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Predictive Analytics for Forecasting Chemical Raw Material Imports and Inventory Optimization in Paint, Ink and Plastics Manufacturing

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Abstract: Resins, pigments (titanium dioxide), solvents, plasticizers, and petrochemical monomers are a small range of internationally traded chemical feedstocks whose lead times and prices are highly volatile and critical to the paint, ink, and plastics manufacturing industries. This paper investigates and discusses the possibility of using predictive analytics, including classic time-series econometrics, machine learning, and reinforcement learning techniques, to predict import needs for chemical raw materials and to optimize inventory decisions in the chemical value chain. Based on the peer-reviewed literature in operations research, the paper summarizes methodologies, industry evidence, and architectures for linking forecasting outputs to inventory management policies such as the economic order quantity (EOQ) model, dynamic safety stock, and multi-echelon optimization. The practical challenges related to data quality, organisational preparedness and the volatility resulting from geopolitical and logistical uncertainty are also discussed, followed by managerial recommendations for resin, pigment and solvent-intensive manufacturing procurement and supply chain functions.

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I. INTRODUCTION

The specialty & commodity chemicals value chain is interconnected, with paint, ink, and plastics manufacturing being integral parts. Importation of feedstocks is critical in the production of epoxy and acrylic resins, ethylene, propylene, butadiene (monomers) used to make these resins, pigments like titanium dioxide, and various solvents, plasticizers, and additives (CEPE European Council of the Paint, Printing Ink, and Artist's Colours Industry, 2021). These raw materials are often sourced from a limited geographic area and are sensitive to crude-oil price variations, currency fluctuations, and trade policy changes, so manufacturers always have to deal with uncertainty about the price and timely availability of the materials on which their production plans are based (Chen et al., 2024). In 2022, automotive, construction, and packaging applications accounted for the growth of the global paint and coatings market, valued at approximately USD 161 billion that year (Grand View Research, 2023), and the market was hit by the COVID-19 pandemic and the resulting supply chain disruption, which caused significant shortages of raw materials, extended lead times, and price inflation (Pilcher, 2023).

Traditional inventory planning in manufacturing with more of a chemical focus has traditionally been done with relatively simple deterministic tools, most notably the economic order quantity (EOQ) model first developed by Harris (1913), with manually adjusted safety stock buffers. All of these methods are based on relatively stable and constant demand and fixed lead times, which are increasingly difficult to maintain in raw material markets where feedstock availability is limited, prices are variable, and shipping times are tightened but not fixed (Gonçalves *et al.*, 2020). The operational cost of forecasting and inventory systems that are unable to predict disruption is evident in the paints and coatings raw material crisis that occurred in 2021–2022, when almost a third of surveyed manufacturers reported that they had to re-formulate products because of shortages of substances and their inability to be available, as stated in the industry literature on the crisis of raw materials in the paints and coatings sector (Sikharulidze & Fuschi, 2023).

Predictive analytics broadly refers to the group of tools used for statistical forecasting, machine learning, and increasingly models based on reinforcement learning to solve these limitations (Sarka, 2021). Multiple information sources such as historical consumption, macroeconomic indicators, supplier lead times, freight indices, and price signals can be merged into a predictive model to produce demand and price forecasts that capture the reality better than rules of thumb do. Multiple information sources can be combined in a predictive model to obtain demand and price forecasts that are simultaneously more responsive to real conditions than are rules of thumb (Zhu et al., 2021). These forecasts can be combined with inventory optimization frameworks to inform both the amount of a raw material to order, as well as when

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to order it, the quantity of safety stock to have on hand, and how the risk of procurement should be spread across suppliers and regions (Lee et al., 2022; Mandl & Minner, 2023).

This paper has three objectives. It first provides an overview of the main predictive analytics techniques that are relevant to raw material import forecasting, from classical econometric time-series techniques to machine learning and hybrid reinforcement learning methods. Second, it highlights the application of these approaches in the paint, ink, and plastics sectors, both from a general supply chain perspective and from specific sector evidence from the petrochemical and coatings sectors. Thirdly, it links the elements of forecasting to existing and developing inventory optimization frameworks and explores the practical architecture needed to make predictive analytics "real" in procurement and planning. Finally, barriers to adoption and implications for management are discussed.

II. THEORETICAL AND METHODOLOGICAL BACKGROUND

➤ *Demand and Price Forecasting: From Classical to Machine Learning Methods*

Traditionally, forecasting has been done using time-series econometric models, including autoregressive integrated moving average (ARIMA) models and their extensions for incorporating exogenous variables (explanatory variables) such as feedstock costs or macroeconomic variables (Pandit et al., 2023). They are still frequently employed in chemical and petrochemical price forecasting; for example, an ARIMAX-based model to predict prices of the petrochemical products in the East China market has been developed using the cost of naphtha as a key input to predicting the prices of downstream products, as described by Hu et al. (2024). Such models are well suited for cases where the underlying data-generating process is fairly stable, and relationships are roughly linear, but not so well suited to commodity-created chemical markets, where nonlinear interactions and regime shifts are common.

Classical econometric methods have been gradually supplemented by machine learning methods. Hewamalage et al. (2021) conducted a detailed survey on recurrent neural networks (RNNs) with a special focus on the widely used long short-term memory (LSTM) networks, which are well suited to time series forecasting, especially in the presence of temporal dependencies and nonlinear demand patterns that cannot be captured by conventional statistical models. Ma and Fildes (2021) also show how meta-learning models can be useful, where a superior model selects the forecasting method that is most appropriate for the attributes of a specific series, which is relevant to multi-item chemical raw material portfolios where the demand behavior varies between raw materials.

Ensemble tree-based techniques, such as random forests and gradient boosting frameworks, have also been found to be useful in commodity and industrial demand forecasting applications. Analogous to the domain of chemical feedstock forecasting in which extreme gradient boosting (XGBoost) was found to outperform traditional statistical methods, XGBoost models have been demonstrated to perform best in predicting non-ferrous metal prices in the domain of metal and mineral commodity price prediction. This evidence is immediately applicable to chemical raw material forecasting because several major raw material components of the paint, ink, and plastics industries, such as titanium dioxide, resins, and petrochemical monomers, have price dynamics similar to those of chemicals.

Another methodological step relevant to forecasting the demand for chemical raw materials is the combination of demand forecasting with information about the individual supply chains. Evidence from the pharmaceutical industry, provided by Zhu et al. (2021), suggests that including supply-chain factors, including order signals from the upstream suppliers and inventory positions, into machine learning demand forecasts significantly boosts forecast accuracy over models that rely only on past demand. This is a natural extension to chemical manufacturing supply chains, which are similarly coupled by the availability of feedstocks in the upstream tier and customer order patterns in the downstream tier.

➤ *Reinforcement Learning and Hybrid Decision Frameworks*

In addition to prediction, several recent papers combine predictive models directly into the procurement decision-making process via reinforcement learning (RL). In the context of the petrochemical industry, Lee et al., 2022 present a two-stage data science system: The first stage is a prediction of the price of a key raw material, butadiene, based on the supply rate, demand rate, contract price, and the information of the upstream and downstream markets; The second stage utilizes the analytic hierarchy process with reinforcement learning to determine the optimal procurement policy to minimize the total procurement cost. Even if the price gap is 10 percent, material profitability gains can be realized, as raw material procurement can account for 70 to 80 percent of the cost structure in industries based on raw materials from petroleum (Lee et al., 2022).

Mandl and Minner (2023) embrace this intuition in a broader operations management context and develop data-driven optimization models for commodity procurement when there is price uncertainty, showing that policies based on probabilistic price forecasts beat static procurement policies, especially in highly volatile markets. The findings are particularly relevant to paint, ink, and plastics manufacturers because they are often charged for their resin and pigment inputs based on volatile benchmarks in the petrochemical industry.

➤ *Inventory Optimization: From EOQ to Data-Driven Safety Stock*

The classical inventory theory is based on the economic order quantity model (EOQ) developed by Harris (1913) for the ordering of a product with deterministic and constant demand. In reality, however, this assumption is difficult to meet, especially in the case of chemical raw materials with seasonal construction cycles and demand patterns in the

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automotive sector, with limited availability from suppliers and with fluctuating prices. When demand is random and variable, the optimal replenishment quantity is best determined by first forecasting demand for a planning horizon and then using an inventory optimization rule (Arunadevi and Umamaheswari, 2026).

Significant methodology development has been carried out for the concept of safety stock – inventory carried beyond expected demand due to uncertainty of demand and/or lead time. In a recent systematic review, Gonçalves et al. (2020) showed that there is a transition from pure statistical formulations towards optimization-based approaches and, more recently, machine learning approaches for determining safety stocks. They note those that include risk-pooling effects, guaranteed service-time formulations and multi-echelon considerations – each of which applies to chemical manufacturers who carry stock at various points, from bulk feedstocks imported from overseas to intermediate blends to the finished product like paint or ink.

More recent applications have taken the next step and directly integrated machine learning into the process of estimating safety stocks. In a study that included linear regression, decision tree, support vector machine, and neural network models, the linear regression model was determined as the most accurate and interpretable model for predicting safety stocks in the cosmetics and beauty sector, where, like coatings, customers have volatile demands due to changing product preferences and regulatory requirements across jurisdictions—preserving the findings for practitioners who have to find the balance between the accuracy of the model and its interpretability and auditability when dealing with regulatory requirements in the manufacturing sector (Bustos et al., 2025). Research has proven that while the EOQ is still the conceptual underpinning of inventory theory, its application is starting to rely more and more on machine-learning extensions that attempt to overcome its limitations: the assumption of stationary demand, the single-item assumption, and the assumption of constant lead times (Alnahhal et al., 2024).

III. APPLICATION TO PAINT, INK, AND PLASTICS MANUFACTURING

➢ *The Structure of Raw Material Dependency*

The main raw material components of paint and coatings formulations are 4 types: binders or resins (acrylics, epoxies, alkyds, polyurethanes), pigments and extenders (led by titanium dioxide as the dominant white pigment), solvents (both petroleum-based and more and more water-based systems), and additives (dispersants, rheology modifiers, biocides) (Rust Bullet Australasia, 2025). In the coatings industry, about one-third of the feedstock volume comes from non-petrochemical sources, whereas the rest is linked to petrochemical feedstock chains (Al Mestneer and Bollino, 2024). There is significant overlap in the resin and pigment chemistry between ink manufacturing and coatings, as well as in the use of olefin monomers (ethylene and propylene) and polymerized derivatives between plastics manufacturing and ink manufacturing.

A raw material import forecasting problem is generally not a one-variable problem because the feedstocks are localized in a small number of production areas and go through several intermediate conversion processes before arriving at a paint, ink, or plastics manufacturer. It must take into account movements in crude oil and naphtha prices, intermediate petrochemical spread economics (also known as the ‘crack spread' between the price of feedstocks and products), available shipping and freight capacity, and the manufacturer's own downstream demand signals, from construction, automotive and packaging markets to consumer end markets (Diggle and Walker, 2022). This multi-layered structure is explicitly modeled in the literature of petrochemical price-forecasting, which uses naphtha and crude oil prices as leading indicators for prices of more downstream petrochemical products like those used in resin and plastics production (Hu et al. 2024; Lee et al., 2022).

➢ *Evidence of Disruption and the Case for Predictive Capability*

As the global supply chain crisis that began in 2021–2022 continues, there is a natural opportunity to examine the price of a lack of forecasting and inventory resiliency in the coatings industry. When surveyed, most of the coating manufacturers experienced shortfalls of raw materials, and some raw material suppliers were still out of stock in some market segments through 2024 (Pilcher, 2023). High raw material inventories built up during the period of shortage triggered a wave of destocking in both raw material and coatings manufacturing sectors as growth in demand slowed and inflationary pressures remained in place in late 2022 (Pilcher, 2023). This “whipsaw” phenomenon, of going from acute shortage to rapid destocking in a period of about eighteen months, is one of the types of regime shifting behavior that is not well captured by classical deterministic inventory models, and for which machine learning-based demand and price forecasting is expressly created to capture, by its power to model structural breaks and volatility clustering (Hewamalage et al., 2021).

In particular, the coatings market is embracing digital procurement and price forecasting as a strategic approach to this volatility, and the rest of the chemicals/petrochemicals sector is following suit. Industry-facing forecasting services, like ICIS, make statements about the obvious nature of the forecasts as decision support tools for business decisions – whether on the sale or purchase of goods – in a rolling multi-month series of prices for feedstocks such as crude oil, naphtha, propane and butane (ICIS, n.d.). The fact that there is a commercial market for such predictions is proof enough of the business use that manufacturers make of predictive price intelligence for raw materials from importation.

➢ *Applying Machine Learning Demand Forecasting to Plastics and Resin Inputs*

The biggest challenge for plastics manufacturers, and therefore for the resin inputs for paint and ink formulations, is the price forecasting of monomer and polymer feedstocks that are closely tied to crude oil and naphtha prices. Two-stage butadiene price forecasting and procurement framework by Lee et al. (2022) directly addresses this class

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of problem by combining prediction using recurrent neural networks with a reinforcement learning-based butadiene procurement policy, whose empirical results show better forecasts in terms of accuracy and better total procurement costs, as compared to baseline approaches. Similar applications use system dynamics, multiple linear regression, and artificial neural networks to predict prices of petrochemical products and naphtha for production scheduling and planning, followed by the coupling with mixed-integer linear programming models to design optimal operational and inventory control policies when facing price uncertainty (Hu et al., 2024).

At the firm level, Feizabadi (2022) shows more broadly that demand forecasting based on machine learning leads to better performance of the supply chain than traditional statistical methods, which have a major impact on improving inventory positioning and reducing the number of stockout and overstock events. Similarly, Sharma et al. (2020), in their study of machine learning applications in sustainable supply chain performance, report that predictive analytics helps to create resilient and responsive supply chain configurations—with direct application to plastics and resin supply chains, where cost efficiency is a must, but exposure to feedstock volatility is not.

- *Illustrative Forecasting-to-Inventory Workflow*

For purposes of the preceding discussion of the methodology, an illustrative but representative example is offered: a medium-sized paint manufacturer importing titanium dioxide pigment from one supplier, acrylic resin from a second, and mineral spirits solvent from a third supplier, each from a different region of the world. A traditional planning method would have been to use a safety factor to determine reorder points based on the average consumption of the previous 12 months, but this approach proved ineffective when, in 2021–2022, spot prices for titanium dioxide climbed and supplier lead times were extended from weeks to several months (Pilcher, 2023). A predictive analytics-based workflow would, rather, integrate three of these streams of data for each material: internal production scheduling and historical consumption data; external price and freight data, such as the crack-spread and naphtha price signals that proved to be ahead of the curve for downstream pricing of petrochemicals and resin, and lead-time data from the suppliers, preferably at a greater frequency than the typical planning cycle.

The model to be implemented would be a recurrent neural network or a gradient-boosted ensemble forecasting model of the type presented by Hewamalage et al. (2021) to produce rolling multi-month forecasts and prediction intervals for the resin and pigment inputs identified as having the highest frequencies in cost-share and supply-concentration screening. These intervals will not only feed a risk-pooling or guaranteed service-time safety stock formulation (Gonçalves et al., 2020) but will also increase automatically when the forecast uncertainty grows, e.g., when naphtha prices are volatile, and decrease when the forecast uncertainty decreases, e.g., during periods with less volatility in naphtha prices. The solvent input showed a more stable historical demand pattern and fewer suppliers, making a simpler model such as exponential smoothing or ARIMAX more likely to be able to obtain a similar accuracy at significantly lower implementation cost, consistent with the meta-learning principle that "Keep it simple, stupid" (KISS) the more complex the model the more it should mirror the characteristics of the series (Ma & Fildes, 2021).

The importance of predictive analytics in this space isn't just a breakthrough algorithm; it's a systematic marriage of forecast uncertainty to inventory policy and the disciplined use of analytical sophistication based on the criticality of the raw material and data characteristics.

IV. INTEGRATING FORECASTING WITH INVENTORY OPTIMIZATION: AN APPLIED FRAMEWORK

- *From Forecast to Order Policy*

A predictive analytics system that's designed to help chemical raw material import decisions in paint, ink, or plastics manufacturing can be broken down into four stages of a pipeline. The second is data integration, where the internal consumption and production data are combined with other external factors, such as price, freight, and macroeconomic indicators, Zhu et al. (2021) show that the use of supply-chain-specific variables in addition to historical demand significantly improves the accuracy of machine learning forecasts compared to demand-only models, which can be directly applied to the task of forecasting raw material imports, where the variables of supply-chain suppliers and their lead times serve as analogous variables.

The second stage uses a forecasting model (one of the specification set in the statistical ARIMAX, a recurrent neural network, a gradient-boosted tree ensemble, or a meta-learning framework that chooses the forecasting model based on the nature of a particular demand series for a given raw material to produce a point forecast and, ideally, a band of uncertainty for each imported raw material, for the planning horizon of interest.

The third step is to convert these forecasts into inventory parameters. Instead of directly applying the classical EOQ formula to a point forecast, which implicitly ignores the uncertainty in the forecast, the more robust models propagate the uncertainty in the forecast to the safety inventory calculations, such as those most commonly referred to in the literature (Gonçalves et al., 2020); these include the risk-pooling models and the guaranteed service-time models that apply to multi-echelon inventory positions ranging from bulk import stocks to intermediate processing stocks to finished-good buffers.

The fourth stage involves the implementation of the forecast and inventory parameters to an actual procurement policy, which not only addresses the quantity and timing of orders, but also, if more than one supplier or shipment mode is available, how procurement is broken down across sources to take into account cost and lead-time considerations, and

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supply risk (Lee, Chou, & Huang, 2022; Mandl & Minner, 2023).

➢ *Multi-Echelon and Portfolio Considerations*

Paints, ink, and plastics producers usually buy several dozen to hundreds of different raw material SKUs, and there are significant differences in their volatility, supplier concentration, and importance to production continuity. As per the systematic review of machine learning applications to inventory control, most of the classical inventory models, which start with the single-item EOQ formulation, neglect inter-item dependence, and in real manufacturing environments, a portfolio-level prioritization of items is needed. Such an approach, first off categorising raw materials based on their importance and criticality using multi-criteria decision making techniques, followed by machine learning-based forecasting of demand for the most important and critical items, is practically feasible for allocating the limited analytical and managerial effort in this context (as described in the supply chain machine learning integration reviews, which integrate frameworks like fuzzy analytic hierarchy process and VIKOR with genetic-algorithm-optimized neural network-based demand forecasting) (Bergsma et al., 2025). Generally speaking, a paint company would invest in such an advanced level of forecasting sophistication for major resin components and titanium dioxide, which comprise a large fraction of the cost and are a concentrated commodity, but less so for lower-volume specialty additives, which could be managed with simpler statistical or rule-based approaches (Raabe, 2023).

➢ *Data, Infrastructure, and Organizational Requirements*

The successful application of predictive analytics to raw material forecasting requires an infrastructure that integrates enterprise resource planning (ERP) into raw material forecasts, raw material data feeds, and market intelligence data sources. In their exploratory case study of the use of artificial intelligence in operations and supply chain management, Helo and Hao (2022) conclude that the level of implementation is less dependent on the sophistication of the underlying algorithm and much more dependent on the quality of data integration into the systems and the adoption of AI-driven recommendations within the current planning process and the existing capabilities of the workforce. Sharma et al. (2022), who focus on the broader scope of AI applications in SCM, also note that organizational and data-readiness issues are often the limiting factor for value creation from predictive analytics investments, not the performance of predictive models.

Additionally, blockchain and distributed ledger technologies have been suggested as complementary technologies to enhance the traceability and reliability of the upstream data used by predictive models, especially in multi-tier chemical value chains where the data of provenance and compliance documentation matters (Saberi et al., 2019). Although blockchain is still in its early stages compared to forecasting analytics, it can be used to enhance data integrity throughout supplier tiers to complement the forecasting and inventory optimization framework introduced above.

V. BENEFITS, LIMITATIONS, AND RISK CONSIDERATIONS

The literature reviewed above indicates that some commonly observed benefits of the adoption of predictive analytics in raw material forecasting and inventory optimization are: minimizing forecast errors and thus the related stockout and excess inventory (Feizabadi, 2022); reducing the overall procurement cost by optimizing the timing of procurement in the light of the forecasts (Lee et al., 2022); making the overall procurement process more resilient and tolerant to demand and price shocks, because machine learning models can detect regime shifts and can uncover nonlinear volatility patterns which are not represented by classical models (Hewamalage et al., 2021); criticality based distribution of planning efforts over a large raw material portfolio (Lee et al., 2022).

Meanwhile, there are several restrictions and hazards to be mindful of. First, machine learning models require a lot of data and, for lower-volume specialty chemical raw materials, the historical data may not be deep enough to justify the use of a complex model; there are several practical solutions around the constraints of data, such as meta-learning, where the choice of model complexity is a function of the series characteristics (Ma & Fildes, 2021). Second, a predictive model based on past data is only as useful in predicting truly novel shocks (such as pandemic disruption, geopolitical conflict, or sudden change in trade policy) as it has close historical analogues, as Ivanov and Dolgui (2020) have argued: structural measures of supply chain viability (such as supplier diversification and contingency inventory positions) should complement such a predictive model. Third, model selection should not be based on the most complex technique available, since in the regulated manufacturing environment where procurement decisions need to be auditable, simpler linear regression models can perform as well, if not better, in some safety stock applications.

Lastly, there are often organisational and change management hurdles that are identified as the main constraint of realised benefit. Both Helo and Hao (2022) and Sharma et al. (2022) highlight that successful application of predictive analytics outputs is less about the sophistication of the algorithm and more about making them fit into current planning and procurement processes and adapting the skills of current planning staff.

A second thought is how to measure and regulate predictive analytics performance after it is in use. The information provided by a forecast accuracy metric is useful, but the downstream impacts of forecast error on the inventory or forecast cost are not. The downstream impacts of forecast error on the inventory or forecast cost may be superior for a model that is marginally less accurate on average but has less variability and volatility in the forecast errors than a marginally more accurate model that has more variability and volatility in the forecast errors. In paint, ink, and plastics manufacturing, therefore, there should be inventory-level outcome metrics (stockout frequency, excess inventory carrying cost, service level attainment) as well as the

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traditional statistical accuracy metrics, and they should be reviewed regularly on a cycle that would identify the regime shift that occurred in the coatings sector in 2022 from shortage to destocking (Pilcher, 2023). Periodic back testing against actual results with explicit documentation of the forecasting bias by commodity type gives a practical mechanism for keeping confidence in the model over time and the ability to determine when a commodity's demand or price pattern has changed to the extent that the model needs to be retrained or that a different price forecasting method should be adopted.

VI. DISCUSSION AND MANAGERIAL IMPLICATIONS

As leaders of procurement and supply chain functions in paint, ink, and plastics manufacturing organizations, the research literature presented above would indicate an approach whereby predictive analytics is adopted through the use of steps. The first step is to classify raw materials for advanced forecasting in line with multi-criteria classification techniques taking into account cost share, concentration in supply, and criticality in production, with advanced machine learning and reinforcement learning reserved for the highest priority materials like titanium dioxide and resin base, where there is empirical literature on procurement cost improvement and accuracy in the petrochemical industry (Lee et al., 2022). For lower criticality materials in the portfolio, simple statistical forecasting models coupled with meta-learning frameworks may suffice as they provide model selection based on simplicity/complexity (Ma & Fildes, 2021).

Second, the forecasts themselves must be incorporated in inventory management parameters such as safety stocks, reorder points, and multi-echelon buffering explicitly and not be seen as standalone forecasts that have nothing to do with execution. A systematic review of safety stock calculation methodologies by Gonçalves et al. (2020) provides a set of formulations, ranging from risk pooling to service time guarantee models, suitable for multi-echelon inventories in paint, ink, and plastic producers.

Third, companies ought to see prediction as a supplement but not a replacement for resilient supply chains. The case of the 2021-2022 materials crisis in the coatings industry serves as an example that even good predictions cannot serve as a full replacement for diversified supplies, buffer inventories, and formulations in the absence of historical precedence for disruptions (Ivanov & Dolgui, 2020; Pilcher, 2023).

However, success is just as dependent on the organization's ability to invest in its data architecture and workforce capability as well. Any enterprise system combining internal manufacturing data with external signals from market and freight, as well as lead time from suppliers, serves as the basis for the operation of any model regardless of how complex it may be (Helo & Hao, 2022).

VII. CONCLUSION

Lastly, effective implementation relies on organizational commitment to data infrastructure and capacity just as much as choosing the right type of model. Enterprise solutions that are capable of bringing together the production data internally available with signals from the market, transportation, and supply chain lead times represent the bedrock for any forecasting algorithm, regardless of its sophistication level. Helo & Hao (2022) Predictive analytics provides paint, ink, and plastic makers with a range of practical tools to cope with the unpredictability of the market for imported chemical raw materials. The step-by-step development of forecasting models presented in the literature creates an escalating scale of methods tailored to the use with the raw materials of different importance and available data volume. Through systematic connection between forecasting results and inventory optimization processes such as safety stock and multi-level buffer models, manufacturers get the means of minimizing the likelihood of both stockouts and excess costs.

However, the facts mentioned above also highlight the fact that predictive analytics is not a replacement for structural resilience in the supply chain: the experience of the coatings industry in the face of a lack of raw materials in 2021-2022 shows that no matter how accurate the forecasts may be, there will always be vulnerabilities to disruptions where there is no historical precedent. The best way forward for manufacturing companies in this segment is criticality-based forecasting prioritization, strict forecast integration in inventory management, further development of the data infrastructure, and structural buffers for the residual uncertainty.

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