2016.03.014
R054	Raut et al. (2021)	Big data analytics: Implementation challenges in Indian manufacturing supply chains	Supply-chain/operations planning capability	Big data analytics	10.1016/ j.compind.2020.10336 8
R055	Belhadi et al. (2021)	Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation	Supply-chain/operations planning capability	Artificial intelligence	10.1007/s10479-021-03956-x
R056	Baryannis et al. (2019)	Predicting supply chain risks using machine learning: The trade-off between performance and interpretability	Supply-chain/operations planning capability	Machine learning/deep learning	10.1016/ j.future.2019.07.059
R057	Ivanov et al. (2020)	A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0	Supply-chain/operations planning capability	General planning/information-processing capability	10.1080/09537287.20 20.1768450
R061	Long et al. (2025)	Leveraging synthetic data to tackle machine learning challenges in supply chains: challenges, methods, applications, and research opportunities	Supply-chain/operations planning capability	Machine learning/deep learning	10.1080/00207543.20 24.2447927
R064	Abolghasemi (2025)	The power of information sharing: evaluating POS and order data for hierarchical forecasting in multi-echelon supply chains	Supply-chain/operations planning capability	Predictive analytics	10.1080/00207543.20 25.2532756
R066	DuHadway et al. (2017)	A Simulation for Managing Complexity in Sales and Operations Planning Decisions	Sales and operations planning (S&OP)	Predictive analytics	10.1111/dsji.12134

ID	Author–year	Study title	Planning domain	Primary category	DOI
R067	Roscoe et al. (2020)	Stakeholder engagement in a sustainable sales and operations planning process	Sales and operations planning (S&OP)	General planning/information-processing capability	10.1002/bse.2594
R069	Abay et al. (2026)	Stochastic Multi-Objective Sales and Operations Planning with Plan Stability Objectives and Supply Order Allocation Using Simulation–Optimization	Sales and operations planning (S&OP)	Prescriptive analytics/optimisation	10.20965/ijat.2026.p0189
R083	Riad et al. (2024)	Enhancing Supply Chain Resilience Through Artificial Intelligence: Developing a Comprehensive Conceptual Framework for AI Implementation and Supply Chain Optimization	Demand planning and forecasting	Artificial intelligence	10.3390/logistics8040111
R084	Keswani (2026)	An intelligent decision-making system integrating fuzzy logic and machine learning for pharmaceutical closed-loop supply chain and production planning in an uncertain environment	Production planning	Machine learning/deep learning	10.1108/ijphm-05-2025-0078
R085	Shen et al. (2025)	Integration of Machine Learning-Based Demand Forecasting and Economic Optimization for the Natural Gas Supply Chain	Demand planning and forecasting	Machine learning/deep learning	10.3390/en18236172
R086	Abdi et al. (2025)	A Machine Learning-Based Approach for Multi-Objective, Multi-Product, and Multi-Period Supply Chain Optimization via Demand Forecasting	Demand planning and forecasting	Machine learning/deep learning	10.1109/access.2025.3600092
R087	Rao et al. (2025)	Demand Forecasting and Allocation Optimization of Green Power Grid Supply Chain Based on Machine Learning Algorithm: A Study Based on the Whole-Process Data of Power Grid Materials	Demand planning and forecasting	Machine learning/deep learning	10.3390/su17031247
R088	Elmir et al. (2023)	Smart Platform for Data Blood Bank Management: Forecasting Demand in Blood Supply Chain Using Machine Learning	Demand planning and forecasting	Machine learning/deep learning	10.3390/info14010031
R089	Saivijayalakshmi et al. (2026)	Forecasting Regional Coffee Demand by Comparative Analysis of Various Machine Learning Techniques, Along with Supply Chain Optimization	Demand planning and forecasting	Machine learning/deep learning	10.58346/jisis.2026.i1.019
R090	Bais et al. (2026)	Machine Learning-Driven Demand Forecasting in the Automotive Supply Chain	Demand planning and forecasting	Machine learning/deep learning	10.1155/acis/3548471
R092	Aldahmani et al. (2024)	Demand Forecasting in Supply Chain Using Uni-Regression Deep Approximate Forecasting Model	Demand planning and forecasting	Machine learning/deep learning	10.3390/app14188110
R093	Ma et al. (2023)	Deep Learning Combinatorial Models for Intelligent Supply Chain Demand Forecasting	Demand planning and forecasting	Machine learning/deep learning	10.3390/biomimetics8030312
R094	Lau et al. (2018)	Parallel Aspect-Oriented Sentiment Analysis for Sales Forecasting with Big Data	Demand planning and forecasting	Big data analytics	10.1111/poms.12737
R095	Jasiński (2024)	The demand planning renaissance: A data-driven approach	Demand planning and forecasting	Artificial intelligence	10.69554/xmob6236
R096	Nagadevi et al. (2025)	XGBoost-Based Demand Forecasting in Supply Chain Management Using Machine Learning Algorithm	Demand planning and forecasting	Machine learning/deep learning	10.3991/ijim.v19i18.57253
R097	Xu (2025)	Enhancing Supply Chain Demand Forecasting Through Gated Graph Neural Networks and Federated Learning Systems	Demand planning and forecasting	Machine learning/deep learning	10.31449/inf.v49i31.10292

ID	Author–year	Study title	Planning domain	Primary category	DOI
R098	Amellal et al. (2024)	An integrated approach for modern supply chain management: Utilizing advanced machine learning models for sentiment analysis, demand forecasting, and probabilistic price prediction	Demand planning and forecasting	Machine learning/deep learning	10.5267/ j.dsl.2023.9.003
R099	El Filali et al. (2022)	Machine Learning Applications in Supply Chain Management: A Deep Learning Model Using an Optimized LSTM Network for Demand Forecasting	Demand planning and forecasting	Machine learning/deep learning	10.22266/ ijies2022.0430.42
R101	Wang et al. (2023)	Demand Forecast of Railway Transportation Logistics Supply Chain Based on Machine Learning Model	Demand planning and forecasting	Machine learning/deep learning	10.4018/ijitsa.323441