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# Leveraging Big Data Engineering for Predictive Analytics in Wholesale Product Logistics

Journal of Electrical Systems

**Abstract*:* -** Unlocking the latent insights of Big Data has been a holy grail of predictive analytics since the term Big Data was coined. Yet, it is only very recently, on the back of technological advancements, with scalable data engineering tools, an ecosystem of data lakes, massively parallel processing analytical databases, predictive modelling libraries and, of course, the rise of cloud computing, that this goal has become achievable. What had always been a herculean task of extracting value using predictive modelling, has, thanks to these Big Data-ready tools, transitioned towards an almost cookie-cutter capable endeavour. Delivering production-level models at arbitrary workloads and presenting the options to individual stakeholders has now become possible for an organisation's sizable analytical support team. This paper intends to showcase one such use case within the landscape of wholesale product logistics: at large scale, automating demand forecasting with predefined intelligence - a mixture of pre-learned or commonly known pieces of information – for the creation of demand plans of a considerable product segmentation for a large customer base. Delivering daily production forecasts at daily warehouse replenishment levels, monitoring and controlling variability of predictive performance to continue to administer a key influence area of much of logistics execution. The objective being the increase of operational efficiency, improvement of service levels with data-driven decision-making, and even influencing tangible aspects outside the enterprise when creating a plan that balances demand against partner replenishment capabilities. It uses the previously mentioned tools to solve the need of future demand planning through volume indicators which serve to take replenishment actions, considering product storage capacities at different partner companies: those are wholesalers, retailers and distributors.

***Key Words*:** Big Data, Predictive Analytics, Data Engineering, Data Lakes, Parallel Processing, Analytical Databases, Predictive Modelling, Cloud Computing, Production-Level Models, Demand Forecasting, Predefined Intelligence, Product Segmentation, Customer Base, Warehouse Replenishment, Predictive Performance, Operational Efficiency, Service Levels, Data-Driven Decisions, Demand Planning, Volume Indicators.

## 1. Introduction

The logistic operation is a key decision domain that influences the effectiveness of inventories for wholesale companies, as it manages orders of variable size throughout the year to transport finished goods in bulk from factory to the destination country. Several optimization models propose to minimize transportation costs, but only a few consider the inclusion of data-driven decision-making procedures. Predictive analytics, based on supervised machine learning models, may provide a way to turn available data into clearer and faster actionable intelligence for both wholesale and retail businesses. It will recommend the best matches to optimize inventory levels.

This investigation proposes two alternative predictive analytics models using Big Data-centered approaches that are able to provide actionable and timely recommendations. The first model addresses the question of which country the product demand will be for at the time of the purchase order creation, and the second one addresses the question of the percentage of the predicted product demand for each country. A highly informative public observatory manages large data records with characteristics such as industry classification, product description classification, destination country codes, and order values of products for export. The database has the advantage of having a large number of records divisible into intricate product classifications and with coverage up to the latest years due to its recent inception. However, it presents some disadvantages, which we present in the next section.

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**Fig 1 : Big Data in Logistics**

### 1.1. Overview of the Study Context

Big data enables the collection, management, storage, and analysis of vast amounts of dynamically generated data in various application domains. The logistics of wholesale products constitutes one such domain, where bigger and ever-growing data related to the product paths from the factory to the retailer are generated. The adoption and implementation of big data technologies in logistics can effectively address various problems in merchandising logistics. In addition to traditional data processing needs - relating to cleaning, importing, exporting, and applying derived fields to improve data quality and make it fit for decision support - logistics also create new needs related to data provenance, curation, and heterogeneity. These products are typically characterized by handling and storage costs and dynamic customer demand, have long lead times and high loss of sales potential during stockouts, and usually have no expiration date but may be subject to permanent and transitory markdowns. Predictive analytics is primarily concerned with forecasting the outcome of future logistics processes or product demand-related events based on this business-logistic big data.

Our project aims to illustrate how these needs can be solved or addressed and predictive analytics be performed through predictive modeling on appropriate data mart designs for the business-logistics big data - specifically in relation to predicting wholesale product final customer demand up to a few weeks ahead on a weekly basis, and wholesale product retailer demand up to a few months ahead on a monthly basis - and combinations of big data storage, search, and processing technologies. The product being addressed is a specific setting of the above modeling activity - establishment of predictive models based on industry practices and model benchmarking. These - models, data mart designs, technologies - have only to a lesser extent been addressed and exemplified in industry, and on the basis of either published data or specific case studies.

## 2. Understanding Big Data Engineering

1. Definition and Scope

Big Data Engineering (BDE) is a scientific subfield of Data Science that concentrates its fundamental and applied research on the systematic construction of adaptive software infrastructures capable of ingesting, processing, and analyzing continuously streaming, unstructured data of incredible speed, volume, variety, volatility, and complexity, with the purpose to deliver on time useful and trustworthy information, knowledge, or predictions from any of the many, if not all existing dedicated traditional Data Science models. In a sense, BDE is to Data Science what Software Engineering is to Computer Science. In its fifth decade, and continuously adapting, with the emergence of new groups of techniques, new technologies and tools, and new processing and analysis design patterns, it is enabling the continuous and systematic generation of value from Data-Information-Knowledge-Prediction supply chains, in a multitude of different sectors including science, business, and society at large. Predictive Analytics in Wholesale Product Logistics relies on a BDE state of the art, to construct a BDE solution that answers the question of this paper. Both the BDE state of the art and the proposed solution are detailed in sections 2 and 3 respectively.

2. Key Technologies and Tools

At present and in the very near future, Hadoop, Spark and their compulsively temporaneous innovation-driven ecosystems are the BDE state of the art. More particularly, these ecosystems are composed of a steady influx of new technology and tools releases grouped into functional clusters, at different functional abstraction layers, able to solve an ample type of data processing and analysis problems for different types of Big Data salarying firms, that include technology and tool suites specialized in storage and logistic; computing resource and cluster administration; data ingestion and exporting; data security and privacy; data manipulation, ingestion and exporting, and analysis; data and software deployment and orchestration, and engineering; several high-level programming frameworks; specialized data structures; access programming libraries; cloud software-defined data centers; and kernel user domain wrappers.

**Equation 1 : Demand Forecast Function** $$\hat{D}_{i,t+1} = f(H_{i,t}, P_t, E_t)$$

$\hat{D}_{i,t+1}$: Predicted demand for product $i$ at time $t+1$

$H_{i,t}$: Historical demand

$P_t$: Promotional or pricing factors

$E_t$: External variables (e.g. weather, holidays)

### 2.1. Definition and Scope

The unique characteristics of big data lead experts to adopt novel approaches and methodologies for different fields and applications. These approaches are gathered in a research area called big data engineering. Engineers implementing data-driven solutions are called data engineers. This chapter answers the question that arises: What is big data engineering? Data engineering is an updated expression of traditional software engineering that must be applied in big data contexts. Here, the scalability requirement is a must due to the exponential growth of the volume, variety, and velocity data characteristics of big data. The volume, variety, and velocity of big data make available classical data engineering rules adopted when applying the software engineering principles to ordinary data problems no longer adequate to guarantee the correct and efficient implementation of data-solving processes in big data engineering.

Big data engineering is related to the data layer of the data solution stack, which contains traditional and data storage and processing technologies. The focus of this chapter is to introduce the reader to a big data engineering definition, the technological aspects and tools that support its application, and the data processing techniques adopted. According to a definition influenced by the industry and university research communities, big data engineering is a new area of computer engineering and science. This area is responsible for data storage, processing, and operations that require managing a scalable data layer. The data layer must support data model requirements, implement data processing techniques, and ensure the quality and integrity of the exposed data throughout their lifecycle.

### 2.2. Key Technologies and Tools

The massive amount of data generated by the emerging and exponentially increasing use of massively parallel connectivity changes the traditional models of computing, and calls for entirely new ecosystems of software and hardware abstractions. Several key technologies, including Cloud Computing, Data Storage and Management, Data Processing and Analytics, and Machine Learning Accelerators, are necessary in order to embrace Big Data Engineering. Nowadays, the powerful and widely used architectures of cloud computing run on massively parallel storage, communication, and processing frameworks that serve a data-centric programming model with distributed computing capabilities. Key cloud drivers include economics of scaling, abstraction and automation, low economic barriers for startups, massively scalable platforms, multiple innovative services, and Cloud Operating System. The Cloud combines the advantages of the Internet and Data Centers.

Data centers use several types of storage, protocols, and distributed file systems, such as large volume unstructured object stores that are increasingly being used for cloud-based data storage and analytics. Warehouses, which originally began life as third-party data stores for customer analytics, have been enhanced and are now popular as big data general storage and processing solutions. Additionally, scalable distributed SQL and NoSQL-based solutions, which originally traded off ACID semantics of transactions for horizontal scalability, are converging toward commodity high-performance scalable transactions. More recently, cloud providers have introduced innovative serverless SQL, NoSQL, and streaming analytics services that offload and automate the data processing pipelines and analytics on cloud-based data warehouses, reinventing the layers beneath the SQL and NoSQL abstractions with capabilities and performance that are orders of magnitude more efficient for common processing and analytics workloads.

### 2.3. Data Processing Techniques

A wide variety of applications exist in data processing techniques called data preprocessing. Data preprocessing is a systematic procedure which transforms the collected raw data into an understandable format. Data processing forms part of the bigger picture or system development life cycle which includes collecting, organizing, and analyzing the information. The purpose of preprocessing the data is to • To ensure that the data is in a format which can be modeled successfully without errors • To ensure that the data is consistent • To make certain that the data is complete with no bad or missing data • To remove duplicate data which would skew the results • To remove inaccuracies or errors which would skew the results • To format the data to match or meet the requirements of the model. Data preprocessing should lead to improved understanding of the processed data by a human or system model. If this is done then it stands to reason that the modeling would produce better results. There are several techniques that can enhance the modeling.

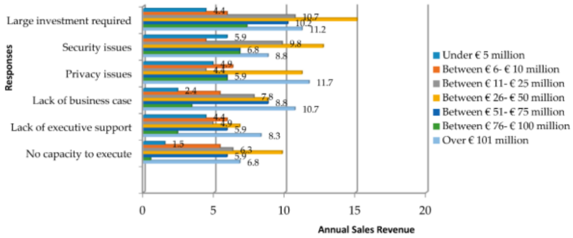


**Fig 2 : Big Data Analytics on Company Performance in Supply Chain Management**

Data preprocessing techniques consist of data mining as well as statistical and machine learning methods for manipulating the data, removing noise or extraneous information and validating the inferred data. It can also include visualizing the data to better understand and enhance what the model learns from the data. Further, it can make the model's solution easier to discover and understand. It may be an iterative process where upon performing a visualization or modeling, it becomes evident that the data requirements need to be enhanced by either gathering more data or improving the quality of the current data. Data preprocessing techniques include identifying different data types and making a detailed description of each attribute of the data set.

## 3. The Role of Predictive Analytics

Big data analytics involves the application of the data set of sufficient size and complexity to require access to specialized processing, algorithms, and tools from the domain of data, information, and knowledge engineering and including areas such as Big Data Storage, UX Design, and Data Modeling, Management and Curation, Natural Language Processing, Machine Learning, and Data and Knowledge Engineering, on large and diverse data sets from sources such as data warehouses, data lakes, data streams, and data graphs, within a distributed computing framework, to accomplish one or more information-based tasks such as anomaly detection, diagnosis, estimation, prediction, forecasting the future, and prognostics. Data analytics thus refer to the general, and in the case of big data, highly specialized, activities and processes, such as "the art of turning data into information" and the "science of turning information into knowledge," while predictive analytics are software solutions and processes specifically focused on forecasting possible future events using Historical Data Manipulation and Modeling and High Performance Computing.

One of the key philosophies supporting the application of predictive analytics is encapsulated in the saying "Those are the biggest problems that often have the simplest solution." Predictive analytics provides an answer to the pressing questions like Do any of the multiple possible causes know the biggest problems?, How do we know that the answer is do nothing?, What is the best suggestion for solving the problem? In the field of predictive analytics, mention all problem situations that fall into the following four areas – recognition of not easily identifiable disorders rather than avoidance of nasty surprises. Predictive analytics are being applied increasingly often for different applications in different fields including Business, Utilities, Telecommunications, Healthcare, and Social Services, Attack Management, Sports, Applied Science and Technology.

### 3.1. Overview of Predictive Analytics

Predictive analytics systematically extracts knowledge from historical data to build and evaluate a model, and then applies the model to new data in order to predict the unknown values of specified variables. The process includes four steps: definition, model building, evaluation, and application. Observations must first be generated using historical data and knowledge of the subject area; this is necessary, as the building algorithm usually cannot automatically find the optimal raw data transformation. After the observation generation process, the predictive model is built using one of the several supervised learning algorithms. Then, the quality of the generated model is evaluated. An evaluation indicates whether the model is sufficiently accurate for the desired business purpose; if the model is not satisfactory, the previous steps are changed and repeated until a suitable model is developed. If the model is adequate, it can then be applied to previously unseen data. These predicted values can subsequently be used in decision-making.

Predictive modeling can have several purposes. It can be used, for example, to infer hidden causes for the data; give insight into the implicit data relationships and correlations; identify unusual individual cases for diagnosis, surveillance, or fraud detection; or apportion the risk of an event in groups of similar individuals or for an actual event. However, one of the most important purposes for predictive modeling is classification. This process assigns some categorical label or class to the record based on the values found in the record; the label may denote some future event or a description of the record. After being labeled, the record can then be used, for instance, in marketing activities, respondent-based promotions for business-to-business services, fraud detection in business transactions, etc.

### 3.2. Importance in Logistics

The emergence of new technologies and the increase in electronic storage has enabled the collection of huge amounts of raw data, making data analysis increasingly important. The data analyst's role is to extract predictive and/or descriptive knowledge from the available data. Predictive analytics is the term that has been coined to refer to a wide range of traditional and innovative statistical modeling, machine learning, data mining, and intelligent data analysis methods and techniques that employ the use of statistical or machine learning algorithms. They identify and exploit the correlation structures in the data to predict future events based on past observations. Logistics activities usually involve the forecasting of certain values. For example, in inventory management, we forecast future demand for stock items; in vehicle routing, we forecast future traveling times for each section of each road in the network, etc. Obviously, the associated forecasting models must be predictive in nature, since we need to make decisions about future events based on the past. However, the traditional forecasting techniques typically used in logistics do not fall under the term predictive analytics. There is no attempt to tradeoff bias against variance. There is generally no use of the phylogenetic structure of the sample; rather, all similar looking series are forecast identically. And it is rare that the problem is one of predicted relative values, where choice of family of models is strategic.

### 3.3. Common Predictive Models Used

Predictive analytics modeling is used to identify the probable outcome of a process, workflow, or scenario given a defined set of inputs and historical data. It provides the foundation for businesses to translate big data into reduction of risk while taking advantage of opportunities to gain profit. It examines historical data and comes up with an estimate of how likely a particular event or behavior will happen based on probability. Predictive analytics can predict many potential outcomes, from likelihood that a customer buys a specific product to the chances of mechanical failure at specific times of the year. Predictive analytics provide companies a roadmap to revenue maximizing strategies while minimizing risks. It often affects our day-to-day life. How are the predicted trends? Predictive analytics take multiple datasets including historical data, industry benchmarks, and other data relevant for what you are trying to achieve. These datasets are cleaned up, filtered, and transformed to form a useful analytics dataset. Predictive specifications which specify what are you trying to achieve are then used to develop the predictive model, i.e., will a customer buy product A or product B or both, or how do customers behave in store X compared to customers in store Y, or what are the critical windows for machinery failure, etc. The model is batched on historical data for success and then applied to the applied new data. The answers are delivered as predictions specifying what actions need to be executed. This process keeps iterating as new data is realized and the predictions are applied.

**4. Wholesale Product Logistics Overview**

Big Data Engineering for Predictive Analytics 49 4. Wholesale Product Logistics Overview Wholesale logistics budgets consume more than 90% of total logistics budgets, while it remains a largely non-digitized effort. This section discusses the dynamics of product logistics in wholesale supply chain networks followed by its challenges and innovative solutions for the challenges. 4.1. Supply Chain Dynamics Wholesale supply chains ensure the constant flow of finished products through a nation's distribution and retail networks. Finished products, generally sourced and transported from manufacturers, are received at large wholesale distribution centers before transferring to local wholesale branches and smaller-scale retailing throughout the territory. The physical flow of products through these networks comprises inbound and outbound logistics functions to and from the distribution centers and branches across multiple tiers. The operations involve important logistics decisions such as demand forecasting, sales order processing, inventory replenishing, product picking and packing, shipping scheduling and dispatching, fleet management, etc., supporting multiple areas of performance, such as service levels, delivery costs, inventory levels, asset utilization, and operation capabilities.

The logistics activities consume up to 90% of the budget from wholesale supply chain efforts. However, wholesale distribution remains a largely non-digitized effort, relying on manual records and actions complemented by ad hoc software tools, mostly point solutions. The traditional approach to logistics operations in wholesale distribution involves setting separate monthly sales quotas by products, customers, territories, and salespeople, establishing channel pricing levels, incentive programs, and promotional discounts guidelines for salesforce to stimulate demand, and periodically reviewing local inventories and adjusting for stock outs or overstocks and achieving service level.

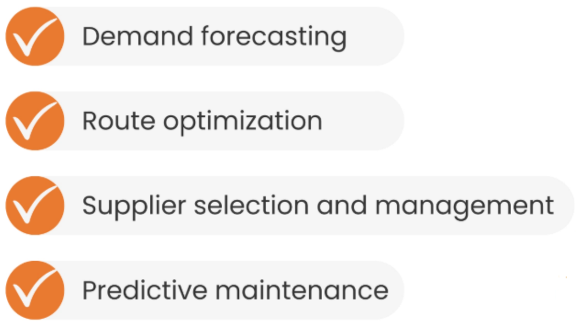


**Fig 3 : Data to Improve Wholesale Logistics**

**4.1. Supply Chain Dynamics**

The logistics and transport sector covers a large part of the supply chain and is essential for the successful operation of any business model. The activities concerned include warehousing, planning and managing inbound, outbound, intra-facility, and transit transportation, as well as monitoring logistics concerns. Logistics also includes other value-added activities such as material handling, protective packaging, inventory management, as well as protection, security, and sales support. We can define logistics as a critical component of the supply chain that covers the movement and storage of material and data. The supply chain, on the other hand, covers every aspect of a company's lifecycle — from raw materials extraction to the sale of completed products. Therefore, logistics can be understood as fulfilling the requirements of the wider supply chain. Indeed, logistics is responsible for the efficient execution of the supply chain in order to avoid delays and unexpected costs.

Large volumes of data are generated by logistics and supply chain processes and activities. Suppliers send order notifications, which are automatically converted into a supplier's system. Based on the available stock, a supplier will prepare different incoming and outgoing documents that will be managed by their business applications as well. The process of sourcing involves planning and coordinating material and data flows to secure a constant supply of materials and spare parts. The purpose of this process is to get the right material at the right time, to minimize problems in internal processes while taking into account cost and quality constraints. To achieve this goal, close collaboration with suppliers is needed. They are notified about specific needs by sending Purchase Orders. Suppliers manage their own supply chain and logistics activities by preparing stock for shipments. They rely on external service providers to control the movement and storage of their products. Logistics service providers have their own systems to manage this data.

**Equation 2 : Predictive Stock Replenishment Model** $R_{i,t} = \max(0, \hat{D}_{i,t+1} - S_{i,t})$

$R_{i,t}$: Required replenishment

$\hat{D}_{i,t+1}$: Forecasted demand

$S_{i,t}$: Current stock level

### 4.2. Challenges in Wholesale Logistics

In the wholesale product logistics, distribution centers receive thousands of units of products from manufacturers every day. The products are put into storage nearly immediately by workers or automatic systems using storage systems and equipment like automated storage and retrieval systems. When needed, items are delivered to clients on demand, either directly through the distribution centers, or by merchants and retailers at a later point in time. The distribution facilities operate at a relatively low efficiency throughout, while incurring higher operational costs typically using multiple handling and movement systems in parallel. For example, bulk product deconsolidation and pathfinding are typically sequenced with low traffic on the picking path for cost minimization of distribution activities. Routing and scheduling are done primarily via an external human effort or through simple automated systems, while the distribution problem is usually managed through easy wiggle room buffers, negotiating release times and product handling constraints to suit varying operational conditions. The distribution network and logistics operations still incur high costs due to multiple handling operations and delays during pathfinding, relying on a mix of expensive human and low-cost automated labor to expedite the necessary high-volume operations.

In order to improve efficiency and reduce costs, logistics managers and executives are investing in new technologies like radio frequency identification systems that automate movement monitoring and serve as a key input for system optimization and predictive analytics. The new systems are used in conjunction with new data monitoring and collection systems based on automated cameras and image recognition, together with sensors for tracking products and sensory visualization. When deployed at the various nodes in a logistics network, these systems exponentially increase the quantity of historical data on activity volumes and durations available for management. With low latency shallow learning or even deep learning tools capable of sympathetic forward modeling, logistics solutions that manage costs through fast predictive analytics are becoming a reality.

### 4.3. Current Trends and Innovations

Logistics systems are continuously evolving, responding to environmental changes both internally and externally. External pressures drive the development and incorporation of new technologies, reshaping the means through which logistical resources are controlled and how supply and demand are balanced. Within both wholesale and retail logistics systems, the increase in accessible information is ready to be leveraged, supporting and enhancing logistics operations. Companies are facing and adopting new logistical approaches as well as investing in new technology for logistics support.

Demand for new innovative distribution structures for attaining better service with lesser delivered costs is driving the structural development of distribution systems. The trend toward deregulation of the transportation industry, with more of the actions being left to the shipping and carrier companies, raises the issue of who decides what to carry on which carriers, and why. Competition in the services offered and adjustments in the quality of service are a direct result of transportation deregulation. Improvements in service reliability and speed of delivery made possible by advances in technology are additional factors driving the trends toward just-in-time and quick response logistics. The introduction of just-in-time, make-to-order, and flexible manufacturing, with their high reliance on successful logistical operations, have important relationships with the developed distribution structures.

The concept of integrating all the logistical operations, along with the support of communications and computer technology, is evolving and has begun to be implemented. The premise of a logistics information system is that virtually unlimited amounts of data can be collected on the status of logistics operations. The development of domestic and international operational facilities has created the need for global integration of logistics operations. Today, logistical resources are often located in widely separated geographical areas. Integrating these resources ensures that companies compete on the basis of efficient logistics operations.

**5. Integrating Big Data with Logistics**

Wholesalers receive data from various channels, such as operational data, interface data, and external data. Operational data in wholesale logistics plays an essential role in policy-making and covers everyday operations. For example, historical distribution and operation reports specify what volumes are involved in deliveries to Hungary and other substantial derivatives. Some parties complain about the unreliability and low quality of this data, using it only to operate their own warehouses. In addition, historical information connected to energy demand ranks high in the category of interface data sourced from power transmission companies. It indicates how much power and on what level of the voltage network has been used. Faced with the volatility of electricity pricing and the increasing amount of energy consumed in distribution services, which should reach several billion kilowatts within the next few years, the examination of energy utilization is critical. External data can be categorized into two large segments: economic and social data, coming from different state administrations, and traffic data, provided by logistics networks, mainframe and data warehouses. Economic and social data describe the economics of the monitored wholesalers and the territory, the population size and growth, changes on the consumer market, and so forth. Information regarding traffic jams has considerable importance in real-time routing.

Based on the provided data types, the recommended data integration method utilizes business intelligence tools in the performance process. The mentioned method supports preparing all kinds of statistical reports, allowing for optimal routing of the data warehouse, considering the results of current analysis and estimates. In addition to data warehouse design, one implementation method is based on online analytical processing, on analysis and forecast, which fills the data warehouse with aggregated data on daily, weekly, monthly, or even yearly bases. Other utilization methods beside operational production and managerial control exist. Real-time data utilization plays a major role in wholesaler data warehouse activities and is the form whereby clients receive the greatest added value. Such services can predict expected cross-border distribution volumes next week for the current pricing according to an identified logistic regression depending on fuel prices, repair, or construction works on the route, temporarily paralyzed bridges and border crossing points, other capacities, etc.

**5.1. Data Sources in Wholesale Logistics**

The operations in wholesale logistics generate and/or utilize a significant amount of information and knowledge resident in various business systems as a part of their core functions. The most common information systems are Enterprise Resource Planning for support of internal functions, Warehouse Management Systems for storage and inventory control, and Transportation Management Systems for management of logistics carriers and execution of freight transportation operations. Each of these functions and corresponding supporting information systems generate and collect event data which changes with the progress of time, and represent potentially valuable sources of insights about system performance and customers. Some traditional suppliers and customers may not be supported by such systems: such operations are performed manually, without automated data generation and flow.

Despite the advantages of ERP, WMS, and TMS in facilitating logistics operations, these are closed internal systems due to their proprietary design and characteristics, and require investment in capital costs, resources and time to implement. Moreover, it is unlikely that a wholesaler partner with capabilities to invest in such complex and comprehensive systems is his primary source of product demand. On the other hand, market-based suppliers and buyers usually have less sophisticated logistics operations and associated challenges. Availability of information from outside the identified logistics systems but useful for coordination of core trade activities warrants attention. The accelerated rate of innovation in mass communication technologies has facilitated emergence of various convenient, inexpensive, and non-invasive sources of big data that enrich the customer logistics profile.

### 5.2. Data Integration Techniques

In the smart era, data integration for predictive analytics considers multiple aspects. Analytics implementation should adopt methods and techniques, aligned towards the smart supply chain concept. Smart supply chain concept indicates moving away from simple optimization techniques on volume maximizations, profit, and revenue based models. The answers, therefore, require research towards behavioral and sociological consequences from prediction results. Artificial decision making alone does not either ensure compliance or the answer to 'Why' predictions. The predictive results should, therefore, consider consumer behavior modeling, demand influencing factors impacts, and constraints and uncertainty propagation mapping along logistics. These additional dimensions to predict analytics towards wholesale product logistics predictive analytics since the key question of 'What' needs an answer based on smart supply chains. Predictive questions need an answer based on reasons and not just 'Did it happen' questions.

Smart predictive analytics in wholesale product logistics, therefore, requires a two-level predictive problem solving, data integration, and analytics hierarchy. The hierarchy includes Smart data integration as groundwork towards smart analytics implementation using machine learning. Smart integration would further enable feedback-based implementation and observation orientation along predictive levels. Such an implementation avoids resource wastage and provides support to key decision-making at all levels in decision-making hierarchy. The predictive analytics in the big data era provides insights into predicting demand, customer preferences, and order fulfillment patterns, enabling overcoming challenges like unsold stock and missed sales by being agile towards customer needs. The novel technology speeds up data processing for big-data volumes within the conventional demand chain logic, helping to build data-driven models for demand sidelining towards outlier volumes.

### 5.3. Real-time Data Utilization

Recall the biggest nightmare a Logistics Manager can think about… Drivers waiting and not being loaded.

We cannot think of a bigger word for disaster coordination than supply chain management without real-time data usage. In the wholesale product logistics environment, it is definitely a status quo to operate thanks to historical information, for instance DSO or transport lead time. Nevertheless, the fact most of the time is where they are not, i.e. the wholesale centre is not anymore – and is that is how we have been taught to think during the past twenty years – authorizes a necessary readjustment of the guiding principles if we were to go a little bit further in the search of an even smoother operation of the product flow. Current ubiquitous technologies like Digital Twin, IoT, AI, Blockchain, and Cloud Computing, on top of which everything relates, make it possible to set feedback loops into the business model.

With that in mind, we are able to provide our clients with a complete electronic CM that makes it possible to track every CM of every channel for every transaction at any time, based on order-provided information like the WMS reading of last mile delivery products movement: is it outside or around scheduled time? Our algorithm notifies any CM that is bushed into a vulnerable situation, dragging along all logistics players. Security teams notify drivers at danger and all then switch on their GPS and mobile to synchronize action; supervision teams take radio control and start contacting authorities to get the truck ready for entering a sortie; Corporate Com. prepares Corporate Publications…

The Cloud is linked with the CM at risk. A photo is sent to his office, mobile, whatever… It can only be seen by the chosen person and the chosen authorities, hence nobody can tell if it is a real or fake event.

## 6. Predictive Analytics Framework

Predictive analytics is a way to use big data to gain insights about future events. In this chapter, we present a predictive analytics framework development based on the input-output data distributions and time-lags. This framework covers data collection, model development, and validation stages. The goal of predictive analytics in general is to maximize the model predictions quality while minimizing the model generalization error.

Due to the variety of models of predictions, we will support that there is an input-output distribution behind each output variable of interest. A naïve model to estimate it is to consider the use of the last available input values, which are constant over time. However, since inputs to logistic models do not usually have a stationary behavior even at a particular period, it is likely to be associated with a predictor that depends on a few previous time-lagged input values. We understand that in this case it can be formulated as a prediction task for each variable by using supervised learning. In addition, some novel requirements will be also included in the supervised learning framework formulation that allow answering these logistic model inputs through a novel input definition. Once the model that gives the best performance is considered, a validation task will estimate a log predictive distribution in the unknown horizon of the future. A prediction can be seen as a density prediction that can be obtained from a prior predictive distribution. Note that for the validation and prediction tasks, it will be considered scenarios of known and of unknown future holidays, respectively. The probabilistic outputs will be modeled with the flexible quantile regression forests, adapted to estimated arbitrary density functions. This proposal will consider some new components to be considered in the modeling processes.

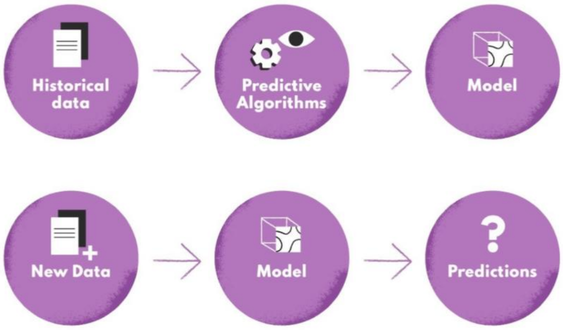


**Fig 4 : Predictive Analytics for Supply Chain Optimization in Consumer Goods**

### 6.1. Data Collection and Preparation

Predictive analytics relies on data that is suitable for the modeling task at hand. In the context of Wholesale Product Logistics (WPL), regression predictors such as price or sales characteristics and delivery delay depend on decisions made at the product supplier's location. Therefore, to predict delivery delay for Canadian customers of a Belgian company exporting meat products, we need data from Belgian customs that includes all previous shipments made by the supplier in question, in addition to an export – import data pair with the corresponding delivery delay. Such data is hard to come by, especially for imports. This feasibility study relies on actual data from one of the seven largest Belgian exporters of meat products. The data covers WPL for a period of 3 years, including both import and export data for the Belgian supplier. Other than for perishables with limited shelf life, this is the longest period of time we are aware of ever being made available for a logistic supplier – customer relation.

Collection of products in the product supplier's port of exit from the European Union is often done for groups of buyer importers related to food distribution chains in Canada. Because we are dealing with bulk food products, we can assume that for such deliveries, Canadian importer buyers combine orders together to minimize transport costs. Also, since we are working with a company that refines live animal products for immediate consumption using a kosher production chain, the shelf life is limited. Meats must arrive in Canadian cold storage distributor warehouses or biscuit manufacturers at least a month before Passover. With these special assumptions for totally different products, we start from actual data made available putting effort on quality control. The quality is needed for the modeling phase and also for quantitative research aimed at policy recommendations in the business world.

### 6.2. Model Selection and Development

Visible data characteristics alone are rarely enough information upon which to make final conclusions about the data. For the purposes of predictive analytics, in particular for predictive precision, the so-called holds, meaning that there is no model that on average performs correctly on every function maximum available population. This goes beyond model characteristics. It states that mathematics for all forms of functions gives no better information on predictions than flipping a coin. As far as approximation theory goes, model selection goes beyond just correlation or squared correlation. Thus, model selection affects predictive precision. However, predictive precision is also affected by a model's degree of freedom or number of basis functions in that model. High model degree of freedom models will continuously fit all the points and have zero squared correlation on the training data. As a result, model selection goes beyond just predictive correlation or overall predictive stability measures.

The model form and specific parameters can be selected in a variety of ways, with considering the model's predictive capabilities on distinct independent data, typically called being the most accepted. Model selection can be performed separately from training. Independent data not used for training can be used to compare model training methods or model families, among many other criteria, and develop model experts. The cross-validated prediction error, and not the squared correlation, should guide the selection strategy. Although a training algorithm may take a set of parameters for a given model, if the model is not trained simultaneously across the entire canonical parameter grid, the low predictive error achieved by one combination may be misestimated. To summarize, the two parts of model development are general form specification, where the general reduced model is invoked for the family of specific parameter sets, followed by parameter estimation and model selection.

### 6.3. Validation and Testing

The choice of a good performance measure is sometimes problem-specific, and a wide variety of models can be tested with different assumptions. It is essential to create a framework where data flow is validated with a sample of data while it is being populated in the database. Initially, some experiments, such as provisioning forecasting, sales forecasting, and others, can be done before clearing the entire data warehouse. This section will also explore the validation and testing part of the two-phase modeling techniques and real-time algorithms through an example of a provisioning forecast model. Later, the data flow can be established to feed all the relevancy models and product patterns at regular intervals.

Any statistical technique can have associated assumptions, advantages, and limitations. It is essential to evaluate a variety of models based on the most critical metric, which most closely resembles the business objective. For example, the average absolute error is relevant for average shipment size forecasting, while demand ramp-down and launch are more related to business revenue than forecasting accuracy. Thus, a model capable of detecting the beginning and end of a product's demand pattern, which has a reliable reverse demand cycle, should also be evaluated. In a similar fashion, the challenges of matching a technical solution to a business idea should be reviewed in relation to the proposed metrics. Ideally, an understanding of the limitations of the models at a high level should be presented at the beginning of the debugging process, along with business-oriented approval on metrics.

## 7. Challenges and Limitations

Despite the growing interest in applying predictive analytics to wholesale product logistics, leveraging big data engineering in this domain presents many challenges and limitations. First and foremost, access to quality data remains a key barrier to enabling end-to-end digital transformation in wholesale logistics, as a lack of interoperability between wholesale logistics partners poses integrity issues. Indeed, the quality of data can either enhance or undermine the accuracy of predictive algorithms, which also depend on the underlying data types and skilled auxiliary human resources. In wholesale product logistics, transactional data often gets dispersed across multiple platforms, preventing organizations from obtaining a holistic view of their buyers. Often data is also shared only through static files with less than optimal performance, turning real-time data processing infeasible. As wholesale logistics is a highly dynamic and volatile field, any data fatigue originating from integration issues can delay a buyer's cycle event identification, which if extensive, may also render predictive analytics less relevant. Moreover, many wholesale products come with a lead time of a few weeks, during which any logistical event is subject to a high degree of uncertainty. Hence it is crucial for organizations to access their wholesale transactional data quickly so that predictive models can detect any abnormality before a buyer submits a product order.

Secondly, the increasing amount of available data, due to the growing digitization and continuous improvement of data collection technologies, poses serious issues of scalability and high computational costs for organizations. It is important for wholesale logistics organizations to design measurement programs that support the deployment of predictive models capable of detecting irregular buyer cycle events in real-time on ultra-large volumes of transactional data. Any delays instigated by the limitations of traditional data processing systems will only render the need for predictive capabilities in wholesale logistics more pressing, as heightened e-commerce demands will make wholesale profit margins ever more volatile. A timely and relatively inexpensive solution to deal with both the rising volume of wholesale transactional data and the heightened logistics complexity involves storing the data in a cloud database and querying it directly using managed big data computing services.

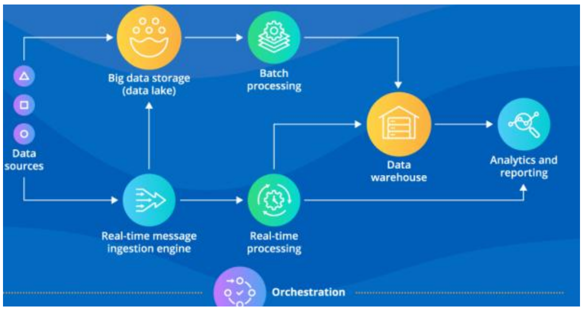


**Fig 5 : Big Data Implementation**

### 7.1. Data Quality and Integrity

The scope and conceptual nature of big data creates quality problems quite different from normal data quality management. Traditional data quality dimensions, such as timeliness and accuracy, need to be revisited when enforcing quality management, as they differ in relevance from a normal data management perspective. For example, big data is often observed in motion or near-real time. In this case, data is relevant for an extremely short time and has to be discarded as soon as this exceptionally short time period has passed. In that case, requests for having expected high accuracy levels seem to be naive, since the effort to maintain the data's accuracy would far exceed the immediate value of the data at the moment of the request.

Further, and quite opposed to the normal demands towards data quality, big data is often characterized by having low reliability and being highly subjective. The sources of big data are innumerable, and their reliability is hardly known. Journalists that publish short news may not be known to publish honest or truthful statements. Content produced by users on social media platforms is also driven by the urge for the extraordinary and the filtering mechanisms of these systems. The potential for biased samples would therefore argue against the expectation of quality levels that can be demanded from normally used forms of data, such as organizational records.

Nonetheless, at the moment of the analysis, would it not be appropriate for decision makers to define requirements on the quality of the input data? The concept of data in data-driven decision making considers data as facts that have previously been established by sensor input. The affordance of set-manipulating actions has the potential to no longer regard data as true statements about the world, but can display data for what it is: a means to depict the world and assist in making inferences about it. Moreover, the process of arriving at these inferences may also include the assessment of the quality of the input data.

### 7.2. Scalability Issues

The design of a system for processing big data that can be applied to many companies is a challenging task. The data involved in descriptive analytics operations is large by definition, so as the number of companies serviced through such a system grows, the overall load on the system increases. In the case of big data processing, it usually means that single operations take longer to process, which may result in exceeding the time limits for performing the operations. In terms of predictive analytics, we are dealing with significantly less data per company, due to the difference in frequency between historical events and analytics operations. Consequently, developing a system that could apply predictive analytics at a larger scale does not seem as hard as coming up with a concept for descriptive analytics.

It needs to be noted that the increase in the volume of data per company does not come only from a larger amount of products and orders but also from an increase in the number of companies. In the domain of wholesale distributors for products related to temperature-controlled logistics, such as food, there is a tendency for companies servicing a group of different countries to emit a larger quantity of orders packed into a smaller amount of time. This fact, together with the batch nature of the data processing operations, encourages the exploration of methods for batch predictive analytics at a larger scale. However, the scalability is also limited by the kernel of the analytics – the number of predictive models that need to be applied in terms of handling the predictions of demand during the intervals in which the orders are emitted and the clustering of the companies into similar demand trademarks. These possibilities are at the same time some of the key points of scaling predictive analytics over the quantity of batch operations as a whole.

### 7.3. Ethical Considerations

Big Data engineering for predictive analytics in product logistics supports data-intensive research and promotes qualitative interactions in scientific knowledge transfer. As it is not at the core of the predictive analysis, ethical considerations are not particularly vivid in their contributions. Possible ethical issues arise though inadvertently when predicting future trends, and shapes of future curves, such as demands, restocking cycles, and seasons implying special event planning. Hence, these ethical issues may not exclusively arise in product logistics but also be equally applicable in analytics from other spatial-temporal data domains.

For example, the research in graphics concerns ethical questions on business decision-making such as spatial-temporal market predictions in cities. Other contributions argue for and against ethical prediction algorithms. Their arguments relate to the trade-off between biased human formalization, which is monitored by the prediction, and comprehensible algorithms that do not consider ethical implications. Although not directly applicable to the predictive analytics in product logistics, these considerations are nevertheless inspiring by revealing aspects which influence the ethical use of predictive analytics.

Arguments for and against the ethical trade-off relate to practical relevance and by-product measures, such as being warned on where dangers may arise. The sensitive ethical relation revealed by the trade-off stands beyond the question where, when scalably available Big Data means too many during daily allocation for convenient demands, and when, when predicting critical events from cyber world education requires validation and control.

## 8. Future Directions

Data Engineering for Big Data is here to stay. In addition to the features and results summarised in the previous sections of this work, explanatory service engineering for collaborative consumption and the sharing economy leads to the hypothesis on the following main future directions for Big Data Engineering for actionable analytics. First, smartphones with Data Enabled LBS have entered emerging markets, which include second-tier megacities that reside in developing countries. In addition, Data Enabled geolocation service and contactless payment systems have also been adopted in these markets at record speed. Widespread adoption of these technologies must also lead to the emergence of new kinds of provider-consumer interactions that require some adaptation to culture and business practices. It is hard to believe that the strategies and the economic models of established companies in the existing markets drift towards the business models explored by disruptive startups that successfully leverage such amazing technologies in emerging countries. A new emphasis on exploration in Data Driven regional, national and global Applied Economies is called for. We do create some business scenarios given the current state of the art of Data Engineering explaining the bottlenecks of Big Data for Data Driven Autonomy. Important questions arise, not only explaining how to overcome such bottlenecks for Data Engineering Workflows, but also how to analyse such strategies and business models.

Our second main motivation for proposing future work is to analyse how Big Data Data Engineering collaborates with Intelligent Deep Learning Actionable Predictive Analytics especially in the Area of Predictive Analytics of Product Logistics in the Wholesale Marketplace related to the understanding of Cooperative Behavior in Business Ecosystems. Big Data Engineering offers the tools for understanding Data Enabled Marketplaces, as it helps Data Scientists to collect Dirty Data that is essential for their research in Predictive Sociologic Tools and predicting Economic Market Fluctuations for Investment and Financial Management, using advanced Speedup products. Big Data Engineering activity is additionally important as it favours New Paradigm Shifts towards a Global Wormhole Paradigm, that anticipate the second Industrial Revolution and the Autonomous Economy Society, New Era that Artificial Intelligence imbricates with Predictive Analytics.

### 8.1. Emerging Technologies

Emerging technology areas for the next generation of predictive analytics in product logistics include portable devices embedded with five or more hardware sensors, software development kits and inexpensive sensory hardware that allow developers to easily create Internet-of-Things applications, as well as IoT and plugin hardware and modules that support state-of-the-art wearable, domestic, and commercial machines and devices for collective big data generation. These products and services provide ubiquitous big data capture environments for the communications, sensors, and other capabilities of personal computing and communication devices. New data cloud services and development tool sets, employed together with existing data science libraries and frameworks, provide easy-to-use development environments for young professionals seeking to utilize big data analytics for product logistics.

Use of these technologies, along with inexpensive 3D video capture service capabilities, combined with ever-improving machine learning and artificial intelligence technologies, can support the creation of many new predictive applications for intelligent device systems in contemporary wholesale product logistics through the automatic production of both specialized predictive models and comprehensive domain knowledge using big data generated by supports, such as the devices mentioned previously. The basic capabilities illustrated can facilitate new predictive analytics that require developing dashboards to assist domain experts in monitoring logistics conditions via detailed visual representations of stores, warehouses, and other logistics centers. These dashboards support logistics guidance and system-wide anomaly detection based on time-series predictions as well as operational predictive models.

### 8.2. Potential for Automation

Today's advanced computer systems provide largely complete automation of tasks in predictive analytics. However, the area of product logistics is an important exception, and for lower-expertise users, it would remain valuable to have a system that autonomously makes recommendations about what to monitor, where, using what techniques and patterns, and using what time periods are the most informative. Such recommendations could help to focus attention on those areas that are more complex and which might require expensive closings, and also help to optimize logistics flows for predictive analytics instead of retroactively analyzing events that were simply too important or damaging to ignore. The concept of monitoring makes sense at a very high level, but there is a lot of important detail and expertise that are either innate or acquired through years in industry, be it air logistics, humanitarian supply logistics, or manufacturing. Automating pattern discovery in today's volume of raw logistics data product logistic is difficult especially given that anomaly detection methods are still a niche area in machine learning, and that inventoried products are often affected by seasonality. Another important trend is the lack of consolidated datasets that permit for training of anomaly detection, and consequential validation. To the best of our knowledge, no dataset with product-level logistics flows exists yet. In this paper we arrive at a small, simple example for product logistics, using sensor data for a company in the automotive industry. The advantages of such data are the abundance, the consistency, and the breadth of sensor data available, and the general applicability for almost every manufacturer.

### 8.3. Impact of AI on Predictive Analytics

Recent years have shown a massive impact of AI and machine learning in disparate areas and disciplines amongst the humanities and natural sciences research. However, in the domain predictive analytics research closely builds upon Statistical science then AI and machine learning together with AI and computational prediction analytics are influencing upon the methods and tools developed. Prediction analytics by its nature depends on information connecting the prediction target variable with predictive features. The prediction outcome for the target variable is affected by predictive features, and this serves as the basis of prediction.

Modern computing technology promotes discovery of the predictive relation by increasing the reliability of predictive models and accuracy increases with more power of computing architecture put into practice, and new knowledge is discovered and prediction models are validated on the fly. Sufficient reliable and sound prediction is vital for improvement and in market economy, the more accurate the predictions made, the less the wastes incurred in consumption and production decision rations on both the suppliers and customers sides. The aim of this work is to improve the accuracy of predictive models by adoption of more AI and machine learning components into algorithm technology centering on prediction.

The ultimate aim of Predictive analytics is of course to make accurate predictions about the possibility of success or failure of making investment or market decisions, or just making decisions based on unreliable information to be able avoid any unintentional mistakes at all. Prior research on the meaning of prediction and Predictive analytics are introduced in the earlier chapters, and many previous researchers published profusely on Predictive analytics are reviewed among which we would introduce only the most relevant ones to further facilitate understanding of the contents of this work and for convenience of the prospective readers. We state specific research objectives in order to avoid being misunderstood, and propose a framework for facilitating the concept of paramount importance of Prediction analytics with AI and machine learning.

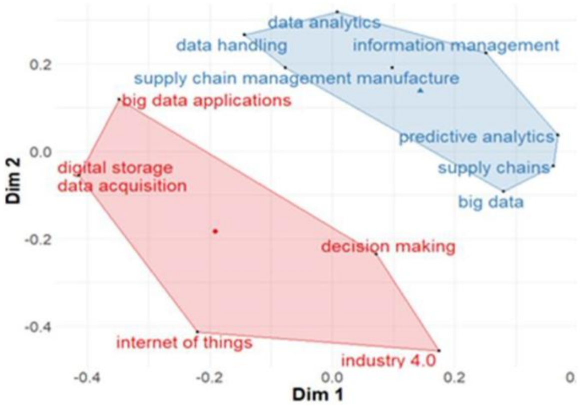


**Fig 6 : Big data optimisation and management in supply chain management**

## 9. Conclusion

The unique nature of wholesale logistics makes it highly challenging and costly to operate. Ensuring the timely delivery of correct quantities of products to the right locations of customers is needed to satisfy demand, while facing increasing pressure on cost reduction and service level is a constant juggling act. In this environment, access to and the ability to utilize and make predictions based on data will be a differentiating factor among companies. Collaborating with customers to obtain and prepare product sales data, joint business planning, and understanding key concepts from predictive analytics may help wholesale logistics companies accelerate the development of predictive models and shorten the time to generate actionable business insights.

The journey from data to insight can be accelerated through the use of focused and concrete engineering, data manipulation, and analysis methodologies. They introduce structure to the process of transforming and enriching raw data for third-party logistics partners and product suppliers sponsoring incentives and promotions for their customers. The pipeline then provides interpretable insights that can be communicated using visualization dashboards that can be used on mobile devices. In turn, this allows organizations to take timely action and instill a data-driven corporate culture. We propose that detailed and early data exploration is a much-needed consequence of a bottom-up action-oriented approach to the development of classic, advanced, and machine learning statistical models aimed at addressing specific business problems. Companies should consolidate steps of the model life cycle and use automated software to promote operational use. In parallel, business users should be trained to engage in the joint model development process, employing interactive analytic model building links.

$$\mathrm{ROE} = \frac{\sum_{j=1}^{n} W_j}{\sum_{j=1}^{n} T_j \cdot C_j}$$

$W_j$: Weight or volume of goods delivered on route $j$

$T_j$: Time taken

$C_j$: Transportation cost

**Equation 3 : Route Optimization Efficiency (ROE)**

### 9.1. Final Thoughts and Key Takeaways

To effectively leverage modern Big Data Cloud technology for effective predictive analytic development, organizations must create a strategic enterprise plan for becoming an effective and proficient data science factory development capability, and have the right tools and eco-system to deliver the required scale and speed of analytics development delivery. Building a capability associated with a data science factory can take time. However, making a strategic discussion and associated early capabilities investment will create a sustainable and enduring advantage in an increasingly fast-paced and increasingly connected marketplace. The automation of a greater proportion of the activities associated with the data science workflow can contribute significantly to developing, deploying, and refreshing predictive analytics in a more timely and effective manner. But automation by itself is not sufficient. Organizations must have sufficient clarity on their predictive analytic opportunities to enable experiments to test and refine the performance of the predictive models built, as well as sufficient volume and quality of data flowing through to support the model and analytic performance needs. Depending on the time-sensitivity of the analytics underpinnings as much as an ever-increasing volume of data, built and blended from disparate sources, will define how effective and efficient predictive analytics become at ensuring that logistics products are presented to the intended consumers at the right time, at the right price, and in the quantities required to both satisfy demand and maximize profitability over the long term. The trade-offs between validating early predictive analytic specifications, the intuition of the data scientists, the validation of the predictive analytics model created, and the implementation and ongoing scalability management of the models are often stretched as organizations seek to minimize time-to-analytic capabilities.

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