Strategic Management Analytics Journal
Vol. 1, Issue 1, 2026

Vol. 1, Issue 1, pp. 46-58, 2026

Predictive Analytics in Strategic Decision-Making: Forecasting Models for Organizational Planning in Multinational Firms in Asia

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Abstract

Predictive Analytics has transitioned from an arcane forecasting capability into a strategic capability that influences a global firm's understanding of uncertainty, planning resources, managing distributed operations, and preparing for future market conditions. The purpose of this article is to critically examine the role of predictive analytics and forecasting models in organization planning in multinational companies in Asia. Draws upon research in business analytics, forecasting, supply-chain management, information systems, and strategic management with a focus on India, China, Indonesia, Pakistan, Taiwan, Thailand, and other supply chains in Asia. The review reveals that the strategic worth of predictive analytics isn't only due to the sophistication of the algorithm. Achieving reliable planning requires that data quality, forecasting horizon, model structure, managerial judgment, cross-border information integration, knowledge of analytics and governance all align. Traditional time-series methods continue to have their uses in situations where patterns are stable and data structures are transparent, but machine-learning, deep learning, hierarchical, spatial and hybrid models have their merits in the high dimensional and nonlinear cases. But evidence also shows that human expertise is still required to interpret the structural breaks, geopolitical shocks, regulatory changes and signals in the market that may not have been picked up by historical data. The best forecasting systems for various multinational companies are therefore those that incorporate scalable analytics and local market expertise and governance frameworks that maintain explainability, accountability, and strategic relevance. The authors argue for an integrated planning approach where predictive models are used to inform sensing and scenario building, manage resources and support adaptive execution, but do not substitute managerial decision making. It comes to the conclusion that the use of predictive analytics is best when it is translated into a dynamic organizational capability and is integrated in organized and learning-oriented decision-making processes between the headquarters and subsidiaries.

Key words: *Predictive analytics; strategic decision-making; forecasting; multinational firms; organizational planning; Asia*

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Article History

Received: 24 June 2026 | Revised: 29 July 2026 | Accepted: 24 August 2026

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1. Introduction

Executing strategic decision-making in multinational companies is becoming more and more volatile, complex and time-critical. Firms that are making decisions across Asian markets face interdependent decisions regarding demand, capacity, sourcing, inventory, investment, market entry, labour deployment, pricing and risk exposure while dealing with varying consumer preferences, regulatory regimes, infrastructure settings, and competition. Such a setting can make planning decisions, made mainly on historical average or managerial intuition, inadequate. Predictive Analytics offers a formal way of transforming the vast amounts of internal and external data to predictions of future conditions, likelihoods and actionable scenarios. Predictive analytics is different from explanatory modeling as a model that explains past relationships is not necessarily optimized to predict future observations (Shmueli & Koppius, 2011). This distinction is of fundamental importance for organizational planning because not only do managers need to understand why it happened but the ability to make reasonably predictable estimates of what may happen next and the performance of alternative organizational actions in the face of uncertainty.

Today, as multinational companies have become digital, the strategic value of analytics has been rising as transactions are linked across enterprise resource planning, ecommerce, customer relationship, supply-chain, sensor and digital environments. The capacities of big data analytics enable firms to integrate technological infrastructure, managerial processes, data resources, and analytical talents to enhance their performance and adaptability (Gupta & George, 2016; Wamba et al., 2017). Overall, evidence from the Indian companies suggests that size of big data analytics positively influences quality of decision making, forecasting processes, and performance of the firm, thus supporting the idea that big data analytics can be a strategic planning tool and not just a reporting tool for operations (Chatterjee et al., 2023). Recent data from Taiwanese MNC electronics companies also show that supply-chain decision agility can be improved through the use of analytics capability, especially when managers are also literate in AI to understand and use the outputs of analytics (Tai et al., 2026).

Asia is a very important perspective on the impact of predictive analytics. The region features well digitized mature economies, fast industrializing developing economies, rich supply chains of advanced manufacturing across several tiers and across jurisdictions, and large markets of consumers. These attributes present a chance and a methodological challenge. The relationships which are represented in these data can often be volatile — changes in demand, technology, policy, exchange rates, logistics capacity and competitive structure can occur rapidly. Multinational enterprise's predictive models must therefore account for cross-sectional heterogeneity, hierarchical product structures, spatial dependence, nonlinear trends, structural change, and short-term operational forecasting versus long-term strategic planning.

1.1 Purpose and Scope of the Article

This paper examines the role of predictive analytics in decision-making and planning within the context of multinational companies in Asia. Its main goal is to describe the different methods of forecasting and how these methods can be used to facilitate strategic sensing and allocation of resources, scenario development and adaptive execution. It includes an overview of conventional time-series approaches, machine-learning and deep learning techniques, hierarchical and multiregional forecasting, hybrid models, and integration between humans and analytics. The article also explores the organizational factors that make the difference in whether or not predictive outputs drive high-level decisions, such as analytics capability, management support, cross-border data integration, strategic agility, and model governance.

1.2 Review Approach

The article uses an integrative review approach. Strategic management, information systems, forecasting, operations management, supply-chain analytics, and business analytics peer-reviewed studies are synthesized and a focus is placed on studies that relate forecasting or analytics to managerial decision-making. Special attention is paid to new empirical evidence from Asian contexts, and some of the

fundamental forecasting and analytics oriented studies are also accommodated if they provide a concept or method that is needed for interpretation. The review is not simply descriptive, but also analytical, dealing with the situations in which models are useful for planning, the situations where they fall short, and how organizations can integrate quantitative forecasts with managerial knowledge. The primary data do not exist, and empirical statements refer to the cited studies.

2. Conceptual and Theoretical Foundations

2.1 Predictive Analytics as a Strategic Capability

Predictive analytics involves the application of statistical, computational and machine learning tools for predicting future events based on past and current data. In an organization it is important because of its strategic relation with analytical outputs and decision making. A technically correct forecast, which doesn't change the way resources are allocated, when or how they are deployed, risk position or strategic decision is not very useful. The resource-based view offers some insights about the way by which analytics systems can provide an advantage: A capability, in the form of data, technology, analytical routines, management processes and skilled personnel, must be joined together to become an advantage that is difficult to imitate (Gupta & George, 2016). An interpretation that focuses on building an organizational system for turning data into action rather than buying software itself.

Dynamic-capability theory further adds the concept that the capability of a firm is the ability to sense, seize, and reconfigure in the face of changing environmental conditions. Big data can be used to enhance these processes, making them faster and more detailed, enabling companies to identify changes in market demand, supply, customer behavior, operational bottlenecks, or new market opportunities. Wamba et al. (2017) demonstrated that analytics can impact performance of the firm through dynamic capabilities, and Mikalef et al. (2019) revealed that big data analytics capabilities can influence innovation via dynamic capabilities, which vary in their degrees of influence based on environmental conditions. Predictive analytics can thus be seen in the context of a whole-scale sensing-and-reconfiguration architecture for multinational companies.

2.2 From Descriptive Analytics to Strategic Forecasting

The goal of analytics is sometimes defined in this progression: Descriptive analysis – What has happened? Diagnostic analysis – Why did it happen? Predictive analysis – What is likely to happen? Prescriptive analysis – What should be done? All four layers are used in the strategic planning process. The descriptive dashboards are designed to provide information on current performance, diagnostics analysis looks for causal or correlational drivers, predictive modeling is meant to estimate what the future may look like, and prescriptive analysis is used to determine the actions that can be taken. But going from one level to another adds in assumptions and uncertainty. Strategic forecasts potentially rely on scenarios involving regulation, technology, competitor actions, currency changes or geopolitical events that may not be fully captured in historical data sets. Therefore, top managers often complement the analytics with their own and stakeholder expertise where long-term decisions are concerned and the resource base of the firm is concerned with change (Orjatsalo et al., 2025).

2.3 Multinational Complexity and the Asia Context

The planning problem of multinational firms is a spatial and necessarily hierarchical one. Forecasts may be done at headquarters by region, at regional offices by country, or at subsidiaries by product, customer, facility or channel. These forecasts go up and down through the organization and need to be coherent. Meanwhile, demand in one market may have interconnections with adjacent markets, via supply chains, substitution, trade, common distribution facilities and macroeconomics. Because of this, hierarchical forecasting methods are appealing as they provide a compromise between the levels of forecasting, and spatial or multiregional methods can account for dependence of markets. In Indonesia, recent studies have

highlighted how spatial time-series models can be integrated with machine-learning techniques to forecast demand in multi-regions, especially when interregional dynamics have an impact on the reliability of the forecast (Prastuti et al., 2026).

2.4 Strategic Agility, Analytics Literacy, and Organizational Learning

Organizational responsiveness is a moderator in the value of predictive analytics. Forecasts are of limited strategic value when decision-making is lengthy, authority is not well defined, or managers' interpretation of uncertainty is limited. The research of multinational corporations in Thailand indicates that strategic agility, organizational learning, and entrepreneurial innovation are the three factors for enhancing performance through the use of big data analytics capabilities. The data from Taiwan also shows that managerial AI literacy can boost the relationship between analytics capability and decision agility in high-tech multinational companies (Tai et al., 2026). The results indicated that the forecasting ability can be described from two aspects: technical and cognitive. Senior managers must have sufficient knowledge of the model assumptions, uncertainty, bias, and validation to be able to determine when to trust an analytical recommendation and when to use local knowledge and scenario judgment.

3. Forecasting Models for Organizational Planning

3.1 Traditional Time-Series Models

When data have stable temporal structure, traditional forecasting models are still very important for organizations' planning purpose due to their transparency, computational simplicity, and often competitiveness. For sales, demand, cash flow, staffing and capacity planning, exponential smoothing models, autoregressive integrated moving average (ARIMA) models, state-space approaches and regression-based time-series models are popular. According to Hyndman and Athanasopoulos (2021), the choice of method should start with the structure of the time series such as trend, seasonality, cycles, autocorrelation and the forecasting horizon. These models are especially valuable if decision makers want a forecast and a confidence interval, but do not want to understand the underlying relationship between patterns and future estimates, since that relationship can be explained to the nontechnical decision makers.

Comparative evidence also points to the continuing use of the traditional approach. Makridakis et al. (2018) demonstrated that machine-learning approaches are not necessarily superior to the classic time-series forecasting approaches in all scenarios. The bottom line for multinational corporations is to not consider algorithmic complexity as a proxy of accuracy. For a well-established product that is cyclic, a seasonal exponential smoothing model might be more accurate than a deep learning network that is trained on a short time series. It is therefore recommended that strategic planning should make use of benchmark models and that advanced methods are necessary to show incremental value using out-of-sample validation.

3.2 Machine Learning and Deep Learning

Machine-learning models are particularly useful when an organisation has a large amount of data with nonlinear relationships, many predictor variables, interactions and high-frequency signals. Random forests, gradient-boosting machines, support-vector regression, neural networks, and recurrent architectures are able to capture patterns that are hard to specify by standard linear specifications. Carbonneau et al. (2008) gave first results on the application of machine-learning in the domain of supply-chain demand forecasting; later research has extended the application of machine-learning to complex multi-product and multi-echelon settings. For instance, Zhu et al. (2021) showed how machine learning can be used to integrate information across product series and integrate downstream inventory and supply-chain information to improve pharmaceutical demand forecasting.

One of the best parts of machine learning for strategic decision making is not just the increased accuracy of points, but the ability to combine a variety of signals. In the case of a business that operates in multiple

countries, the company can integrate history sales data with digital search trends, promotions and macroeconomic data, currency fluctuations, competitor pricing, lead times, weather, social media data and channel inventory. This provides a deeper perspective of the dynamics in the marketplace. But a problem of governance arises in the case of high dimensional modeling. Complex models can be hard to interpret, can be sensitive to changes in the data generating process, and can be susceptible to overfitting. Thus, model monitoring routines, drift detection and recalibration at regular intervals are required. The usefulness of deep-learning models is best suited to situations where there is a large volume and complexity of data, and not to replace simpler models simply because they are newer.

3.3 Hierarchical, Spatial, and Hybrid Forecasting

When planning a multinationals, forecasts are often needed to be internally consistent, across products, regions and organizational levels. This problem is tackled in hierarchical forecasting by producing or reconciling forecasts among a series tree. Hyndman et al. (2011) showed the usefulness of optimal combination techniques for hierarchical time series. More recently, Taghiyeh et al. (2023) proposed a multi-phase machine learning method which leverages the child-level and parent-level data and reported significant improvements in prediction accuracy compared to traditional hierarchical methods. These approaches are directly applicable to companies which need to link forecasts from one country to the next, SKU plans to category and corporate plans, etc.

Also, the spatial and hybrid models are relevant in the case of Asian multinationals as markets and the areas of supplies are not independent. Prastuti et al. (2026) combined the generalized space-time autoregressive structure with support-vector regression and recurrent neural networks to predict the cement demand in interconnected regions of Indonesia. Their results demonstrate a general rule: models can be enhanced by taking into account both spatial dependence and nonlinear temporal processes. Hybrid forecasting is thus ideally suited for forecasting in a multinational context, where planners need to consider cross-border substitution, common suppliers, port or transport congestion, and regional economic spillovers.

3.4 Human Judgment and Model Combination

In many cases, structural breaks, policy changes, competitors actions, product launches and crisis events include information not yet captured in historical data. This ensures a role for management judgment on an ongoing basis. However, there is a potential for judgmental adjustments to introduce bias when forecasters make changes to the output of their models in a non-disciplined manner. Wibowo (2024) demonstrates how causal machine learning can be used to identify when changes to statistical forecasts are likely to be helpful. Brau, F., et al. (2023) also conclude that human judgment, when applied in a structured manner, can enhance the demand planning process. Their human-guided learning paradigm underscores that it is not about human or algorithm, but about how human and algorithm should interact.

This interaction is even more critical for long-horizon planning. Punia (2025) suggests a medium to long term forecasting decision model using machine learning, time-series forecasts, expert judgment and interval. From a conceptual standpoint, this is suitable to multinational strategy, as long-term projections should be frequently communicated as a range and scenario instead of a misleadingly precise point estimate. Human experts can include information on policy, investment plans, market entry, technology transitions, and institutional change, models can offer consistency, historical discipline, and quantification.

3.5 Model Evaluation and Strategic Use

Several measures of forecast accuracy should be used since no single measure reflects all the managerial implications. The measures of mean absolute error, the root mean squared error, the mean absolute percentage error and scaled measures offer varying weightings on the errors and their comparability. But there are also cost-sensitive measures for strategic evaluation. The economic impact of an underforecast which results in lost sales or production shortfalls can be different from that of an overforecast which leads

to higher levels of inventory. Forecasting systems should, therefore, be linked to loss functions in the businesses, service levels, cash flow, working capital or capacity costs. Models should also be tested in a time horizon perspective, since a model that works well over 4 weeks might not work over 2 years of capital plans.

The major forecasting methods pertinent to multinational organizational planning are summarized in Table 1.

Forecasting approach	Primary strengths	Best-fit planning uses	Key limitations
Exponential smoothing / ARIMA	Transparent, efficient, strong benchmarks for stable temporal patterns	Routine sales, inventory, cash-flow and capacity forecasts	Limited handling of nonlinear high-dimensional signals; vulnerable to structural breaks
Regression / dynamic regression	Can incorporate identifiable external drivers and support interpretation	Planning linked to price, macroeconomic, promotional or market variables	Requires specification discipline; relationships may change across markets
Machine learning	Captures nonlinearities, interactions and many predictors	Demand, churn, risk, pricing and complex operational forecasts	Overfitting, data hunger, explainability and model-drift concerns
Deep learning	Useful for large sequential or high-frequency datasets and complex temporal patterns	Large-scale multi-SKU or sensor-rich forecasting	High computation and data requirements; limited interpretability
Hierarchical forecasting	Produces coherent forecasts across products, countries and organizational levels	Regional-country-SKU planning and portfolio reconciliation	Reconciliation design and data hierarchy can be complex
Spatial / multiregional models	Represents dependence between geographic markets	Regional demand, logistics and interconnected supply planning	Requires stable spatial relationships and high-quality regional data
Hybrid human-analytics models	Combines statistical discipline with private or contextual knowledge	Long-horizon planning, structural breaks, policy shocks and launches	Judgment can introduce bias unless integration is structured

4. Evidence and Strategic Applications in Multinational Firms in Asia

4.1 Evidence from Asian Firms

An emerging body of evidence from Asia suggests that the capability to do analytics is linked to improved forecasting, agility, and organizational performance; how that happens depends on the context. Based on the data from 366 respondents of the Indian firms, Chatterjee et al. (2023) discovered that big data analytics has impact on forecast and decision making processes and firm performance. In northern India, Korayim et al. (2024) discovered that data-driven culture and technologically proactive climates enabled the value to be gained from big data use to be enhanced by organizational innovation. These studies suggest that evidence-based decision making yields better outcomes when organizational culture values the evidence, and does not rely on analytics as a technical support service.

The capability perspective is also supported by evidence from Pakistan. Based on this, Yasmin et al. (2020) revealed the interdependence and association of infrastructure, management, human-resource analytics capabilities with firm performance. The finding is relevant for multinational subsidiaries as regional offices

are sometimes given a highly capable analytics platform by headquarters, and do not have equivalent level of data governance, skills or process redesign. Transferring technology without organisational capacity can thus result in a gap in implementation. Big Data Analytics capability of multinational companies is seen to impact their performance in terms of strategic agility, innovation and organizational learning in Thailand (Duangekanong 2025). Tai et al. (2026) find that in Taiwan, both technical and managerial analytics capabilities are correlated to supply-chain decision agility, and managerial AI literacy amplifies their impact. All of these findings imply that planning performance is dependent on complementary managerial capacities.

4.2 Demand, Supply, and Capacity Planning

The most advanced use of predictive analytics for Asian multinationals is demand and supply planning. The regional demand forecast has an impact on production allocation, procurement, transportation, safety stock, positioning of the warehouses, and capital utilisation. Forecast errors can lead to either shortages or surplus working capital, which can ripple through supply networks. These errors can be minimized through advanced analytics that takes into account demand history, channel, inventory, promotion, and market data. Zhu et al. (2021) show the importance of information from the supply chain and the use of cross-series machine learning in pharmaceutical forecasting, and Prastuti et al. (2026) show how the regional dependence can be modelled explicitly in Indonesia. Multinational companies can have similar architectures to coordinate multiple Asian markets that share manufacturing or distribution facilities.

Forecasting also aids in capacity and network design. If a multinational considers expanding a plant, establishing a distribution center, dual sourcing a key item or relocating production from one country to another, they need to make a best guess estimate about the level of volume, variability of lead time, and risk of disruption over a longer time horizon. Such decisions are not made on a routine basis like typical demand planning; they are partially irreversible and impactful. Thus, it is advisable to combine the predictive models with the scenario analysis and sensitivity testing. Planners should ask not for one 'correct' future, but what are the performances of strategic alternatives in face of plausible demand, cost and risk futures.

4.3 Market, Customer, and Portfolio Planning

Predictive Analytics is not just about operations, it's about market strategy as well. Multinational companies can predict churn, product uptake, promotion response, prices sensitivity, lifetime value and channel switching. Such predictions can be used to guide allocation of resources across brands and countries. But it needs to be strategically transferred across markets. For instance, consumer behaviour learned in one Asian country may not translate into another due to varying cultural preferences, income distribution, digital-platform usage, regulation as well as channel structures. Therefore, multinational firms should take a balance between the global model standardization and the local calibration. Shared architecture can enhance scalability and governance, and subsidiary-specific features can keep them relevant.

4.4 Financial, Workforce, and Risk Forecasting

Financial forecasts and human-capital forecasts are also required when making organizational plans. Predictive models for revenue, cash flow, foreign-exchange exposure, working capital, headcount, demand for skills, and attrition. By connecting these predictions, companies can determine if strategic plans are feasible from an operational point of view. For instance, forecasts of new labor requirements for a technology market might need to be accompanied by forecasts of labor availability, labor costs, suppliers' capacity, and infrastructure limitations. The key is to integrate forecasts, not to optimize each function. Predictive analytics can become more useful if it establishes a common set of facts for cross-functional planning.

4.5 Challenges in Cross-Border Predictive Planning

However, predictive analytics has a number of limitations in a multination Asian context. First, data quality is not the same across the subsidiaries as information systems, information definitions and reporting discipline are different. Second, regulatory frameworks may impose data transfer restrictions or mandate data localization, which hampers the development of centralized data sets. Thirdly, structural changes can lead to a rapid decline in model performance. Fourth, managers might be too impressed with the quantitative products, since models seem objective. Fifth, there may be some resistance to centrally-developed models that fail to include market-specific knowledge by local teams. Lastly, black-box algorithms may lead to accountability issues if predictions are used to guide employment, credit, pricing or decision-making regarding scarce resources.

These constraints serve as a reminder of the socio-technical nature of analytics. According to Vidgen et al. (2017), organizations must balance a complex mix of technology, people, processes and governance to create value from business analytics. Similarly, Raisch and Krakowski (2021) state the automation-augmentation paradox: AI can free up some managerial duties at the same time it becomes more necessary than ever for human judgment. Thus, disciplined augmentation should be the goal for multinational planning. Models should automate the detection of repetitive patterns and computation of scenarios, but managers are responsible for assumptions and exceptions, as well as for ethics and strategic commitments.

4.6 Cross-Functional Planning and Forecast Integration

Another strategic challenge is that forecasts may be siloed within functions of the organisation. The sales staff might provide projections of commercial revenues, the finance staff might provide projections of revenues and cashflow, the supply-chain staff could provide projections of what number of units will be required to be sold, the human-resource staff could provide projections of workforce requirements and the strategy staff could provide macroeconomic scenarios. If the forecasts are based on varying assumptions, then multinational firms may develop plans which are internally inconsistent even though each plan may be technically sound. A shared set of scenarios, explicit model interactions, and a reconciliation process, where functional forecasts are reconciled to shared constraints, is needed for integrated planning. For instance, if sales are projected to grow fast, then the questions should include, among others, production capacity, supplier availability, logistics throughput, number of employees, working capital and capital expenditures. Predictive analytics can be of great strategic value if it can reveal these interdependencies before they are too late for management.

Such a cross-functional integration is particularly crucial in a multinational organization, where a single decision can have various impacts in different countries. A regional promotion can increase sales in multiple markets while causing a production constraint at a common plant; a currency devaluation can enhance the exporter subsidiaries' margins while raising the cost of imported inputs in other subsidiaries; a disruption at a supplier in East Asia can affect production plans across a broader network. Therefore, companies should create planning models that will enable forecasts to cascade through interdependent financial and operational variables. The aim is not a one-size-fits-all algorithm for the entire enterprise, but a system of governed local models that share the same vocabulary of definitions, the same scenarios and assumptions, and the same reconciliation rules. This integration also enhances organizational learning since managers can identify when which of their assumptions were inaccurate when actual outcomes deviate from what was planned.

Table 2 summarizes the key findings from the Asian evidence related to multinational planning.

Context	Evidence	Strategic implication
India	Big data analytics associated with improved decision-making, forecasting and firm performance (Chatterjee et al., 2023)	Analytics should be integrated into planning processes rather than confined to reporting

Context	Evidence	Strategic implication
India	Data-driven culture and technological proactivity strengthen innovation-related value from big data (Korayim et al., 2024)	Culture and managerial sponsorship are complements to forecasting technology
Pakistan	Infrastructure, management and human-resource analytics capabilities are interdependent (Yasmin et al., 2020)	Regional subsidiaries need capability development, not only platform deployment
Thailand MNCs	Analytics improves strategic agility, learning, innovation and performance (Duangekanong, 2025)	Forecasts create value when firms can act on them quickly
Taiwan MNCs	Analytics capability and managerial AI literacy support supply-chain decision agility (Tai et al., 2026)	Executive analytics literacy should be treated as a strategic capability
Indonesia	Hybrid spatial-time-series and ML models improve multiregional demand forecasting (Prastuti et al., 2026)	Cross-region dependence should be modeled explicitly in shared supply networks
China / wider digital Asia	Digital transformation and analytics-intensive operating models are increasingly linked to efficiency and adaptive performance	Forecasting should be embedded within broader digital-transformation and governance programs

5. Strategic Implications, Governance, and Conclusion

5.1 Building an Integrated Predictive Planning Architecture

For multinational companies in Asia, predictive analytics should be an enterprise planning architecture, not a series of stand-alone models. Data integration – common definitions, master data, reliable pipelines and governed access across subsidiaries is the first layer. The second layer is called modeling, which can involve comparing statistical models, advanced machine learning models (when applicable) and hierarchical or spatial reconciling (if markets are interdependent). The third layer is decision integration: forecasts need to be integrated into the planning cycles of sales and operations planning, budgeting, portfolio reviews, workforce planning and strategic scenario analyses. The fourth layer is learning: Error in forecast, managerial override, and realized outcomes should be recorded and used to enhance models and decision processes.

5.2 Match the Model to the Decision Horizon

Do not choose models based on technological fad but rather on the decision problem. High frequency data and the use of machine learning nonlinear models can be useful for short term operational decisions. Hierarchical forecasts across products and geographies may be needed for medium-term planning. In long-term, strategic decision making, scenarios, intervals, causal assumptions and human judgement (rather than historical relationships) should be given greater weight as the horizon lengthens. This principle will stop companies from using the same forecasting infrastructure on each issue. It also sorts out expectations: a strategic forecast must provide strong decisions in the face of uncertainty and not provide false certainty.

5.3 Strengthen Managerial Analytics and AI Literacy

Empirical evidence from Taiwan's multinationals reveals that managerial AI literacy is not incidental, but rather influences the extent to which analytics translates into agility (Tai et al., 2026). Executives don't need to be data scientists, but they should know the difference between correlation and causation, bias, drift, data leakage, feature importance and validation and what they mean. They should also be able to ask themselves if the training data reflect the present market situation. Therefore, training should be geared toward decision oriented analytics literacy, rather than just software operation. At subsidiary level, local manager(s) should be involved in model review to ensure that local knowledge is incorporated into the model in a systematic way and not as an informal resistance or override.

5.4 Governance, Ethics, and Model Risk

Strategic decisions are based on predictive models which need governance equivalent to any other material organizational risk. Companies should have model inventories, owners, schedules for validation, documented assumptions, override policies, and escalation thresholds. High impact models should be challenged stand-alone, in particular if they impact employment, customer treatment, investment or supply commitments. Level of explainability should be commensurate with the consequences of the decision. If you're replenishing the same products every day, a very complex model might be fine if you've been using it for a while and it's been well validated; if you're divesting or restructure your workforce, you need interpretable evidence, uncertainty ranges, and scenario explanations. Governance is also required to avoid 'automation bias' when decision makers take an algorithmically generated ‘prediction' on face value.

The issue of cross-border comparability and fairness should also be tackled in governance. History can be embedded in the data with unequal market access or biased customer treatment or legacy operational constraints. Predictive systems can reproduce these patterns in the future plans if they are treated as neutral signals. Multinational firms should, therefore, differentiate between forecasting of what is likely to happen in the given situation and decision making of what should happen in the light of corporate strategy or ethical considerations. There may be local legal restrictions that a centralized analytics function is unaware of, and model review committees may request sensitivity data on various groups—demographic, geographic or subsidiary. When forecasts are passed from one country to another, it is especially crucial to document model limitations, as a model's apparent success in one environment does not necessarily mean it is valid in another.

5.5 Research Implications

Longitudinal and multi-country designs would be interesting in the future to explore predictive analytics in multinational companies. Many of the current data are based on the findings of one-off surveys, providing only associations and not fully demonstrating how the capability of analytics improves over time and how it helps to make decisions. The model performance should be compared among subsidiaries, the role of headquarters-subsidiary power dynamics with regard to adoption should be explored and the implications of data localization and regulatory fragmentation should be analyzed. Studies that relate forecast accuracy to strategic measures like investment quality, resilience, capital efficiency and market-entry performance are also needed. As generative AI and foundation models become more prevalent, additional uncertainties are raised about synthetic scenarios, unstructured data, explainability, and the governance of AI-powered strategic planning.

5.6 Conclusion

For multinational companies doing business in Asia, predictive analytics is now a key strategic capability, helping them to better predict demand and manage geographically scattered operations, analyse scenarios and make decisions in uncertain environments. The evidence discussed in this article has shown that big data analytics, machine learning, hierarchical approach, spatial models, and systematic incorporation of human judgment all have the potential to improve the quality of forecasts. But the most effective ending isn't just technical. Predictive Analytics adds value for a company when it has the backup to gather reliable data and decipher the model's results, align forecasts at different levels of the organization, integrate lessons learned into the model, and rapidly take action based on new data.

There is no single system that is completely centralized or completely local that will be a successful system of predictive planning for multinational firms. Headquarters can supply common data standards & platforms, model governance and cross-market learning; subsidiaries can supply context data & market specific calibration. Such a mix enables the organization to leverage scale while simultaneously not stifling local intelligence. Predictive analytics is an adaptive, governed, learning-oriented decision capability that,

when applied to the rapidly evolving markets of Asia, will help firms leverage uncertainty as a source of strategic responsiveness, rather than a constraint in planning.

References

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? International Journal of Production Economics, 182, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

Brau, R., Aloysius, J., & Siemsen, E. (2023). Demand planning for the digital supply chain: How to integrate human judgment and predictive analytics. Journal of Operations Management, 69(6), 965–982. https://doi.org/10.1002/joom.1257

Carbonneau, R., Laframboise, K., & Vahidov, R. (2008). Application of machine learning techniques for supply chain demand forecasting. European Journal of Operational Research, 184(3), 1140–1154. https://doi.org/10.1016/j.ejor.2006.12.004

Chatterjee, S., Chaudhuri, R., Gupta, S., Sivarajah, U., & Bag, S. (2023). Assessing the impact of big data analytics on decision-making processes, forecasting, and performance of a firm. Technological Forecasting and Social Change, 196, 122824. https://doi.org/10.1016/j.techfore.2023.122824

Choi, T.-M., Wallace, S. W., & Wang, Y. (2018). Big data analytics in operations management. Production and Operations Management, 27(10), 1868–1883.

Cui, L., Wang, Z., Liu, Y., & Cao, G. (2024). How does data-driven supply chain analytics capability enhance supply chain agility in the digital era? International Journal of Production Economics, 277, 109404. https://doi.org/10.1016/j.ijpe.2024.109404

Duangekanong, S. (2025). The impact of big data analytics on firm performance through strategic agility in multinational corporations (MNCs) in Thailand. Global Business and Finance Review, 30(2), 72–85. https://doi.org/10.17549/gbfr.2025.30.2.72

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. Information & Management, 53(8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

Hyndman, R. J., Ahmed, R. A., Athanasopoulos, G., & Shang, H. L. (2011). Optimal combination forecasts for hierarchical time series. Computational Statistics & Data Analysis, 55(9), 2579–2589.

Hyndman, R. J., & Athanasopoulos, G. (2021). Forecasting: Principles and practice (3rd ed.). OTexts.

Korayim, D., Chotia, V., Jain, G., Hassan, S., & Paolone, F. (2024). How big data analytics can create competitive advantage in high-stake decision forecasting? The mediating role of organizational innovation. Technological Forecasting and Social Change, 199, 123040. https://doi.org/10.1016/j.techfore.2023.123040

Makridakis, S., Spiliotis, E., & Assimakopoulos, V. (2018). Statistical and machine learning forecasting methods: Concerns and ways forward. PLOS ONE, 13(3), e0194889. https://doi.org/10.1371/journal.pone.0194889

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. British Journal of Management, 30(2), 272–298. https://doi.org/10.1111/1467-8551.12343

Munir, M., Jajja, M. S. S., & Chatha, K. A. (2022). Capabilities for enhancing supply chain resilience and responsiveness in the COVID-19 pandemic: Exploring the role of improvisation, anticipation, and data analytics capabilities. International Journal of Operations & Production Management, 42(10), 1576–1604. https://doi.org/10.1108/IJOPM-11-2021-0677

Nasiri, M., Ukko, J., Saunila, M., & Rantala, T. (2020). Managing the digital supply chain: The role of smart technologies. Technovation, 96–97, 102121. https://doi.org/10.1016/j.technovation.2020.102121

Orjatsalo, J., Hussinki, H., & Stoklasa, J. (2025). Business analytics in managerial decision-making: Top management perceptions. Measuring Business Excellence, 29(1), 1–17. https://doi.org/10.1108/MBE-09-2023-0130

Prastuti, M., Pujawan, I. N., Widodo, E., & Kuswanto, H. (2026). A predictive analytics method for multiregional supply chain demand forecasting with spatial time series and machine learning. Decision Analytics Journal, 19, 100706. https://doi.org/10.1016/j.dajour.2026.100706

Punia, S. (2025). Medium- to long-term demand forecasting in retail and manufacturing organizations: Integration of machine learning, human judgment, and interval variable. Journal of Forecasting. Advance online publication. https://doi.org/10.1002/for.70030

Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation–augmentation paradox. Academy of Management Review, 46(1), 192–210. https://doi.org/10.5465/2018.0072

Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. MIS Quarterly, 35(3), 553–572. https://doi.org/10.2307/23042796

Taghiyeh, S., Lengacher, D. C., Sadeghi, A. H., Sahebi-Fakhrabad, A., & Handfield, R. B. (2023). A novel multi-phase hierarchical forecasting approach with machine learning in supply chain management. Supply Chain Analytics, 3, 100032. https://doi.org/10.1016/j.sca.2023.100032

Tai, Y.-N., Ruanguttamanun, C., & Hsiao, L. H. C. (2026). Big data analytics capabilities and supply-chain decision agility in multinational enterprises: The moderating role of managerial AI literacy. Science, Technology and Society, 31(3), 574–594. https://doi.org/10.1177/09717218261466729

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. European Journal of Operational Research, 261(2), 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

Wamba, S. F., & Akter, S. (2019). Understanding supply chain analytics capabilities and agility for data-rich environments. International Journal of Operations & Production Management, 39(6/7/8), 887–912. https://doi.org/10.1108/IJOPM-01-2019-0025

Wamba, S. F., Dubey, R., Gunasekaran, A., & Akter, S. (2020). The performance effects of big data analytics and supply chain ambidexterity: The moderating effect of environmental dynamism. International Journal of Production Economics, 222, 107498. https://doi.org/10.1016/j.ijpe.2019.09.019

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009

Wibowo, B. S. (2024). When and how to adjust statistical forecasts in supply chains? Insight from causal machine learning. Journal of Business Analytics, 7(1), 25–41. https://doi.org/10.1080/2573234X.2023.2248203

Yasmin, M., Tatoglu, E., Kilic, H. S., Zaim, S., & Delen, D. (2020). Big data analytics capabilities and firm performance: An integrated MCDM approach. Journal of Business Research, 114, 1–15. https://doi.org/10.1016/j.jbusres.2020.03.028

Zhu, X., Ninh, A., Zhao, H., & Liu, Z. (2021). Demand forecasting with supply-chain information and machine learning: Evidence in the pharmaceutical industry. Production and Operations Management, 30(9), 3231–3252. https://doi.org/10.1111/poms.13426