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Chapter 12: From predictive supply to cognitive retail: The future of intelligent manufacturing-to-market systems

2.1. Introduction

What is the future of intelligent manufacturing-to-market systems? This is one of the key questions for companies competing in the 10 Spheres of Supply: What will the supply ecosystem of the future look like? What will the Principle Processes and Core Component Decision Systems be, including how will they be exploited and synchronized? What will be the operating environment; including how will supply be forecasted, demanded and actually flow into and out of the enterprise at the physical and meta levels? What firm characteristics will manifest themselves through collaborative, intensive, evolving relationships among the enterprise and its market information sources, its interfaces to them? What are the strategic and tactical shapings of the enterprise, the markets and the service and product definitions?

This chapter explores some new theories about the answers to these questions. It attempts to map the future, to describe what the future will be; and therefore how to approach strategic planning, forecasting and making critical business decisions today given that future. In discussing the future, it discusses how business is likely to change and what will be the elements of this change. It also discusses why business will change, debates the key sequences of drivers of the future business path. The vast and rich research in many disciplines through which these futures discussed come is rich, ongoing and growing (Min, 2010; Lee et al., 2015; Wamba et al., 2017). The purpose of this book chapter is to put this body of work into a framework with which a business concerns use it. In this sense, this book chapter is not a self-supporting work; rather it is a map of a possible world. Its primary contribution is as a proximate cause of more intelligent and prescriptive thinking and busying acting about the future (Xu et al., 2021).

12.2. The Evolution of Supply Chain Management

In order to comprehend the fundamental alterations in supply chain philosophy, it is helpful to first review the successive time phases of development in supply chain management. More than 150 years ago, preindustrial societies relied on internal household supply chains to meet their basic necessities of food, clothing, and shelter. Following the development of manufacturing firms and industrial organizations, and especially the return of soldiers and the baby boom of the 1940s and 1950s, marketing and distribution take center stage. The focus was not on the cost of producing the product, but on the cost of moving it from the factory to the customer. However, insufficient emphasis was placed upon the management of these distribution systems; and costs continued to remain significantly high.

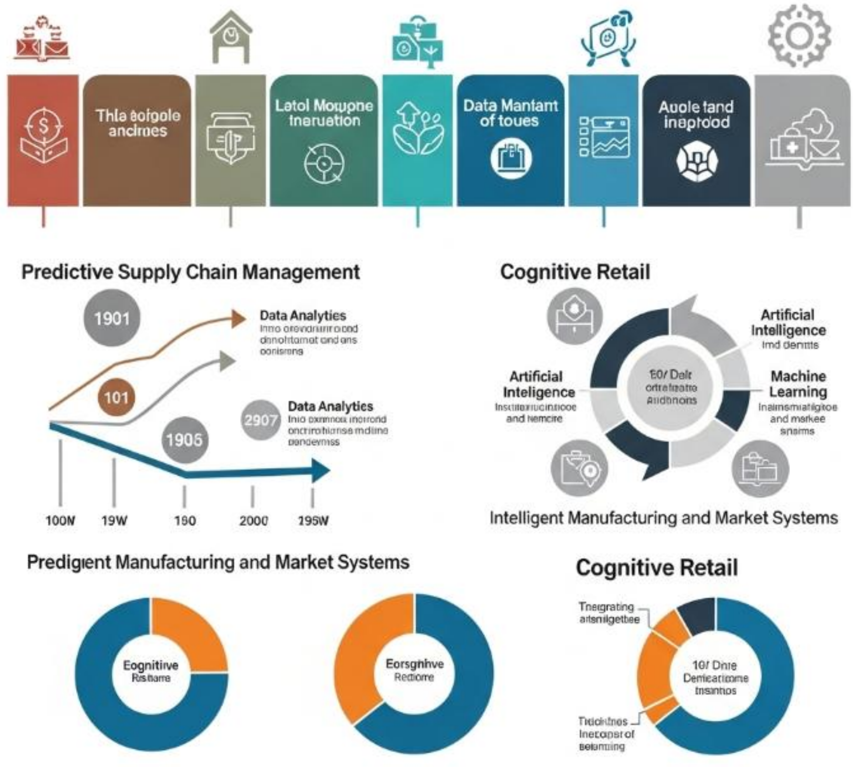

Fig 12.1: AI in predictive manufacturing

This began to change in the 1960s with the introduction of transportation rationing, combined with severe traffic congestion. The effect of excess inventories in channels, which had previously obscured the influence of distribution costs, increased from six months in 1960 to two years in 1970, and materials shortages began to occur, especially in the auto and aerospace industries. In response, firms and their trade partners began to experiment with simple forms of managing the distribution process to simultaneously reduce costs and assure service. These included distribution center consolidation, computerized inventory routing, and other such rudimentary, yet highly focused, process improvements. Concurrently, organizations began to group products and services into logistic categories depending upon their distribution service requirements or their impact upon cost. The concept of logistics and, in particular, activity-based costing of logistics gained acceptance among managers.

12.3. Predictive Analytics in Supply Chains

The future of production and distribution, as defined by intelligent manufacturing-to-market systems, will depend heavily on Supply Chain 4.0 technologies. This will connect the flow of products and services with the flow of information and the needs of consumers, creating a seamless process. However, while increasing numbers of businesses look to take advantage of these advantages, the skills shortage will remain a major inhibitor. Improvements in the analytic proficiency of many firms will not only help reduce the analytics gap, but will also contribute to the building of competing clusters and economic corridors that will make regions globally competitive.

One technology that is expected to play a key role in SC 4.0 is predictive analytics. Forward-looking decisions made utilizing predictive analytics can vastly improve supply chain decisions, with better forecasts and enabling companies to switch from a model. The successes with predictive analytics will be at the most basic level the move from a data-poor environment to a data-rich one, collecting many more external business metrics and then using that data in conjunction with more advanced modeling techniques, such as artificial intelligence, machine learning, digital twinning, and simulation. Many end users are expected to undertake predictive analytics in self-service fashions.

12.3.1. Understanding Predictive Analytics

Analytics is a powerful tool for advanced supply chain management. More than 80 percent of organizations using or planning to use analytics perceive it as an essential ingredient for success. Enterprises use or plan to use predictive analytics to enhance the customer experience, manage risk, and increase profitability, and analytics improves their business profitability and risk management. Forecasts are used in every aspect of supply chain management, such as demand planning, inventory management, production planning, material requirements planning, logistics consolidation, and transportation. Forecasts at higher aggregation levels are the basis for forecasts developed at lower aggregation levels. At the demand transactional level, forecasts are performed at the item store level or the item store day level. Sales forecasts at the item store day level are complemented with distribution forecasts to specific stores. Short-range forecasts are most useful for tactical supply chain decision making.

Supply chain decision making is facilitated by decision support systems based on models of the supply chain. Decision support systems with predictive capabilities can significantly enhance decision making in complex or non-intuitive problem situations. Models can range from simple linear regression to complex, expensive software, and focus on transactional, historic, or predictive capabilities. Data can pertain to actual sales during a previous time period, distribution costs of prior distributions, past advertising costs, or sales data of analogous items. Predictive analytics solutions offer collaborative infrastructure to blend and deliver information, trigger responsive actions, and reduce risks in business processes. Predictive analytics can help organizations build predictive models, understand what drives their business, and then use that information to make predictions that drive better business outcomes.

12.13.2. Applications in Supply Chain Optimization

From strategic to operational levels, predictive analytics applications can be found in literally every aspect of supply chain optimization. Because many data-rich organizations are already interested in measuring the efficiency and effectiveness of their supply chain activities, predictive modeling may be a reasonable feature – and step – in introducing more intelligence to their management. Key performance indicators generally focus on costs, customer satisfaction levels and supply chain flexibility, on-time delivery, inventory management, and financial ratios. Specifics for such measures might be innovation cycles for product development, fulfilment times for order processing, forecasts for demand planning, or the relationship between selling price and forecasted demand. As data availability grows – data expose the history of what has happened, i.e., the past already stored in internal databases, the real-time data from business transactions, and new data streams, for instance, from social media – so does analytics budget spending.

Analytical decisions impact the most important sources and consequent drivers of supply chain cost structures: manufacturing lead times, distribution costs, logistics, warehousing, and inventory holding costs. A predictive view allows companies to reduce their working capital through reduced inventories, less air freight through improved lead time reliability, requested customer service levels through harmonized production planning, seasonality of products through return on investment optimized decision windows for new product introductions, and establishment and maintenance of trusted supplier relationships through proven strategic sourcing that anticipates the need for critical parts. Analytical supply chain decisions should, therefore, be incorporated in the earliest stage of a corporate supply chain strategy and be aligned with the product cycle.

12.4. Cognitive Technologies in Manufacturing

What is the role of cognitive technologies in manufacturing? Cognitive technologies are a key enabler of intelligent manufacturing as they help optimize the utilization of manufacturing systems and support businesses provide better solutions to customers. More specifically, cognitive technology is able to help predict new trends as they are shaping up, predict how much of every product will be needed at every geographical area and time horizon, develop advanced product configurations, provide better services, execute order promising with more certainty, enhance the utilization of manufacturing systems, reduce capital costs, allocate better finances and cash, improve supplier reliability, and be more agile and responsive to demand changes. Manufacturers have two main challenges and opportunities to make better use of cognitive technologies. The first one is to improve the impact of products assays and models on downstream activities such as order promising and the manufacturing of products. Manufacturers can take better advantage of data analytics to improve the operational performance in terms of inventory reduction, better service levels, and lower unutilized capacities, to name a few.

In most multinational companies, decisions on products assays and models are taken centrally at a very high level for the entire business. Such decisions do not take advantage of the additional data provided by the market such as client segmentation. Such modeling and product assay processes can be optimized through advanced data analytics techniques and models. Data analytics can provide two main benefits to manufacturers downstream activities. One is to improve the forecasting accuracy by better modeling the considerations that companies take into account when deciding, at short notice, on the adopts product configurations that drive demand, for different market segments and countries.

12.4.1. Artificial Intelligence in Manufacturing

The key role of artificial intelligence (AI) in manufacturing, and in specific domains such as manufacturing defect detection and industrial computer vision, is magnified by the following key responsibilities AI bears in the evolution of managed systems today, noted in no particular order of importance: (1) AI acts as an enabler, allowing the development or creation of new intelligent products and services. In this way, AI adds business value to what was a traditional and perhaps obsolete manufacturing and service paradigm; (2) AI is helping improve traditional or existing products or services, making them smarter and more appealing to customers. In addition, AI adds options to existing products, thus influencing product or service life cycles; (3) AI helps improve processes, thus generating direct impact on operations in manufacturing or service delivered. It is at the level of operations that we find today engineering applications of various AI technologies – neural networks, logic programming, and knowledge-based systems. Classical applications are in the area of process diagnostics and control; and (4) AI is helping design systems, thus providing engineering support for products and processes. While we are not addressing the design role, we underline that it is becoming less and less clear in an economy where operations endure intense and continuous pressure to become ever more efficient and competitive.

This inability to focus sharply on one or other way artificial intelligence adds capabilities, and thus value, to managed systems motivates us to use the term "cognitive systems", i.e. a system such as a managed system pairs excellent sensing and control capabilities with a deep ability to reason, learn from an unpredictable and dynamic environment, and make decisions amid uncertainty, risk of failure, and adverse consequences. We will use the term "cognitive products" and "cognitive services" to describe the new intelligent assets manufactured, and the associated services provided within the context of the service-centric economy and society that characterizes the Western world in particular today, as well those assets that bear, embed, or are coupled with the enabling technologies for such cognitive capabilities, for example information and communications technologies, and which in turn are the product of a particular type of managed systems: the intelligent knowledge-intensive manufacturing systems.

12.4.2. Machine Learning Applications

In contrast, advanced machine learning applications focus on less structured data analysis, as part of broader applications. The goals of this research direction are often substantially broader, including vision and object/person identification, natural language processing, sentiment analysis, common sense reasoning, machine creativity, and robotics. In particular, such capabilities enable computers to conduct tasks requiring similar human brain processing. The ultimate goal is to replace human brain effort, which is limited and costly. Compared to general storage/memory or processing speed, machine cognition capabilities are many orders of magnitude weaker. Importantly, machine cognition abilities appear to evolve faster than such general capabilities, thus shifting substitution possibilities towards a larger range of tasks assigned today to humans.

As key components of these advanced applications, dozens of machine learning techniques are still evolving. Applications and capabilities of interest vary considerably by business area. For example, storage, processing, and learning tools/models specific to big data (along with sensor integration, including imaging technologies of all kinds) drive rapid advancements in machine vision, robotics, and machine creativity. In retail, key machine learning applications transform and combine new tools and capabilities in natural language processing/sentiment analysis, time-series forecasting, market-basket analysis, and customer segmentation to enhance many cognitive functions across the demand/supply system. For example, natural language processing/analytics enable better understanding of customer demand on heterogeneous market platforms and its interaction with design, production, and delivery of products/services in physical, digital, and mixed spaces. As a result, better tuning of product assortments, pricing, advertising, promotion, delivery, and service can be applied.

12.5. The Shift to Cognitive Retail

Due to considerable advancements in sensory and computation technology, the Internet of Things (IoT) is transitioning from the collection of low-level event data to the ability to perform higher-level cognitive functions such as human and object perception, social behavior analysis, and even decision making. The integration of higher-level cognitive functions into IoT is known as cognitive IoT (CIoT), and will lead to the next wave of digital transformation in intelligent manufacturing-to-market systems. Market and supply chain pressure to reduce costs and agilities from demand and supply groupings has created a retail system that is flooded with inventory and challenged for profitability. It is a modern miracle that value is extracted from such a wasteful and unproductive system. The challenge is to reduce excess costs while not compromising needed performance or consumer choices. Clearly this can only come from new levels of intelligence in what B2C retailers do that can reward them in both the bottom line and in stock price. Continuous optimization in this rapidly changing world cannot simply be done by econometric models. They are not sufficiently adaptive enough to respond at the needed speed or to a sufficiently large scope to address the challenges and opportunities facing today's retailers. Decision-making for performance has to involve considering not just current prices and promotional strategies, or how sales are now affecting other sales, but also all the multitude of consumer choices, some across products some not affected at all, but all reflecting on the sales volume, profits, and relative performance of each item in the product line. Those decisions have to be integrated to deliver optimal performance. This means using a combination of machine learning techniques to predict outcomes and performance-driven optimization techniques capable of keeping the solution space flow enough to provide direction and alternative choices for decisions a consumer is about to make.

12.6. Integrating Manufacturing and Retail Systems

The increasing pace of technological change in retail systems is pushing more and more towards tight integration with manufacturing systems. The push for custom products, on the order of one per customer, means that there is little time to communicate a demand signal back to a centralized manufacturer and have the product made and shipped. Instead, small batch, highly flexible manufacturing technologies will be used in close proximity to retailers in order to fulfill customer requests rapidly. These custom requests are largely shaped by decisions that the retailers make — including how they merchandise products, and what products, and what product features they merchandise. In many cases, such decisions should appropriately take into account not only expected demand but also manufacturing cost structures.

Such tight coupling presents significant challenges, particularly for brick and mortar stores where the costs of customizing products might often exceed the expected additional revenue. However, the exploratory nature of many customers' store visits means that in many cases small additional incentives might greatly increase the chances of a purchase but have a minimal impact on the retail cost structure. That is, consumers might be willing to pay a large premium for certain specialty products that are bought infrequently relative to their overall expenditures. Store sales personnel can be given financial incentives to push these expensive products when the customer expresses an interest; similarly, product features that are requested frequently could be merchandised more heavily in order to attract customer purchases.

The increasing pace of change in retail, particularly in specialty retailing, means that this type of coupling will become more necessary. Moreover, because artificial product and feature customizations are often more visible and more readily communicated between customers than other types of products and features, decision support systems will soon need to be implemented as investments in unified manufacturing and retail inventories. If this happens, we should expect tight integration of retail and fulfillment systems along not only the demand channel, but the supply channel as well.

12.6.1. Challenges in Integration

Traditional supply chain management has focused on the manufacturing side, optimizing demand signals received from retail and used to determine manufacturing lot sizes and offsetting the cost of producing different products in volatile quantities. The retail function has focused on selling at least the full lot size shipped, and the cost of not selling a product is also incurred by the manufacturer. Intelligence has had a compartmentalized perspective on the two supply chains, with the retail end of the chain subject to processes for Demand Scaling (predictive analytics from historical sales data to estimate possible sales volume for a SKU, for instance), while the Manufacturing end of the chain has been exposed to Demand Shaping (using historical data to shape possible manufacturing schedules and/or shape demand to make it look like the desired schedule) and Demand Collaboration (multi-item collaboration between manufacturer and retailer to promote sales of less popular products requiring only forecasted quantities). A vertically integrated chain thus has been built up using intelligence to correct demand forecasts provided retail customers to manufacturers as inputs to manufacturing optimization models to determine order quantities, timing and routing; promotion-style Demand Shaping models on the other hand, selecting combination displays valued at the cheapest price that can be used to enhance sales of products when combined with their trigger/mortar items.

Major challenges may thus be witnessed when developing an integrated solution: first, from having multiple products and their allocations to multiple channels/locations change simultaneously, thus needing disjointed heuristics to come up with integrated plans satisfying all the constraints and thus minimizing the sum of retail and manufacturing costs over the planning horizon, and second, a retailer's manner of incurring a greater shortage cost than the package price of the product in its SKU identified by the manufacturer while being off-shelf. If the shortage cost on product sales arising from expired sales forecasts and the duration of time for which sales forecasts stay expired at each point are high compared to the actual product sales, Demand Scaling models would overscale while Demand Shaping models underscale. If one could overcome the first issue, the second could be resolved by needing state-rate data for purchasing both hardware and estimated sales from customers and overriding Demand Scaling, Demand Shaping, and Demand Collaboration while controlled.

12.6.2. Benefits of a Unified System

The many-to-one relationship between products and stores, along with the interconnectedness of diverse functional processes, and the hyper-personalization and responsive logistics are some of the retail-specific challenges addressed in the unified system introduced herein. These challenges are examined in detail. Herein, we summarize the benefits of a unified system, leveraging the customizable framework described and the concepts proposed. Intelligent Cognitive Manufacturing-to-Market Systems have synergy benefits throughout the functional and supply value chains, either in functional operations or in supply chain operations. The summation of benefits from functional operations and supply chain operations leads to an increased enterprise value, enabling the implementation and adoption of intelligent CMMS.

Specific CMMS functions enabled by the interaction between the manufacturing and retail systems improve sales forecasting, strategic decisions, such as time-phased product availability status decisions, improved consumer experience, and joint product lifecycle management. Broader production supply and retailing horizons increase the impact of integrated demand/supply forecasting processes in the MTS mode for mass manufactured products, extremely cyclical seasonality demand products for which seasonal demand/supply is innovation and/or product newness variables have a more determinant impact.

12.7. Data-Driven Decision Making

The pervasiveness of information in the digital age has enabled innovative methods to exploit data for decision making in organizations. Data-driven decision making (DDDM) is a tool that helps business executives imbue their organizations with the thoroughness, discipline, and fact-based precision of scientists. The need to persistently and habitually demand data in support of every business decision is crucial. Making every decision in business, from approving the idea of building a factory in an area or determining its design and cost to implementing and monitoring how the factory works after it is built, managerially intelligible, it is crucial to back those decisions up with factual data, as well as relevant insights, gathered through a careful analysis of that data. Businessmen ought to realize that they are no more than data shells without insight.

The increasing importance of big data has created a newfound necessity to employ advanced techniques capable of deciphering that data in useful ways. Today, organizations deal with vast amounts of very fine-grained data collected from diverse sources, sensors, and networks in their business ecosystems. This has raised the stakes associated with these efforts. For example, the emergence of the 'internet of things' is creating both the opportunity and challenge of integrating multitudes of sensor-generated data with business processes and transactions in an automated manner. In the intrinsic logic of the current period’s general system theory, the maintenance of unanticipated state changes in the actual behavior of products and processes during their life cycles in the market requires an equally intrinsic competence for up-to-date, continuous de-coupling of fact-based analysis and insight generation coordinated with in-action decision making.

12.7.1. Importance of Big Data

Big Data refers to data collections that are so vast and complex they cannot be analyzed using traditional business intelligence or data warehousing tools, or without advanced computation. Big Data is characterized by quantities of data too large for traditional tools to create, curate, manage, or process—in terms of at least one of volume, variety, or velocity. Big Data is the large volume of data—both structured and unstructured—that inundates a business on a day-to-day basis. But it’s not the amount of data that’s important. It’s what organizations do with the data that matters. Big Data can be analyzed for insights that lead to better decisions and strategic business moves. Big Data describes the information assets characterized by such a high volume, velocity, and variety to require specific technology and analytical methods for its transformation into value.

The importance of Big Data comes from its potential risk and reward. At one end of the spectrum are promises of increased efficiency, new products, better customer experiences, reduced stock-out costs, and the transformation of entire industries into data-driven enterprises to capture margins that may be many times higher than average. At the other end are fears of loss associated with the failure to use advanced analytics to prevent product recalls that cost millions or billions, consumer data breaches that destroy brand value, or ransomware attacks that put entire companies out of business. For entire industries, understanding the larger impact of the appropriate degree of data-driven decision making is the key to capture rewards and mitigate risk. Too little data-driven decision making for retail means enormous stock-out costs from poor forecasting accuracy. Too much data driven decision making means the inability to keep data clean, act on insights quickly, or automate decisions, leading to lost sales and vendor fines. Understanding the balance among costs, risks, insight value, and reward potential is key.

12.7.2. Real-Time Data Analytics

Real-time insight on ongoing conditions, especially on mission-critical tasks like logistics execution, is perhaps the biggest missing piece of a digitized decision-making system. It is essential to update the digital models underlying these decisions continuously, so warehouse and logistics conditions are mirrored digitally as closely as possible. This offers the entire supply chain support for query and exercise data-driven decision-making. Specialized analytics from a variety of tools can have their interrogated for updates, and driven triggers can notify for defined condition changes at multiple levels of granularity and magnitude. Each analytics tool may have differing update periods, or none at all, based on its data model, data algorithm, and data synthesis cadence. For example, systems like a traffic conditions map would be updated every few seconds, while a warehouse slot allocation examination might only be done every couple of hours. These tools can also help in preemptive decision-making, or what we call brainstorming as a service. For example, a model fueled by sales forecasts based on offers planned and customer demand alerts can interrogate how often demand exceeds forecasts, and identify the next few customer's goods locations for possible offer changes. Merchandising planners can challenge previous offers for these customers.

Additionally, these tools generate insights for gate-control decisions based not only on incoming shipments but also on warehousing and outbound distribution conditions. Real-time data can help with order allocation for order fulfillment across distribution clusters, and thus real-time analytics can provide feedback via triggers points for changes in work instructions. Meanwhile, exception management can be embedded in the process templates at the hyper-care effort and throughpins priorities. Technologies, such as the digital twin, can provide one of the functionalities in real-time updates.

Fig 12.2: Intelligent Manufacturing in the Context of Industry

12.8. Customer-Centric Approaches

One, companies may aim to bring more precise ad messages to the right customers at the right time, so that they are easier to make purchasing decisions. The reason is that consumers face an information overload in the digital world, and relevant ads in the right customer journey and appropriate context will significantly increase conversion rates. Two, companies may attempt to enrich customer experiences and optimize customer journeys on brand-related touch points. Here, the reason is that customers are not always loyal to brands, and they tend to associate brand experiences with not only purchasing occasions but all touch points, which consist of a series of interconnected interactions over time. The distinguishing characteristics of an omnichannel context are that these touch points may consist of both online and offline channels, and both inbound and outbound marketing efforts. Three, companies may utilize AI since it holds the potential to transform the entire customer relationship management processes, to create more efficient campaigns or to optimize customer engagement.

Below, we will examine two aspects in more detail: understanding customer behavior and improving personalization in retail. The first point is about gaining an in-depth understanding of customer behavior, which can be done in a predictive way and in a descriptive way. To predict customer behavior, companies may use approach based on customer journey prediction and optimized decision-making. To describe customer behavior, companies may utilize techniques in behavioral data analysis from predictive and prescriptive perspective. Overall, an in-depth understanding gained from both approaches will assist companies in doing retailing right, and thus, improve customer experiences.

12.8.1. Understanding Customer Behavior

There has been a dramatic move towards being heavily customer-centric. Since the advent of major retail players, retail has been transformed with the products and services being delivered to meet customer expectations of availability and convenience. Retailing has become entirely different than what it used to be earlier. Unfortunately, while the majority of manufacturing and supply actors in the value chain have embarked on a journey of introducing new and enabling technologies to improve their efficiency and productivity, retailing has primarily relied on solving operational issues with ad-hoc information technology solutions. Decisions are still largely taken based on experience rather than cognitive systems. However, with vast quantities of information being generated and collected through social media and through in-store and online scans, there is an opportunity to revolutionize this part of the chain to deliver a superior experience to customers resulting in improved business outcomes.

A critical differentiating factor that could allow this to happen is the capability to understand how customers choose between products and services. Surprisingly, advances in econometrics have only recently introduced mathematical models that could be easily reproduced that allow researchers to understand and predict what trade-offs customers would make between attributes of products and services. These models show great promise and can be applied to a wide variety of choices, including the sections of promotions, bundling and other product attributes. However, despite the availability of the models, research has primarily been limited to academic papers. There is a need for retail analytics and visualization systems that will allow appropriate analysis with easily shared icons that allow managers to drill down into connecting different product and service attributes to a variety of demand numbers. Such systems would allow managers to share data and create a consensus when making decisions with trading partners and would allow customer decision models to be embedded in cognitive decision support systems. Such systems would assist managers in determining pricing, assortment decisions, and market-timing decisions for promotions not just locally within a specific store, but at a globally integrated level across the supply chain and across all channels.

12.8.2. Personalization in Retail

Reimagining the retail value delivery chain as constructed around the needs and demands of consumers creates opportunities to reevaluate the application of new collecting, analytics and communication technologies to the long-standing goal of the retailing functional discipline: delivering the right product at the right time at the right place for the right price in the most productive way possible to consumers based on their unique and individualized needs and demands. New data science technologies can be applied with skillful dexterity to fashion individualized retail environments that steeped the shopping experience for the customer with relevance, seamlessness and joy. Those advances in business analytics deployed with cutting-edge retailing practices possess the capacity to redefine the essential economics of the retail value proposition while enhancing the likelihood for creativity transformation of the entire consumer experience.

Selective consumer outreach, instead of blanket mass communications with low conversion rates and low margin challenges, can improve bottom line performance. Gathering extensive data on personal preferences, motivations, desires and needs can permit retailers to select those consumers who are more likely to buy their offerings. An advanced understanding of the customers and their lifecycles can convince consumers to divulge their shopping preferences, which are mapped into customized deals through individualized consumer microsegments. Connecting the data-driven retailing with the customer experience at the time of shopping can further enhance the value proposition for customers as well as retailers, assuaging fears that a retailing relationship is an untrustworthy transaction rather than an enriching relationship. The convergence of customer data technology and advanced marketing analytics functions create unique, real-time deals for individual customers based on their preferences and a retailer’s business model while generating personalized interaction opportunities during the customer’s shopping experience.

12.9. Sustainability in Intelligent Systems

An important responsibility for intelligent systems is to help organizations promote sustainability. The types of intelligent systems we review in this chapter – which help organizations and individuals predict, describe, evaluate, optimize, and automate decisions and knowledge-based business processes – can support efforts to promote internal and external eco-friendly practices. In the following subsections, we discuss how intelligent coalition systems can lead to more eco-friendly companies and supply chain practices.

In recent years, eco-friendly manufacturing practices and principles, also known as green manufacturing, have gained attention. Green manufacturing involves reducing harmful inputs and byproducts from manufacturing processes. Intelligent systems such as the cognitive systems we earlier described can support the use of green manufacturing strategies such as design for environment, sustainable product life cycle, and resource-efficient manufacturing. Automated, intelligent planning and scheduling systems can expedite the implementation and use of these green manufacturing strategies. In addition, intelligent prevention, detection, and analysis of defects can lead to resource-efficient manufacturing by cutting down the number of required parts and products.

Prior research on green manufacturing supported this statement by showing that green manufacturing practices can contribute to the triple bottom line of people, planet, and profit, improving a company's financial performance while also making positive contributions to the environment and society. Intelligent systems such as the ones highlighted throughout this chapter can support these research findings, implementing enabling technologies that make the additional costs of incorporating green practices unnecessary. Data-rich environments, such as those from smart factory or Industry 4.0 infusions, can allow analytical intelligent systems to be constructed at reasonable cost.

12.9.1. Eco-Friendly Manufacturing Practices

Sustainable manufacturing is producing manufactured products through economically-sound processes, with a minimum impact on the environment. Sustainable manufacturing employs eco-friendly practices that reduce negative environmental impacts, conserve energy and natural resources while assuring a high level of safety and health for employees, customers, and communities. Embedding sustainability factors into product design/prototyping, process planning, production systems, and logistics can lead to the development of an environmentally sustainable supply chain. The challenge is to balance cost with responsibility, finding a level of environmental stewardship that also makes good business sense. Sustainable manufacturing is a multi-objective decision that evaluates a variety of conflicting criteria such as energy and raw material consumption, waste generation, product quality, and production lead time during the manufacturing process.

Several criteria can be adopted to pursue eco-friendly practices in manufacturing, including recycling and eco-friendly recyclable materials selection, product design, processes for using less energy, processes for generating less scrap and waste, reuse, remanufacture, refurbish, disposal, and packaging. Novel green manufacturing processes are now being adopted to comply with contemporary government regulations regarding carbon emissions trading objectives and implant technological tools for the execution of green product design as well as for the planning and control of the novel planning and control paradigms that are associated with green manufacturing.

12.9.2. Sustainable Supply Chain Strategies

Although theoretically a truly closed-loop supply chain is as effective as an eco-friendly supply chain, by adopting the latter strategy, many companies are still bypassing externalities caused by end-of-life products that have not been channeled through their supply chains. To this aim, the external financial and reputational pressures moved by consumers and NGOs are resulting in dramatic shifts in the strategy orchestration of these players. Many companies worldwide are now first and foremost expected to ensure that the negative social and environmental impacts of processes and activities are avoided, minimized, and mitigated along the supply chain vertically down the very beginning of the commodity supply process. As increasingly mandated by potential customers and particularly watchdogs, a firm may also be required to guarantee governance and traceability of the toil levels and ecosystem preservation practices upstream in the entire supply chain.

The “no-man-left-behind” adage, referring to social issues connected, among others, to human rights violations, child labor, and lower-than-sustainable wage payment policies in a direct or indirect supplier of a focal company, has therefore become an overarching ethos designating a shift from shareholder to stakeholder capitalism. Interestingly, its implementation particularly in end-of-life product channels can in several ways also be strategically leveraged to affect the entire supply chain and mitigate or offset its ecological footprint. Among these, the most effective seems to be eco-labeling branding schemes set up at product end-of-life.

12.10. Future Trends in Intelligent Manufacturing

Real-time demand information appears to be in short supply in the manufacturing process. Digital and physical technologies have the potential of bridging the digital, physical, and social domains that are typically traversed as products pass through the intelligent manufacturing system. The convergence of prediction, control, and decision-making within the intelligent manufacturing system are expected to bring about radical changes in manufacturing, with large-to-small companies no longer differentiated by technology and access to capital, but rather by the intelligence embedded in the people operating the technology and the systems. Intelligent manufacturing, with cognitive capabilities within a worldwide manufacturing-to-market system, is leading to rethinking conventional approaches to managing production, throughput, inventory, logistics, and collaborative relationships with everyone in the supply chain. Emerging technologies appear to be coalescing that can pave the way to preventing devastating supply disruptions before they occur and responding to the disruption in a nimble manner that minimizes overall impact. These technologies include AI, cloud computing, big data, Internet of Things, 3D printing, blockchain, robotics, nanotechnology, neurotechnology, and biotechnology. They exert a transformational influence on the development of intelligent manufacturing systems. Alterations in manufacturing structure, technology, product design, and market dynamics will need to consider these influences. Model-based systems engineering focuses on development and deployment of manufacturing systems. Manufacturing models include product, process, and shop-floor models for analysis and simulation of complex dynamics. Model bases permit storage and retrieval of libraries of models, commercialized around specialized model types. Embedded sensors on products and in the shop floor are streaming real-time data on changing conditions, and AI and machine learning are inferring what is happening in the real-time environment surrounding products and the manufacturing systems.

12.10.1. Emerging Technologies

The dramatic technological advances of the last 20 years are rapidly spilling into the retail ecosystem, promising a step-change in price, variety, quality, and availability of goods and services offered to consumers (and provided by manufacturers). But unlike past productivity boosts in the retail sector, this surge is coming not from the retailers themselves, but from a related ecosystem of high-tech companies and small start-ups focused on the underlying technology platforms that both support and accelerate retailers' intimate interaction with their customers who increasingly expect customized product offerings to be conveniently available at lower relative prices. In fact, much of the surge that has suddenly reinvigorated productivity growth in the US economy in the aftermath of the pandemic is attributable to large investments by the tech firms in what are referred to as emerging technologies. These investments are triggering the emergence of multiple new core technology platforms that are creating entirely new business models in defense, financial services, education, media, and healthcare. Merchant services are, of course, following suit.

Most of the emerging technologies are based on a phenomenon called the fourth industrial revolution or Industry 4.0 – the idea that the so-called cyber–physical worlds (the digital world and the real world) are going to be increasingly interconnected and converged. While things like cloud computing, mobile technologies, machine learning, and Big Data have accelerated the rate of convergence and improvements in intelligent applications, it is the so-called Internet of Things that is really unleashing an unprecedented flood of cheap data onto the world – cheap because it is data created at extremely low marginal cost through increasingly inexpensive sensors embedded into physical objects like cars, buildings, appliances, and, increasingly, wearables.

12.10.2. Predictions for the Next Decade

Many of our pillars of cognitive retail manufacturing-to-market workflow systems are becoming real today, and are expected to have moved up a level in another decade from now. For example, today we are already able to predict retail demand intelligently for the largest retailers and CPG companies. This process is driven by ever-improving predictive analytics capability. Substantial changes are also occurring in the process, scope, and degree of real-time collaboration around the prediction. Today, detailed forecasting is done more frequently than just seasonally, and is augmented with interactive software. Companies are migrating from specific forecasts to extreme predictive analytics capabilities that identify "what sells where in what volume during what time period and at what price," supported by visual big data dashboards, using historical data and applying business intelligence predictive analytics and informatics – the Science of Signals.

Both Walmart and Procter and Gamble are moving their collaborative forecasting relationships from a transactional to a more relational basis to add much more value. Relationships are made much stronger through trust, better understanding of each company's constraints, mutual interest, and working together to jointly overcome limitations. For cannibalization, especially at the SKU-store level, mutual agreement is needed. These forecasts have a much higher value: Each side puts their chips on the table. These transactions have become much more of a joined decision, rather than just a mandate. The primary impact on value and competitiveness for both parties is merchandising and promotion execution performance optimization, shelf set optimization, inventory optimization, and inventory store-level allocation process improvement.

Other companies are moving forecasting collaboration downstream to second- and third-tier suppliers. For a few key items (new launches, key categories), retailers are sharing sell-in orders with brand manufacturers to fill earn-up, ensuring hit rates for the new item roll-outs. Manufacturers, with much better insights and capabilities early in their operations, are moving consignment accounting arrangements upstream done by vendors into retailers' systems after being received for a few companies.

12.11. Case Studies

There is, of course, a growing interest in intelligent manufacturing and marketing initiatives, making a set of case studies appropriate at this point. More and more companies are attempting what could be called intelligent systems. New terms are being created to embrace the ever-expanding boundaries of the intelligent manufacturing-to-market systems including terms like value chain innovation. Not only are companies defining these systems and calling for transformation, but also the consulting firms are engaged with various technologies and approaches designed to expedite the transition. Those companies and consulting organizations that have succeeded in making such systems operational or at least have made great strides toward achieving this difficult to accomplish goal have participated in their definition and design.

The examples below describe selected attempts to implement product and price coordination models, while recognizing that many more examples of intelligent systems exist. The examples illustrate successes and difficulties, some of which were unanticipated in the definition of intelligent manufacturing-to-market systems. The primary difficulties overcome include decision coordination across corporate boundaries, technical barriers to overcoming compute/communication technology limitations, and managerial barriers to the establishment and continuing operation of intelligent systems. What we are probably embarking upon is a new iterative cycle in which those companies that have succeeded pass along lessons learned to those companies that are taking the first baby steps toward intelligence.

12.11.1. Successful Implementations

The prosecution of the intelligent Manufacturing-to-Market vision will take time, as the capabilities required to provide closed-loop visibility and cross-constituency resource allocation are necessarily layered. Nevertheless, the capabilities required to support the intelligent vision can be implemented today. These implementations may not represent production-level solutions exchanged across the entire constituency landscape, but they can prove the value of functionality and enable business and implementation architects to visualize how to scale and interconnect those implementations into a coherent system. Most important, these implementations can demonstrate how indeed to manage the wealth of knowledge resident at the Manufacturing-to-Market nodes as a tactical competitive resource. These implementations must be aligned with the higher-level supplier community objectives. The tactics, when harnessed correctly, can enhance the supply and channel communities. During the past six years there have been a number of tactical implementations. They represent concepts and proof points rather than full-blown systems that trade flow information across the objective landscape. Most commonly reported are visibility or e-Logging tactical implementations. They do not, however, encompass a full "intelligent" objective, nor do they alleviate the "push" mode still being exercised in the channel and supply communities. Many tactical management implementations have been reviewed, from quality programs, best Manufacturing practice to standards, demand and supply matching, continuous replenishment, product lifecycle management, channel financial optimization, demand amplification and storage reduction, to cross-continental supply operations. Each of these has had parts of its knowledge components constructed with some degree of satisfaction, but none of these has actually implemented the vision described in the previous sections. The e-Ordered Log or e-Channel Log, as applied to supply, manufacture, distribute, and channel, is, we believe, one of the more sensible implementations of the vision for the tactical purpose.

12.11.2. Lessons Learned from Failures

As noted in the prior sections, there are many businesses and implementations that start on very innovative paths, only to face its downfalls. While there are many much more examples which have similar stories, we have chosen to discuss Wearable Computing, EU’s Fuel Cell Program, and Hungarian Telecos from the many industries we have covered. We focus on technologies to a large extent in these examples; this is not trivial, as we have explained that pushing technology as a magic bullet does not work and that technological and institutional systems need to evolve together.

However, there are many lessons to be learned from these stories, as they illustrate and support several key points made throughout the essay. One clear lesson is the need for a significant and continued investment to explore the potential of decentralized and hybrid systems; in order to realize the promise of decentralized networks, we need a significant level of investment in Common Pool Resources. Investment in the Bell System and its “first-mover time-in-space” are part of the history of the invention and diffusion of the telephone system: perhaps a similar model is required in other areas. Total investment into supporting research is often needed, especially in areas such as telecommunications: investments both in developing the technology and in exploring demonstrators of uses and design. However, it is clear that such experiments require a longer-term vision and a longer time-frame.

Of course, the alternative of funding the development of just the technology and then having hope for the best – that institution and commercial systems will be developed to exploit new technological opportunities, is proven to be a flawed one, with many arguments provided from various observations and studies of technology diffusion and technology systems.

12.12. Regulatory and Ethical Considerations

While most regulatory initiatives focus on data privacy, product safety, and cyber security, regulations designed specifically for the AI sector will soon impact intelligent manufacturing-to-market systems. The reason regulatory enforcements arise is to ensure fairness, transparency, equity, non-discrimination, accountability, and reliability. Regulations require that companies disclose when they use algorithms to make decisions. AI is considered high-risk when it has a "significant impact on people's safety or livelihood," which includes AI used for recruiting and evaluating workers, determining credit scores, and determining whether a person is likely to commit a crime. These regulations are put in place to protect consumer rights and human safety from companies that prioritize profit above all else. Supply chain systems that incorporate advanced forms of AI, such as data-driven decision making, require certification against benchmark practices. These are just some of the examples of regulatory compliance that affect intelligent supply chain systems. The area of focus for compliance is on biases that arise when databases are created by "cleaning" data based on various heuristics that lead to preferred decision outcomes based on gender, race, background, culture, ethnicity, or beliefs – in short, the algorithms are prejudiced because the data sets are incomplete and therefore, inaccurate. Any intelligent supply chain system that uses predictive analytic decision making uses these inbuilt industrial and firm-level biases to make decisions with unintended but serious consequences.

Cognitive systems that incorporate ethics bypass areas of concern that are already regulated but go further to ensure equitable optimizing and transparency in the decision outcomes. Based on past decisions made by cognitive systems, the ethical challenges phase out what the designer views as unintended bias and that the system views as non-optimized variable, thus addressing a critical concern of bias in the creation of databases and catalysts. In retail, the issue of AI ethics becomes critical as these systems make recommendations, create customer personas, and influence customer decision making.

12.12.1. Compliance in Manufacturing

Complexity is making it very demanding for every player of the intelligent Manufacturing-to-Market Systems to comply with regulatory constraints coming from governments or supra-governments. The ones on the supply-sides are related to a quest for environmental sustainability or integrity of the supplier production base. Regulatory constraints cannot be fulfilled very easily: first, not all the suppliers are visible… which means that it is demanding to have a clear picture of the condition of every actor of the supply-side and of its production in terms of risky events.

This situation of being unable to respect the laws that ensure sustainability and allyship might bring a loss of competitiveness, or, even worse, business closure for the retail and the supplier. Some retail companies have understood this and have started services with digital twin technologies associated with predictive, prescriptive or semantic engines allowing a better control of the suppliers' integration into the corporate policy and a decrease of the impact of these unforeseen black-swan events. The prerogatives of these ecosystems are digital twin technologies that ensure traceability and tracking with the technologies of the blockchain for obvious immutability of the data, AI technologies - which are at the very basis of the regulatory and corporate dashboards that supply side's stakeholders issue, and decision-making dashboards that the actors of the supply ecosystem and retail actors need to issue, alert, trigger or generate processes all along the supply and consumption chain(s).

12.12.2. Ethics of AI in Retail

The ethical implications of AI application in retail scenarios are an increasingly urgent issue with the rapid progression of AI technology. As retail businesses endure organizational pressure for rapid AI adoption, there is a risk that the implementation of AI may overrun the ethical considerations of decision-makers. Common ethical risks that are heavily present in the area of service AI applications include tasks that people ordinarily carry out, such as caring, guiding, protecting, teaching, and selling. Ethical risks arise because moral obligations for such tasks may be flouted, or because the AI is incapable of understanding morality. Additionally, most retail applications of AI have little or no concerns for the privacy of individuals, even if they have been entrusted with sensitive data. Companies must pay high ethical risks here before automated decisions are made. One aspect of decision-making where AI decisions should be avoided is when AI should not be used as a substitute for human source selection judgments, especially in cases of unequal power relations. Ethical risks are especially emphasized when customers stand and observe while deep-learning algorithms act apparently unnoticed behind the scenes. The threat of racism, sexism, or classism could make such retail scenarios difficult.

Not only customers but also employees affected by AI need protection from unethical AI design. By sharing experiences of work influenced by automatic behavior monitoring and workplace surveillance systems, they help navigate the consequences for both physical and mental well-being. To conclude, ethics must be taken into deeper consideration, with some guidance provided to enable a successful, socially accepted, and sustainable embedding of retail AI. Otherwise, technology should not be adopted blindly in preference over an ethical reflection.

12.13. The Role of Supply Chain Resilience

The recent COVID pandemic has urged businesses to reflect on their supply chains: research has found that about 75% of companies are concerned about the resilience of their supply chains. Supply chain management has amplified the discussion of resilience with fundamental disruptions as natural catastrophes, severe disease outbreaks, and economic crises being additional influential events along the supply chain. The Flixborough and Bhopal incidents exemplarily describe the massive outcome of disruptive disruptions. They can add to the costs of companies in bankruptcy, and affected external stakeholders by job losses and loss of markets. Thus, supply chain disruptions might affect local economies as well. Resilience is the capability of organizations to anticipate risk but to be also prepared for the unexpected. It enables businesses to bounce back after disruptions, withstanding supply chain changes in business operations.

Recent research has focused on updating the supply chain design and the physical flow to enable supply chain resilience. Businesses are required to develop a reliable supply with established partnerships, but it is also recommended to take into account alternative suppliers in opposing geographical areas in order to avoid heavy losses. Adverse events should not only be considered in terms of probability but also with respect to the impact a potential adverse event might have. Another way to minimize risk would be to implement a postponement strategy to delay the final assembly in order to maintain flexibility. There is an inherent risk of losing customer orders, leading to customer dissatisfaction. Affected operations are the loss of the deal but lack of responsiveness for remaining customer orders.

Building resilience in supply chains is necessary but creates additional costs. On principle, it leads to a competitive disadvantage; however, current e-commerce strategies have gained a solid basis by offering a wider assortment of goods. Compensating for higher costs is only one potential decision. Affected companies might also want to restrict chosen prices. Other businesses are willing to absorb some of the costs, letting the affected supply chain recover faster from eventual disruptions. Is counterproductive for some organizations, i.e. offering the lowest prices.

12.13.1. Building Resilience in Supply Chains

A first important point we would like to raise is that it is necessary to build resilience into supply chains in order to cope with increasing complexity and higher disruptions risk. Despite globalization, consumer demand has shifted towards exacerbated large variety products, shorter product life cycles, and faster and more frequent deliveries, which has led to increasing transportation and inventory costs resulting in the need of shortening product distance. The terrorism threat and natural disasters have progressively increased risk re-evaluation. Backed by estimated cost of conduct in hypothetical supply chain disruption too high in comparison with expected expense to be incurred for the supply chain resilience, more companies are intensively adopting enablers of supply chain resilience. These enablers comprise enhanced communication and visibility throughout the supply chain members, flexible capacity as well as capacity cushion, proximity, supplier diversification in terms of interdependence degree and sourcing location deployment depth, stock piled at supply chain partners level, information-sharing, relationship with suppliers, and risk management and contingency plan. A second aspect we would like to highlight is that resilience cannot be built simply through enhancing enablers. On the one hand, enabler client requirement is conditioned by the demand risk of the concerned supply chains. On the other hand, type of enablers realized is also subordinated to supply chain type defined by the cost and differentiation leaderships and customer service level. Enhancing resilience too much for a product could result in unmanageable overinvestment embodied by such enablers along the relative, perhaps very short, life cycle.

12.13.2. Crisis Management Strategies

A crisis generates stress and high anxiety levels among people due to its difficulty of understanding and management. Therefore, companies should first establish a culture based on trust, empathy and clear communication with employees, business partners and customers. Employees, who are the basis of the company's structure and an immediate success factor in a crisis situation, deserve special attention. Implementing open communication mechanisms that allow to know opinions and ideas from teams and better listening to needs and concerns are critical factors for employees to feel cared for. Developing a platform that allows you to share short videos with employees explaining the company's reaction to the crisis and their involvement in solving it can also be useful. Creating a task force with representatives from each area of the company to elaborate joint solutions strengthens ties and minimizes stress. Once the internal message is transmitted, the next step is to send the external message as soon as possible. The supply chain is the backbone of a company's performance in any situation, but it becomes particularly critical in health or sanitary crises, when product flows are interrupted, or in digital crises, when demand spikes uncontrollably. Companies must prepare their operational partners to communicate and act in a timely manner. Hence why establishing action protocols in advance is crucial. Some companies have developed a seniors' plan, which consists of having the executives of the company visit suppliers and critical customers once a month. This plan was presented as a congratulations on the year and a commitment to work together. Its value lies in the fact that it guarantees visits during both the good and the bad, and functions as a mechanism to build trust with all external stakeholders.

12.14. Technological Infrastructure

The innovative Intelligent Manufacturing to Market System (IMMS), explicated throughout this work, hinges crucially on a technological infrastructure, which is composed of several components in itself. The major components include hardware and software pieces. Cloud services represent both a hardware and a software infrastructure, along with communication and message brokers. On the hardware side, Cloud services allow the connection of relatively inexpensive computational units – able to run both applications and databases – which companies can access from anywhere they are. They are quite inexpensive, since companies using pay as expenses the actual real utilization.

One of the most likely Cloud applications in Supply Chain Management is where the analytical models are executed. If a given Supply Chain is very large and the models do require considerable computational resources, then, a company can decide to do these activities in-house. So far, Cloud has been used for applications such as Web Services and Enterprise Resource Planning, which means to a lesser extent for Supply Chain Management. There are several reasons for the reduced utilization of Cloud in the case of Supply Chain Management, considering both companies capability and Supply Chain characteristics. In the future, it is likely that such type of Supply Chain applications may increase considerably. Internet of Things or Cyber-Physical Systems is based on the fact that an increasing number of physical artifacts are being embedded with sensors and communicating components, which makes it possible to trace and monitor their state and location in service by a Supply Chain member.

12.14.1. Cloud Computing in Supply Chains

Cloud computing has improved both the computing and communication connectivity of distribution and logistics functions within supply chains, and more widely among manufacturing-to-market participants. In recent years, a series of cloud-based company services have emerged, including cloud-based transportation management services, cloud-based supply chain event management services, and cloud-based demand forecasting services. In addition, many companies have developed and begun using cloud-based systems specifically for collaborative supply chain forecasting, demand management, production planning and scheduling, transportation scheduling, and inventory management. These cloud services have delivery lead times that are as small as half a second. Big Data storage services have also become available at low cost through the cloud, including the capability of managing more than three trillion items.

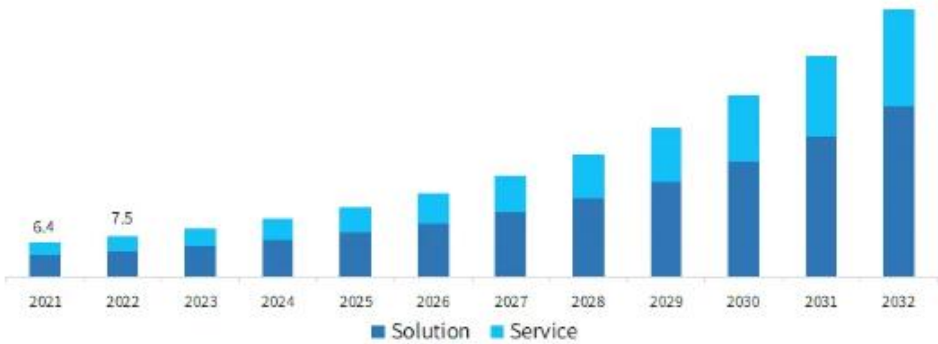

Fig : Cognitive Supply Chain Market Size, Forecasts Report

Cloud computing has also contributed to the creation of the demand-driven supply chain model, enabling supply chain partners to track the depletion of inventories in retail stores and then collaborate to share this information in real time to synchronize replenishment and production decisions. Cloud-based resource sharing and marketplace services are particularly appealing for SMBs, helping them take advantage of scale economies, save on up-front capital investment for IT resources, and improve their ability to innovate and compete, grow revenues, and improve customer service. This helps SMBs create and capture value in ways that would not otherwise be possible, which in turn helps strengthen and stabilize supply chains. Such value creation and capture approaches have been identified as important elements that help SMBs thrive in emerging markets. Companies have reportedly turned to the cloud, allocating more than a quarter of their IT budgets to this technology.

12.14.2. IoT Applications in Manufacturing

The ability to monitor and control machines on the shop floor with IoT is revolutionizing factories, enabling Data Analytics and potentially even AI that extend from the sensor level all the way up the enterprise stack. What we used to refer to as Factory Automation, however valuable, was all about controlling a limited range of capabilities – specifically motion and assembly. While there are several new and important companies emerging in this space, for the most part these forays are extensions of existing, non-AI-based robotics applications, or else robotics-like experiments by expensive-to-implement new companies. What is different about IoT-based automation, by contrast, is that it is holistic and involves not just the mechanisms of product movement and assembly but all aspects of the flow and processing of Materials.

These capabilities have long been recognized as key to improving productivity in manufacturing. For clear and very practical reasons, factories invest great time and money on these software systems. In a world of sensor-based continuous and real-time data, however, many manufacturing processes not well implemented by existing systems could be radically improved. First, there are many important manufacturing processes for which existing systems focus on balancing back-office notions of resource utilization against inventory-reduction needs to help reduce cash budgets. These processes have limited visibility and little ability to guide or control real-time decisions, including what problems are urgent enough for a manager to intervene, decide, and possibly even override existing sequences.

12.15. Conclusion

The previous section has declared that there is a disaster in supply chains, a disaster that has had intense repercussions on companies, on consumers, and industrial ecosystems at large—a disaster that has taught both company CEOs and government chief officers that supply risk is an unavoidable consideration in business models and social orders. But it is also clear that the COVID pandemic has made clear that the rest of the world is unable to represent an alternative supply source at the scale necessary to allow multinationals become entirely independent of China. This accentuated the companies' conundrum: as companies configure their new global manufacturing-to-market systems, they need to minimize logistics and labor costs, avoid tariffs, and implement localized responsiveness while not being too dependent on single-country supply markets.

In this chapter, we have provided a high-level conceptual framework to help industrial companies in the journey that will bring them from solely predictive supply systems, capable of minimizing costs, to cognitive manufacturing-to-market systems, capable of generating added value for their stakeholders and for the planet, while implementing maximum resilience. We have described the four building blocks of B2B Industry 4.0 for Cognitive Supply and in particular the architectures for the data-driven ecosystems that we propose for business-to-business and business-to-consumer manufacturing-to-market exchanges. We have described some examples of digital communication architecture based on distributed ledger technologies, and we have pictured the enterprise architectures, market ecosystems, and governance models needed to implement the cognitive supply vision. Implementing these cognitive supply architectures, market ecosystems, and governance models will enable companies to make proactive supply risk management just as important as cost minimization when deciding how and where sourcing operations are carried out.

References:

Lee, J., Bagheri, B., & Kao, H. A. (2015).A cyber-physical systems architecture for Industry 4.0-based manufacturing systems.Manufacturing Letters, 3, 18–23.https://doi.org/10.1016/j.mfglet.2014.12.001

Min, H. (2010).Artificial intelligence in supply chain management: Theory and applications.International Journal of Logistics Research and Applications, 13(1), 13–39.https://doi.org/10.1080/13675560902736537

Min, H. (2010).Artificial intelligence in supply chain management: Theory and applications.International Journal of Logistics Research and Applications, 13(1), 13–39.https://doi.org/10.1080/13675560902736537

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

Xu, X., Lu, Y., Vogel-Heuser, B., & Wang, L. (2021).Industry 4.0 and smart manufacturing: A review of research issues and application examples.International Journal of Production Research, 59(16), 4865–4887.https://doi.org/10.1080/00207543.2020.1824086