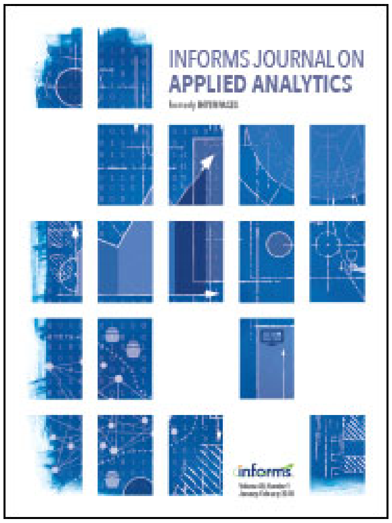

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THE FRANZ EDELMAN AWARD
Achievement in Operations Research

Supercharged by Advanced Analytics, JD.com Attains Agility, Resilience, and Shared Value Across Its Supply Chain

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Abstract. Grounded in advanced analytical techniques and close relationships with its partners, JD.com, the largest retailer in China based on revenue, is committed to an intelligent, integrated, and resilient supply chain that creates value for all stakeholders within the retail ecosystem. Despite challenges in the complex and sophisticated retail supply chain, JD.com has strengthened its supply chain agility, and attained shared value by focusing on supply chain efficiency, supply chain resilience, and customer-demand intelligence. Specifically, JD.com implemented an end-to-end inventory management system based on a dynamic programming model and a neural network model, leading to a reduction in costs and enhancements in operational efficiency. To be able to provide guaranteed service levels for consumers during supply chain disruptions, the company used intelligent techniques, including an emergency classification mechanism and a simulation model, to strengthen its collaboration with critical partners, attain resilience, and benefit society as a whole. For the upstream manufacturers, JD.com implemented the consumer-to-manufacturer system by incorporating state-of-the-art artificial intelligence algorithms and enabled manufacturers to accurately predict customer demand and produce more popular products according to customer preferences, hence creating value for the entire ecosystem. Billions of dollars in increased revenue and tens of millions of dollars in cost savings have been achieved to date since the implementation of the aforementioned techniques, and customer welfare and partner manufacturers' benefits have been significantly enhanced.

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Keywords: Edelman award • supply chain management • supply chain resilience • end-to-end supply chain • risk management

Introduction

The methods used to manage retail supply chains today differ greatly from those of the past. The advancement of the Internet has given rise to exploding customer demands, emerging fulfillment channels, and the deployment of sophisticated technologies (Pasquali 2022). Yet the complexity of the supply chain has grown multifold: proliferation of product variety, different means of order fulfillment, and an extended supply network with a large number of suppliers in multiple tiers. Ensuring efficient and agile operations of such a complex supply chain requires new approaches and evolutionary techniques. The key is to ensure that the benefits and value created as a result of innovative supply chain management provide a high level of service and support to consumers and to the businesses, many of which are small-to-medium enterprises (SMEs). Disruptions like COVID-19 were significant tests for the operation of such supply chains. In a very challenging environment with city lockdowns, widespread shortages, logistics breakdowns, and many SMEs struggling for survival, how can efficient and agile supply chain management support all the members of an end-to-end supply chain?

This paper describes how JD.com, China's largest retailer based on revenue, used advanced analytics and a collaborative management approach to optimize its supply chain network. As a result, it achieved superior operational performance and efficiency, gained deep customer loyalty through servicing customers in difficult environments by effective integration of each component, and created value through accurate prediction of market demand and joint development with partner manufacturers of new products for customers.

JD.com offers more than 10 million stock keeping units (SKUs) and serves about 600 million active users, achieving US$149.3 billion of net revenue in 2021. To provide a better experience to users, it runs an omni-channel business model with multiple online and offline sales channels while operating more than 1,400 warehouses with its own fleet. Its supply chain management practices encompass broad areas including inventory replenishment, warehousing operations, and transportation. With a complex business model and sophisticated supply chain operations, JD.com uses cutting-edge intelligent technologies to achieve high efficiency. For example, its "211 program," which provides same-day delivery for orders placed prior to 11 a.m. and next-day delivery (before 3 p.m.) for orders submitted before 11 p.m., set a new standard in China's business-to-consumer e-commerce sector. With this program, more than 90% of orders can be delivered the same or the next day. In addition, with the stockout rates below 3%, JD.com's recent days in inventory (DII), which is calculated by dividing average inventory value over a given time by cost of goods sold during that period to measure the efficiency of a retailer's inventory management and cash utilization, is 31.5 days, among the best in the industry.

JD.com is a technology-focused enterprise with its supply chain at its core. Its vast investment in supply chain technology benefits both itself and its partners within the ecosystem. Many of its practices demonstrate JD's vision (to become the most trusted company in the world) and core values (i.e., customer first, integrity, collaboration, gratitude, dedication, and sense of ownership), such as providing 100% authentic products for consumers, and delivering medicine to hospitals during the COVID-19 lockdown. To better use its supply chain to foster greater social value, JD.com initiated an enterprise-level project that it called "Constructing a Social Value Focused Supply Chain." The objectives of this project were to enhance its supply chain capability, energize the whole ecosystem, assist operations of all stakeholders, safeguard the supply chain, and deliver necessities of life to citizens during disruptions.

JD.com has always been dedicated to strengthening the capability and increasing the resilience of its supply chain. Its supply chain practices have been anchored on the end-to-end supply chain management methodology proposed by Max Shen (Qi et al. 2023), and the 3A concept, agility, adaptability, and alignment, proposed by Hau Lee (Lee 2004). JD.com views its supply chain capability as the product of supply chain efficiency, supply chain resilience, and customer-demand intelligence. As Figure 1 shows, its supply chain is a sophisticated and comprehensive collaboration between various key stakeholders, such as customers, retailers, and manufacturers, and is empowered by cutting-edge technologies. Using the supply chain capability equation shown in the first row of Figure 1, JD.com not only achieves operational excellence through an efficient supply chain, but also employs technical innovations to assist and benefit other stakeholders within the supply chain. To improve supply chain efficiency, it developed an end-to-end inventory management methodology based on a dynamic programming model and a recurrent neural network (RNN) model, which also significantly reduced inventory holding costs. To achieve resilience against unprecedented crises such as COVID-19 that cause major supply chain disruptions, JD.com used intelligent techniques, including an emergency classification mechanism and a simulation model. To achieve a more accurate understanding of customer preferences and thus better satisfy these preferences with accordingly designed products, JD.com collaborated with manufacturers using a consumer-to-manufacturer (C2M) system based on state-of-the-art artificial intelligence (AI) algorithms, which also created value for upstream manufacturers, promoting growth and innovations within the ecosystem. Via various intelligent technical methods, JD.com built an intelligent, integrated supply chain that benefited itself, its partners, consumers, and the entire ecosystem.

Problems and Challenges

The retail supply chain today is sophisticated yet complex with proliferation of product variety, increased customer diversity, and a vast logistics infrastructure. As an example of such a complex supply chain network, JD.com offers more than 10 million SKUs, serves about 600 million active users, and has more than 1,400 warehouses, hundreds of distribution centers, and tens of thousands of delivery stations located throughout China. To operate and maintain such a large supply chain network and to keep it functioning at a highly efficient level is a challenging task, especially when uncertainty exists in almost every node of the supply chain at any given time. An effective supply chain management strategy needs to address every segment of the supply chain, including retailers, consumers, suppliers, and manufacturers. In this section, we describe the problems and challenges retailers, in particular, face in managing their supply chains.

Challenges in Supply Chain Efficiency

The first challenge relates to supply chain efficiency. Inventory management under demand uncertainty is critical for a supply chain to reduce operational costs, enhance efficiency, and better fulfill customer demand (Federgruen and Heching 1999, Dong et al. 2008). With the increasing level of customer diversity, high level of demand uncertainty, growing variety of products, multi-tiered supply chains with many nodes and links, and higher service level requirements, retailers are facing new challenges in inventory management.

Figure 1. (Color online) Overview of JD.com's Supply Chain Capability and the Capability Equation

The traditional approach for replenishment was based on a sequential approach, first using data to estimate future sales, and then developing a replenishment strategy based on expected vendor lead times (VLT). This type of solution paradigm, first predicting random variables of interest and then incorporating the prediction results into an optimization stage, is referred to as the predict-then-optimize (PTO) solution framework (Levi et al. 2015). Although widely adopted, this approach decouples the prediction and optimization stages. Consequently, the optimization stage does not directly use the input data, and useful information can be lost in the PTO process (Yan et al. 2020, Elmachtoub and Grigas 2022). Additionally, in the operational practice of e-commerce retailers, the large number of SKU types, the highly uncertain nature of customer demand, and unforeseen circumstances can all contribute to substantial forecast errors, which can increase supply chain costs and decrease customer satisfaction.

Hence, it is critical to develop a framework that can quickly identify the optimal or near-optimal strategy for different demand levels and increase supply chain efficiency.

Challenges in Supply Chain Resilience

E-commerce retailers aim to provide high-quality goods and timely delivery to consumers utilizing their sophisticated supply chain and logistics infrastructure. However, they face challenges when unexpected events happen and disrupt part of the supply chain. For example, natural disasters like earthquakes, hurricanes, or floods may destroy roads and logistics facilities, and thus lead to delayed or canceled deliveries. Supply chain disruption has long been an important topic in the area of operations management (Tomlin 2006, Huang et al. 2012) and became particularly important during the COVID-19 pandemic. During the pandemic, truck drivers and warehouse staff were sometimes sick or under lockdown and roads and offices were closed due to the lockdown policies issued by the government. Under such circumstances, it was not always possible to fulfill consumer orders as usual, thus severely degrading customer experiences. For example, in April 2022, more than 81% of JD.com's orders in Jiangsu Province were delayed and delivered later than the original promised delivery time due to restrictions related to COVID-19, and customer complaints corresponding to delayed orders increased 213% in Shanghai. This example clearly shows the importance of supply chain resilience.

Supply chain resilience refers to the ability to quickly and effectively recover from a disruption (Behzadi et al. 2020, Ivanov 2021). When supply chain disruptions occur, a decision maker must act immediately to lessen the impact, resume operations, and recover quickly; this can only be achieved through collaboration within the entire supply chain. Examples of such collaborative activities include notifying customers of delayed delivery, preparing essential supplies in advance, and arranging additional staff to process accumulated orders. However, a prerequisite for doing so is to detect and identify the risks and disruptions as early as possible once a disruption occurs. If the decision maker relies on manual reporting of the disruptions by the local staff using the staff's subjective judgment, the reliability and accuracy of the information cannot be guaranteed.

Hence, an intelligent risk management system is needed to identify disruptions quickly, to grade disruption severity automatically and precisely, and to help coordinate the entire supply chain. Such a system is a powerful tool to ensure the resilience of the supply chain.

Challenges in Customer-Demand Intelligence

In addition to challenges in supply chain efficiency and resilience, retailers also face challenges in accurately predicting customer demand and preferences. Because there could be several intermediate stages between the manufacturer and consumer, the manufacturer may not be able to capture consumer preferences and design new products to meet those preferences in a timely manner. Traditionally, manufacturers try to learn about consumer preferences through field surveys and questionnaires, an approach that is time consuming and might result in products that deviate from the actual preferences of the consumers. The intermediate stages such as distributors between manufacturers and consumers make it almost impossible to independently use data-driven techniques to investigate the consumer preferences and the corresponding sales volume, because manufacturers cannot directly access the complete consumer portrait. The distributors often possess an information advantage (Belhadj et al. 2020) and tend to share their opinions on the consumer needs and favorite features with the manufacturers. However, this could in turn distort the market's true demand because the majority of the opinions are based on distributors' own experiences. In addition, the existence of intermediate distributors means the splitting of profits and thus reduces the profit margins of manufacturers.

As a major retailer in China based on revenue, JD.com not only cares about its own business, but also is dedicated to benefiting its partners in the entire ecosystem, including manufacturers. To use its cutting-edge intelligent and data-driven techniques and enable the manufacturers to better understand consumer preferences is rewarding and challenging for both JD.com and the upstream manufacturers.

Overview of Technical Solutions

To solve the problems discussed in the last section and to overcome the challenges, JD.com's Department of Intelligent Supply Chain Y (Department Y for short) is dedicated to developing technical solutions based on operations research and artificial intelligence (AI) tools. In this section, we first briefly introduce Department Y, and then give an overview of the techniques that Department Y has designed and implemented to solve the corresponding problems for the benefit of retailers, consumers, and manufacturers.

Department Y was established in 2016 to serve the omni-channel retail supply chain and to enable intelligent supply chain management. Its mission is to continuously optimize the cost, efficiency, and experience of the supply chain through digitized and intelligent techniques. Its vision is to support JD.com in becoming a global leader of supply chain efficiency in the retail industry.

Since its founding, Department Y has been dedicated to the automation and advancement of supply chain management, including the areas of inventory management (Lin et al. 2021, Lei et al. 2023, Qi et al. 2023), order fulfillment management (Chen et al. 2022), delivery network planning (Kang et al. 2022), digital twin-driven supply chain optimization (Wang et al. 2022), supply chain resilience (Shen and Sun 2023), and customization of new products (Mak and Shen 2021). Department Y currently has more than 500 employees, the majority of whom are research and development engineers. It is continuously promoting the innovation and implementation of supply chain management using cutting-edge Big Data, AI, Internet of Things, and operations research techniques.

Based on the technical solutions provided by Department Y in coordination with other departments, JD.com built three pillars to tackle the challenges discussed in the previous section. We introduce these three pillars below and provide technical details in subsequent sections.

Supply Chain Efficiency

JD.com's end-to-end inventory management was based on a deep learning model that the company used to develop the best replenishment plan. The model first used historical data to determine the optimal replenishment quantity based on dynamic programming and then built a feature library and generated training samples based on historical sales information, VLT information, initial inventory, and optimal replenishment quantity. An RNN module was used to train the model. Finally, the model provided a replenishment recommendation and predicted the sales and VLT. By shortening the decision-making process and reducing the accumulation of prediction errors in intermediate links, JD.com improved the effectiveness of its replenishment strategy and consequently reduced costs.

Supply Chain Resilience

JD.com established an emergency classification mechanism to notify all the affected parties in its supply chain as soon as a disruption occurred and coordinate the appropriate action for recovery. First, it monitored real-time supply chain indicators in various cities, such as the number of halted orders, the days to clearance of halted orders, and the ratio of order demand and production capacity. By continuously collecting and analyzing the real-time data, it categorized each city into different emergency levels (i.e., normal, warning, yellow, red), and guided each department of JD.com and its partners to react accordingly. For example, the inventory replenishment department needed to confirm the logistics capabilities of suppliers in warning situations. In red situations, its sales promotion plan, advertising strategy, and recommendation strategy would switch to the emergency state to avoid ineffective commercial activities in corresponding regions, and the reserved labor and resources would be made available to replenish stocks and fulfill orders.

To achieve the objectives of the emergency mechanism, JD.com built a discrete-event simulation model to simulate the inventory replenishment, inventory depletion, and order fulfillment processes under different emergency scenarios. In particular, JD.com simulated the evolution of the impact of the emergency, uncovered the bottlenecks in the supply chain by what-if analysis, and provided warnings and alerts, as well as future-trend reports to the decision makers.

Customer-Demand Intelligence

JD.com implemented a C2M platform by incorporating state-of-the-art AI algorithms, such as the deep structured semantic model (DSSM) and general attributed multiplex heterogeneous network embedding (GATNE), which serve, but are not limited to, the design of new products, identification of target consumer segments, and marketing and advertising strategies. Using the consumer decision trees (CDT) model, JD.com quantified the extent of the importance of various product attributes in buying trends of consumers based on massive consumption data and provided feedback to manufacturers for product development. It developed a pricing model based on a clustering algorithm to suggest an appropriate price for new products that did not have any historical data. Moreover, it also developed a new product user model and a free trial selection model to identify target segments of consumers and determine how to attract these consumer segments.

Supply Chain Efficiency: End-to-End Inventory Management

To improve supply chain efficiency, JD.com implemented an end-to-end system for inventory management. The expression "end-to-end" implies that the inventory replenishment decisions are directly generated based on input data without any intermediate steps. In contrast to classical replenishment methods, which usually follow a PTO structure, the end-to-end model avoided error accumulation in the intermediate stages, providing more accurate predictions and improved inventory strategies. Moreover, determining the optimal inventory level is usually a finite-horizon dynamic programming problem, which is typically computationally intensive. In contrast, the end-to-end system generates the demand prediction, the VLT prediction, and the recommended inventory replenishment level simultaneously, thus significantly reducing the computational burden.

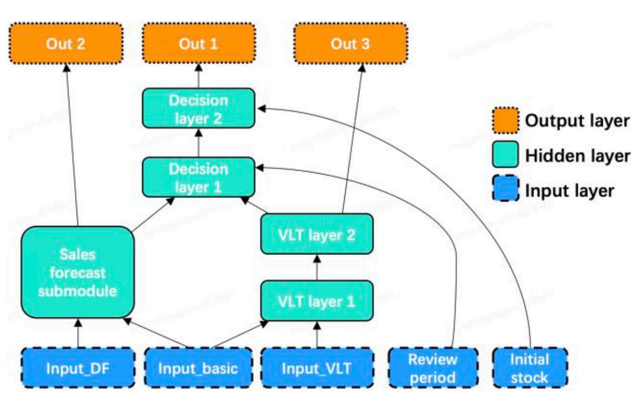
Technical Solution of End-to-End Inventory Management

The technical solution of JD.com's end-to-end inventory management system was an end-to-end model proposed by Qi et al. (2023). Briefly, the system used an RNN model as the surrogate of a predictor to predict the expected sales and VLT and a decision maker to generate a good replenishment strategy. The execution procedure included two main steps. First, the replenishment problem was modeled as a classic dynamic programming model. The mathematical details can be found in the appendix. Second, based on the optimal inventory strategy we mentioned previously, an RNN model was then trained as the core module of the end-to-end system. As Figure 2 shows, the RNN model generates the sales prediction, VLT prediction, and recommended replenishment strategy simultaneously, and a loss function of the weighted combination of the prediction errors of these three components (i.e., the difference between the predicted and actual or optimal values). The inputs of the end-to-end model include five parts: Input_DF and Input_VLT represent features related to demand forecast and VLT. Input_basic is the set of general SKU item-level features, such as product, categories, warehouse locations, and brand names. Review period and initial stock are entered directly into one of the hidden layers (i.e., intermediate layers between the input layer and the output layer to transform the input data into a representation that the output layer can understand) because they are not intended to generate any cross terms with other features. The end-to-end model has three outputs: Out1 represents the main output, the final replenishment decision. Out2 is the demand forecast and Out3 is the VLT forecast.

System Implementation of End-to-End Inventory Management

The end-to-end model was integrated into JD.com's *Intelligent Inventory Platform*, which mainly served the sales managers. Specifically, using massive historical data on sales, VLT, suppliers, prices, and on-hand inventory, the inventory platform recommended a corresponding inventory level and replenishment strategy for

Figure 2. (Color online) Neural Network Structure of the End-to-End Model



Notes. Input_DF represents features related to demand forecast. Input_basic is the set of general SKU item-level features (e.g., product, categories, warehouse locations, and brand names). Input_VLT represent features related to vendor lead time.

a product according to the model selected by a platform user. In general, the user first chose a preferred inventory model (the end-to-end model was the default, although other models were also available) and then made the final decision on the replenishment strategy. The user could accept the system recommendation, make minor modifications, or ignore the recommendation.

The platform required three steps to prepare for and finish the full launch of the end-to-end model and implement it for more than 9,000 products. The key was to validate the performance and robustness of this model, especially compared with other classical models and with a manual strategy. Before the system was launched online, the platform performed extensive offline numerical experiments to determine the optimal parameters and model structure. The results were presented to the sales managers to get their feedback, answer their questions, and gain trust. Then, a small-scale field experiment was run on a limited set of products from February to May 2020 to validate the effectiveness and robustness of this innovative approach. Finally, from May to August 2020, JD.com implemented the end-to-end system in two representative categories, tea utensils and condiments. During this pilot, the algorithm team maintained close contact with relevant sales managers and monitored key performance indicators in real time. The key indicators include the following:

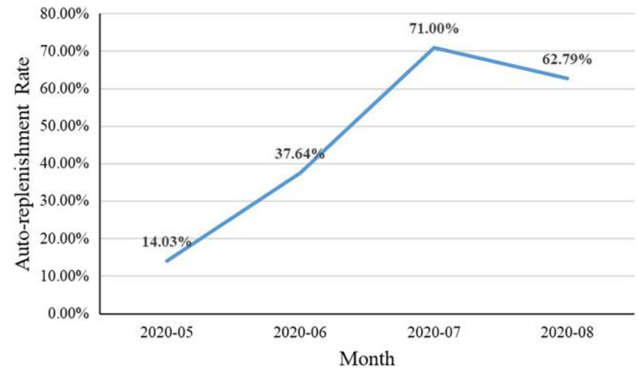
1. The rate of auto-replenishment, which is defined as the percentage of order value generated by the end-to-end model and directly accepted by the sales managers without any overrides.
2. DII, which reflects efficient management of inventory.

As Figure 3 shows, starting from 14.03%, a quite low level in May 2020, the auto-replenishment rate increased by nearly 57 percentage points in two months during the pilot. This result indicates that the sales managers were convinced of the superiority and accuracy of the end-to-end system. Figure 4 shows the DII of the end-to-end system during the pilot. Specifically, the solid line represents the test group, the set of products for which JD.com used the end-to-end system, whereas the dashed line represents the control group, the set of similar products for which it continued using the manual replenishment strategy. The figure clearly shows that the end-to-end system always achieved better efficiency in DII after the start of the pilot in May 2020. To summarize, the end-to-end system simultaneously improved replenishment efficiency by increasing the auto-replenishment rate and reduced inventory holding cost. JD.com has since implemented the system on a much larger scale.

Supply Chain Resilience: Intelligent Risk Management

To ensure operational flexibility and customer satisfaction during the COVID-19 pandemic, JD.com built a risk

Figure 3. (Color online) Rate of Auto-Replenishment During the Pilot

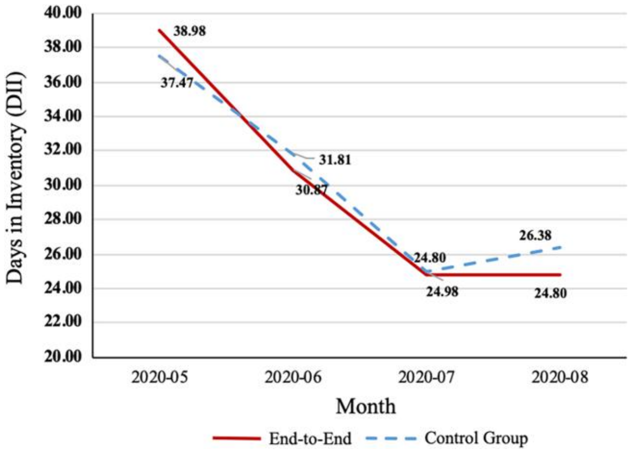


management system, which intelligently classified the prevailing emergency level and helped the firm take actions to respond. The overall structure included three steps. First, the system calculated the constraints in the logistic system, including the capacities of warehouses (inflow and outflow), packaging, shipment, and delivery in various regions and periods. Second, using the sales prediction data, the system then simulated the operational situation in the near future and calculated operational indicators. The key operational indicator is *Order Clearance Days* (*OCD*), which is the expected time for new and backlogged orders to be delivered to consumers. The OCD is critical to the daily operations of JD.com because it relates to logistics efficiency and the firm must respond by dynamically allocating workers and resources to ensure customer satisfaction. Third, based on the operational indicators, the system divided the current state into four emergency levels and suggested strategy modifications accordingly.

Technical Solution of Intelligent Risk Management

The core of the intelligent risk management system was a simulation platform that simulated operations in the presence of a disruption in the near future. As we previously mentioned, the simulation platform was built on the estimated capacity constraints and the demand forecasting results provided by the intelligent forecasting platform. As Figure 5 shows, the platform considered multiple nodes within the supply chain, including the order fulfillment center (OFC), warehouses, delivery stations, and consumers, and simulated the entire process from order placement to delivery to the consumer. The general simulation procedure is as follows. First, the quantities of new orders were predicted for the duration of the simulation horizon. In the simulation platform, these new orders were transferred into the OFC and then distributed to individual warehouses if available. During the pandemic, the quantity of halted orders that remained at the OFC was usually high due to the limited

Figure 4. (Color online) DII During the Pilot



Note. The solid and dashed line represents the end-to-end and the control group, respectively.

warehouse inflow ability and so was the quantity of pending orders at warehouses due to the unavailability of delivery because of the lockdown policy in effect. The pending orders in warehouses were then packaged and shipped to the delivery station facing the estimated capacity constraints and finally delivered to consumers. Using this process, the simulation platform could estimate the expected date of delivery of every active order in transit and of every expected order in the future.

In addition to calculating the operational indicators, the simulation platform was also used to update the date of order delivery, examine the prospect of upcoming promotional events, and assess the impact of operational strategies. For example, JD.com scheduled an annual nationwide shopping festival at the beginning of June 2022, when the Shanghai district had just ended its lockdown policy. JD.com's decision makers were concerned about how a planned promotional event would work while the company was facing a severe backlog of orders, including the halted, pending, and unfinished orders (Figure 5). The promotion could only take place if the warehouse capacity was sufficient, and the delivery capability was close to normal. Then JD.com performed a series of simulations to determine how to best use the limited capacity under these circumstances. Figure 6 presents the estimated delivery duration for new orders (the solid line) and finished orders (the dashed line) under the optimized strategy from May 12 to June 10, 2022. The simulation indicates that the system would achieve same-day or next-day order delivery, which is the ideal state for JD.com, by June 5. Figure 7 presents the estimated quantities of the pending and unfinished orders during the same period. The number of pending orders kept decreasing, and the number of unfinished orders would start to decrease by May 25. Overall, these results predicted that June 5 was a feasible day for the upcoming promotional event.

System Implementation of Intelligent Risk Management

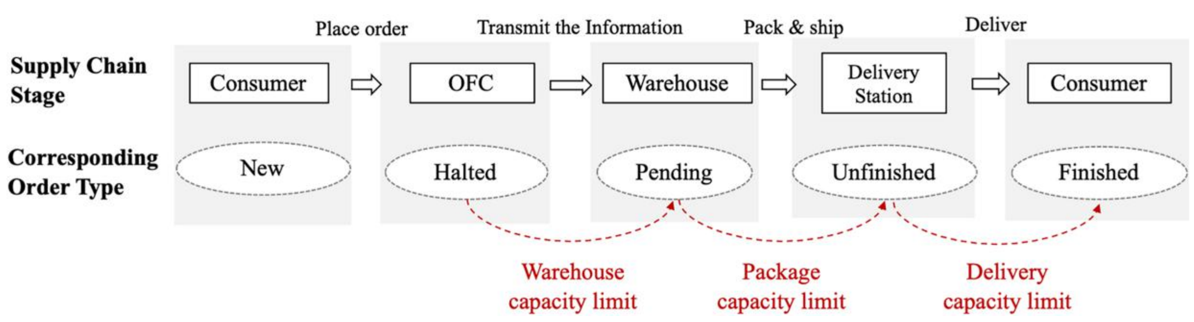
To implement the intelligent risk management, we first calculated two critical operational indicators for operational efficiency:

$$\textit{Live OCD for day } t = \frac{\textit{Quantity of halted orders} + \textit{new orders on day } t}{\textit{Quantity of actual orders delivered on day } t},$$

$$\textit{Normal OCD for day } t = \frac{\textit{Quantity of halted orders} + \textit{new orders on day } t}{\begin{array}{c}\textit{Average daily quantity of orders delivered}\\ \textit{during nondisruptive time}\end{array}}.$$

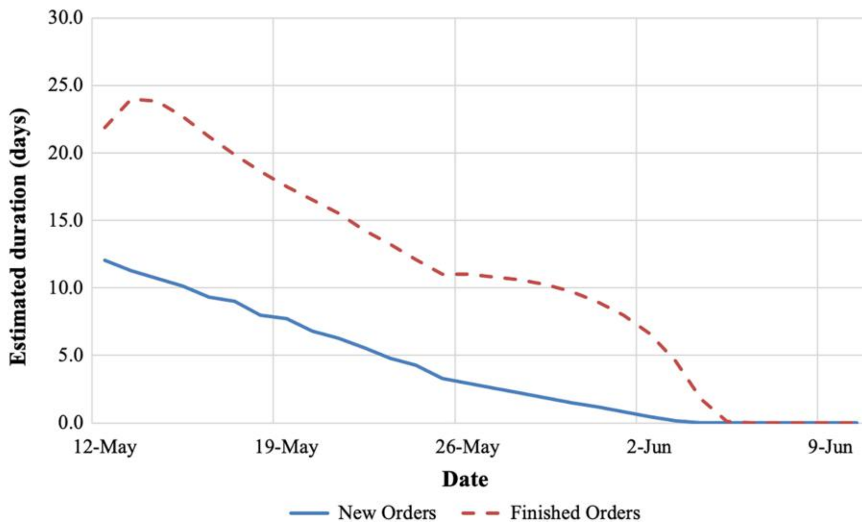
Live OCD for day t was calculated by dividing the quantity of orders expected to be delivered on day t (including the halted orders by day t and new orders placed on day t) by the actual delivery capacity on day t. Similarly, normal OCD for day t was calculated by dividing the quantity of orders expected to be delivered on day t by the regular delivery capacity when no disruption happens. Thus, the live OCD depicted the real-time operational scenario, whereas the normal OCD simulated the situation if the disruption ended immediately and the logistics capacity returned to normal. It is worth mentioning that, using the simulation platform, JD.com could not only calculate past indicators but also estimate future

Figure 5. (Color online) Structure of the Simulation Platform



Note. OFC, order fulfillment center.

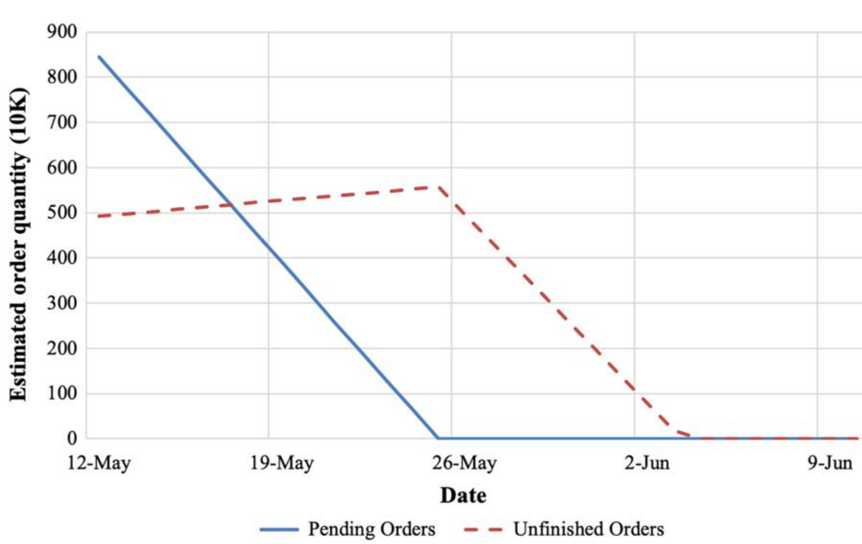
Figure 6. (Color online) Simulation Results on Delivery Duration (May 12–June 10, 2022)



indicators. Thus, a definition of states under disruption and precise estimation for future states helped JD.com be ready to take proactive actions.

Based on the indicators calculated previously, JD.com then defined three emergency states: warning, yellow; red; and a normal state, green. In particular, when the live OCD for a district was less than four, JD.com considered the state to be normal or green. When the live OCD was larger than four for two consecutive days, the district was assigned the emergency state of warning in the risk management system. This state usually occurred when there were prospects for lockdown, or the number of new COVID-19 cases grew quickly. It was then necessary to start monitoring key areas, including the operational indicators and news. When the live OCD was larger than seven for two consecutive days and the normal OCD was larger than three, the emergency state turned to yellow, which was likely to happen when the intra-area transportation was limited, or the logistics network had to be adjusted accordingly. As a response, the system would notify all involved parties of the situation, update the delivery promise for consumers, and take actions to guarantee the delivery date. In the worst-case scenario, the live OCD would be larger than 14 for more than two consecutive days and the normal OCD would be larger than four; this state was labeled as red. Consumers would not receive the orders placed on these days until two weeks later, which was a severe delay for online retailers in China. This scenario often occurred when a city was on full lockdown and all interarea

Figure 7. (Color online) Simulation Results on Order Quantity (May 12–June 10, 2022)



transportation was prohibited. Therefore, JD.com had to cancel the delivery promises to consumers, focus on the necessities for life (i.e., food), and cooperate with the government. Eventually, when the live OCD was less than four for more than four consecutive days, and normal OCD was less than two, the system would return to the green stage. It usually happened after the lockdown was lifted, and JD.com typically took measures to return to normal. Figure 8 summarizes the entire system process.

A related point to consider is that JD.com has examined various solutions to evaluate the risk levels in practice. Initially, the firm only evaluated the emergency states based on the Live OCD. Unfortunately, this indicator was highly unstable; for example, it would be significantly longer when all workers were required to take COVID-19 detection tests. These abnormal temporal indicators led to rapidly switching states, making the response strategies time sensitive and inefficient. Therefore, JD.com identified an abnormal state only if the live OCD lasted over two days. In addition, the abnormal live OCD might be caused by a major disruption such as a strict lockdown policy. The objective of the normal OCD indicator was to exclude such disruptions that were beyond JD.com's control. The specific thresholds were selected to ensure a sequential order of the emergency states. That is, the warning/yellow state should be an early warning of the yellow/red state, respectively, and the green state always followed the red. Based on this principle, JD.com selected the thresholds to make the lead time of the early warning as long as possible.

Customer-Demand Intelligence: The C2M System

In this section, we describe the C2M system that provides a collaboration mechanism with manufacturers, upstream of the supply chain, to support new product development based on consumer preferences. As Figure 9 shows, in a classic supply chain, manufacturers do not typically communicate directly with consumers but instead with intermediaries, such as distributors or retailers. The untimely or even misleading information on consumers' needs then raises challenges for manufacturers in making their product decisions. For example, many new products are costly to develop in terms of time, capital, and resources but may turn out not to be responsive to consumers' needs. In response, JD.com launched the C2M project to help the manufacturers with the design of new products, identification of target consumer segments, and marketing and advertising strategies (Mak and Shen 2021). Based on JD.com's close relationships with both consumers and partner manufacturers, the C2M platform connected the two parties and created value for the entire supply chain.

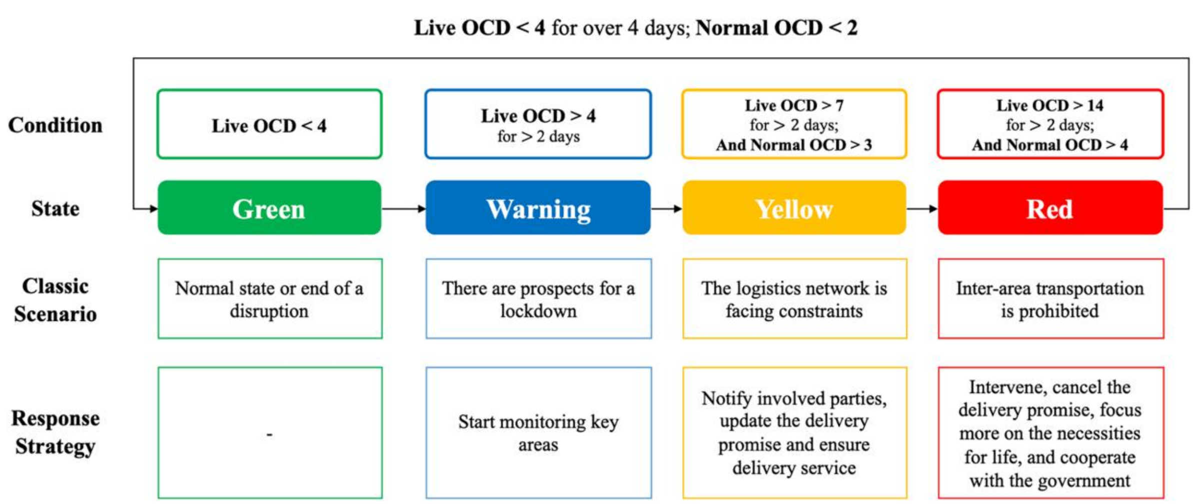
In contrast with the other two projects, the C2M platform had a complicated structure and was highly task oriented. Based on massive consumer data, it answered the following two key concerns for manufacturers:

1. What products should they produce and how much should they charge for these products?
2. What are the target consumer segments and how should the manufacturer attract them?

A Practical Case of C2M: Rice Cooker

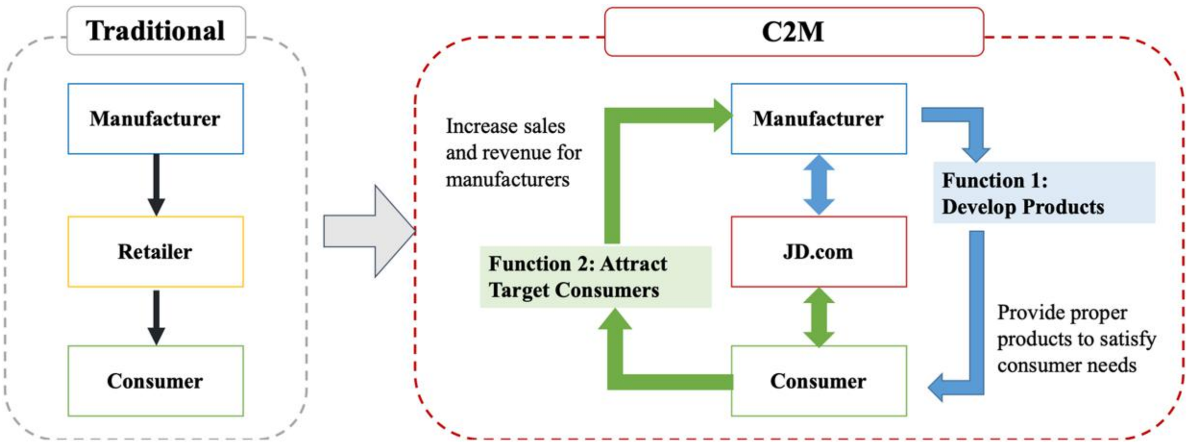
As a practical case, we present the release of a rice cooker with new functions to show how the C2M project helped partner manufacturers. At the beginning of 2021, JD.com received a request from an electrical appliance company to collaborate on the design of a new rice cooker. Figure 10 illustrates the design process. By analyzing the search keywords and consumer feedback, JD.com determined that because consumers were now paying more attention

Figure 8. (Color online) Emergency Classification System Process



Notes. OCD (order clearance days) is the expected time for new and backlogged orders to be delivered to consumers. Live OCD is measured using the current logistics capacity, whereas normal OCD is measured using the capacity when no disruption happens.

Figure 9. (Color online) C2M Project



Note. C2M, consumer-to-manufacturer.

to their health, a low-sugar rice cooker would be an attractive choice. The C2M platform further suggested proper attributes of such a cooker, including

1. Volume: Approximately three liters;
2. Function: Dietary fiber improvement, service with abundant online recipes; and
3. Keywords: Low-sugar, reduced fat, healthy lifestyle.

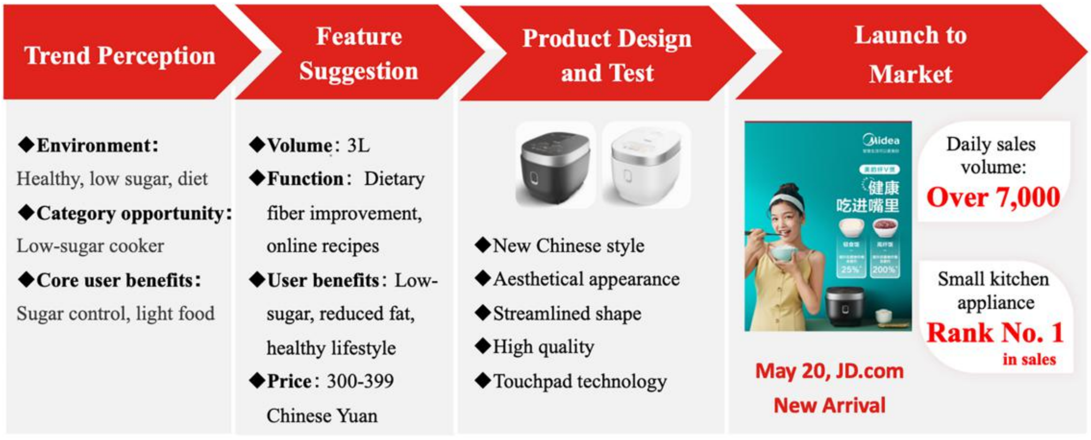
The C2M platform suggested a price interval of 300–399 Chinese Yuan, and the manufacturer completed the subsequent processes of product design, production, and testing. The final product, a low-sugar rice cooker, went on sale on May 20, 2021, with a price of 399 Chinese Yuan. To date, this product has yielded great success. With daily sales of more than 7,000 units, it was the top-selling product in the small kitchen appliances category on JD.com for half a year. This case validated that the C2M program could help manufacturers launch the right product quickly and effectively.

Technical Solution in C2M

As the rice cooker case illustrates, the C2M platform supported the full cycle of product development for partner manufacturers. To acquire insights for the development of new products, JD.com quantified the importance of product attributes for consumers based on a massive amount of transaction data. Moreover, for a product whose features had been previously identified, the C2M platform could suggest an appropriate price interval through an integrated clustering and mapping method.

Exploring Important Product Features Using Consumer Decision Trees. Every product is characterized by a set of attributes or features, such as the shape, color, weight, and power source (e.g., electricity). Based on the amount of consumer and transaction data, JD.com quantified the extent of the importance of these attributes for consumers through the use of CDTs.

Figure 10. (Color online) C2M Process Using an Example of a Rice Cooker



The preliminary concept is the *substitutability rate* (*SR*), which captures the transition probability that consumers will purchase a product or brand within a given category. The calculation process is as follows. First, the historical orders with purchases within a specific category were collected, while the outliers (e.g., bulk orders and enterprise orders) were removed. Then the orders were grouped by features, including product characteristics and customer identifiers, and the *substitutability value* (denoted as S) between products (or brands) a and b in two adjacent orders A and B of consumer i was calculated using the following equation:

$$S(a,b,A,B,i) = \frac{Sales\ of\ a\ in\ order\ A}{Sales\ of\ order\ A} \times \frac{Sales\ of\ b\ in\ order\ B}{Sales\ of\ order\ B} \times Total\ Sales\ of\ orders\ A\ and\ B,$$

where the sales are measured by the amount of revenue generated.

The model then summarized the results across all consumers in the data set, calculated the product-level substitutability, and normalized the final result into probabilities, which add up to one. Mathematically,

$$SR(a,b) = \frac{S(a,b)}{S(a)},$$

where

$$S(a,b) = \sum_{i,A,B} S(a,b,A,B,i),\ S(a) = \sum_{i,A,B,b} S(a,b,A,B,i).$$

The CDT model was then used to evaluate the importance of product features on the substitutability rate. Generally speaking, the model's objective was to determine the most important attributes when consumers purchased different products in the category. The key was a random forest algorithm, where the inputs were the features and the outputs were the SR from the prior stage. The model then generated large amounts of SR data with corresponding input features. Finally, the *Importance* of attribute k, denoted by $I(k)$, was computed as

$$I(k) = average(SR(a,b))\ if\ products\ a\ and\ b\ are\ the\ same\ in\ attribute\ k - average(SR(a,b))\ if\ products\ a\ and\ b\ are\ different\ in\ attribute\ k.$$

To avoid the impact of data imbalance, the samples in each group were restricted to be of the same size.

Suggesting an Appropriate Price. The second task was to suggest an appropriate price for a given product. The product might be new; that is, no historical data exist. Moreover, the prices of existing products were often stable; therefore, historical data usually included limited information on sales made at other prices. As a result, precise suggestions on product prices were not feasible, and thus, we decided to generate several *price intervals*, each with relatively stable sales. We summarize the specific procedure as follows. We first used Gaussian convolution to detect and remove outliers. We then used the clustering method to form a group of similar products. Based on the data generated by the clustering method, the model divided the price range into several equal-length intervals and fit an approximate distribution of sales over each price interval. Finally, it again used the clustering method to group the data into specific classes and to suggest the price interval that would generate the highest sales.

Attracting the Target Consumers Using C2M

In addition to the product features, manufacturers were also concerned about determining who their target consumers were and how to attract these customers. To address who, JD.com ranked the consumers for a given product using machine learning methods. To address how, JD.com matched the potential target consumers with free trial programs to improve the likelihood that they would purchase the product after the free trial.

New Product User Model. The *New Product User Model* aimed to identify the potential consumers who might purchase a specific product in the near future. Similar to the logic it used to develop an appropriate price, it used a GATNE model (Cen et al. 2019) to identify a group of similar products. Thereafter, the model selected the consumers who had followed these products, searched relevant keywords, clicked the products' pages, or added one or more of these products to their virtual carts in the past 15 days. The consumers who had already purchased the products were removed. The model finally used the machine learning method to rank these potential consumers. Specifically, JD.com used a deep structured semantic model (DSSM) (Huang et al. 2013) to transform the consumers and products into vectors and then ranked the consumers by the cosine similarity of consumer vectors and the product vector.

Free Trial Consumer Selection. Free trial is a popular method that manufacturers use to determine potential consumers for new products. The *free trial consumer model* was designed to select those consumers who were most likely to purchase the product after the free trial. This program was based on the *new product user model* mentioned previously. Suppose a firm had n trial spots for a particular product. Then the model selected the top $k \times n$ consumers as potential target consumers and asked these consumers to join the program when they clicked on relevant pages, where k was the amplification factor and usually set between 10 and 20. Moreover, because a particular consumer might be the target consumer of a group of similar products with a free trial program, the platform automatically restricted the number of free trials available to each consumer. This process ended when n potential consumers accepted the invitation.

Impacts

Our methodologies have strengthened the supply chain capabilities in remarkable ways. By the end of 2022, these intelligent techniques achieved billions of dollars in revenue increases and tens of millions of dollars in cost savings. More importantly, these techniques have enhanced consumer welfare and benefited partners in the supply chain. In addition to the quantifiable benefits, a supply chain supercharged with advanced analytics has brought strategic value to JD.com. Providing reliable service to consumers at the most challenging times during the COVID-19 pandemic has resulted in strong trust and loyalty from these consumers. Collaborating with manufacturers, especially the vulnerable ones, has helped JD.com build a stable and strong supply network. Through the collaboration of all participants, the supply chain network innovated to give the best value to consumers. In this way, advanced analytics have paved the way for JD.com to use its operational excellence to strategically build a strong competitive position. We summarize the key indicators of impacts in Figure 11 and describe impact details in the next three subsections.

Impact of End-to-End Inventory Management

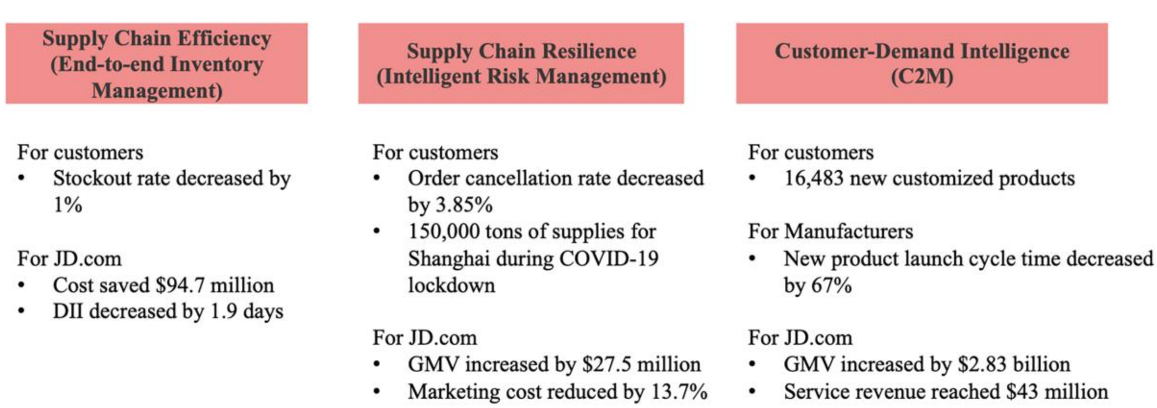
Between February 2020 and October 2022, the end-to-end system was implemented for more than 9,000 individual products within 162 categories, and proved to be effective and robust in practice. In particular, compared with the manual inventory replenishment strategy that JD.com used previously, the new system reduced the stockout rate by 1%, which translated into a better experience for consumers and higher profits for the firm. Moreover, DII was reduced by about 1.9 days (from 25.8 days down to 23.9 days) on average, which reduced the firm's inventory holding costs significantly. Using a simple difference-in-difference approach, JD.com's finance department estimated that the end-to-end system generated incremental annual net revenue of $41 million and saved more than $94.7 million in inventory holding costs during that period. In July 2021, the end-to-end framework was named among the top six supply chain technology innovations for 2021 by Gartner (Gartner 2022). A related academic paper (Qi et al. 2023) also describes this framework.

Impact of Intelligent Risk Management

The intelligent risk management system was launched on March 20, 2022. Until November 16, 2022, the system identified more than 6,612 red, 1,798 yellow, and 2,130 warning states in China. Figure 12 presents the screenshots of the practical intelligent risk system. Specifically, the system reported an overview of the national emergency states as well as the detailed district-level indicators, which provided an effective reference for the company's strategy. In reality, the system had supported the daily operations throughout JD.com's sales process since its implementation. On average, the system's application programming interface (API) was called externally 950,000 times per second to explain the current delivery status to customers.

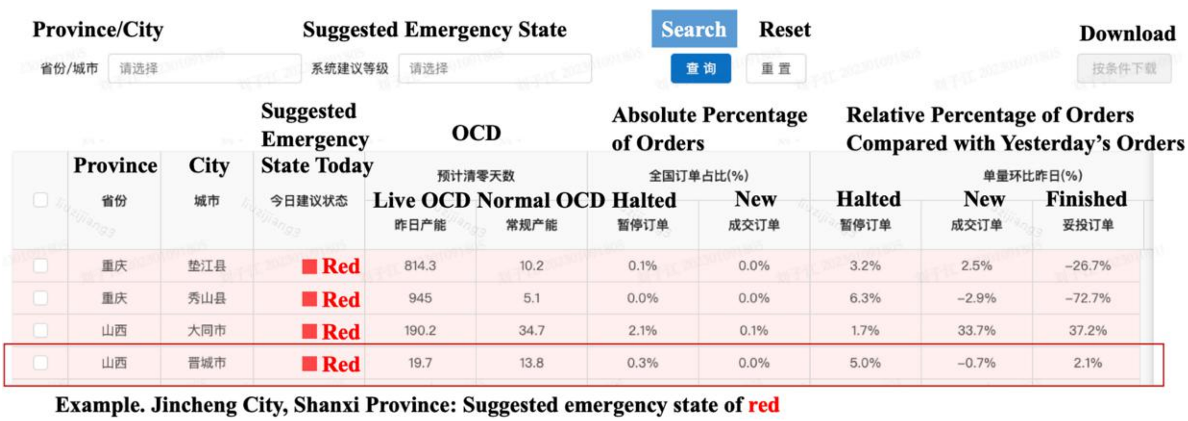
For each district with a (possibly anticipated) emergency, the emergency team proposed alternative response measures and used the simulation platform to validate the measures' effectiveness. By comparing the simulated results with the real data (Figures 13 and 14), the accuracy of the simulation platform and the effectiveness of the response measures were validated. Using the intelligent risk management system, JD.com could identify the disruptions in time, notify customers of a

Figure 11. (Color online) Impacts of JD.com's End-to-End Inventory Management, Intelligent Risk Management, and C2M Projects



Note. C2M, consumer-to-manufacturer; GMV, gross merchandise volume; DII, days in inventory.

Figure 12. (Color online) Detailed Information About the Emergency States in the Intelligent Risk System



Province 省份	City 城市	Suggested Emergency State Today 今日建议状态	OCD 预计清零天数: Live OCD 昨日产能	Normal OCD 常规产能	Absolute Percentage of Orders 全国订单占比(%): Halted 暂停订单	New 成交订单	Relative Percentage of Orders Compared with Yesterday's Orders 单量环比昨日(%): Halted 暂停订单	New 成交订单	Finished 妥投订单
重庆	垫江县	Red	814.3	10.2	0.1%	0.0%	3.2%	2.5%	−26.7%
重庆	秀山县	Red	945	5.1	0.0%	0.0%	6.3%	−2.9%	−72.7%
山西	大同市	Red	190.2	34.7	2.1%	0.1%	1.7%	33.7%	37.2%
山西	晋城市	Red	19.7	13.8	0.3%	0.0%	5.0%	−0.7%	2.1%

Example. Jincheng City, Shanxi Province: Suggested emergency state of red

Note. The English text is a translation of the original Chinese content.

possible delay, and terminate marketing promotions in related areas. Overall, the intelligent risk management system reduced the order cancellation rate by 3.85% and the marketing costs by 13.7%. Corresponding to these rates, the system contributed to over US$27.5 million in gross merchandise volume (GMV), which was critical for JD.com's revenue and profit.

When taking response measures to address emergencies, JD.com considered not only profits but also social value, especially during the most severe state of red. For instance, when Shanghai was on lockdown in April 2022, massive and urgent demand for medicines and necessities occurred. However, many workers and distributors were either sick or locked down, and capacities for shipment and delivery within Shanghai decreased sharply. In response, JD.com allocated more than 5,000 staff across China to support the operations in Shanghai and delivered more than 150,000 tons of supplies. This response was costly because the firm paid all living costs for these brave workers. However, as the results reported by the simulation platform show, this decision significantly contributed to society's stability and helped Shanghai and its citizens recover from the emergency state as soon as possible.

Impact of C2M

The C2M platform has created significant value for both manufacturers and JD.com. Using the platform, JD.com helped customize 16,483 new products from January 2021 to October 2022. The GMV related to the customized products was US$2.83 billion as of the end of October 2022. By providing this service to its partner manufacturers, JD.com has generated additional income from the service fee. From January 2021 to October 2022,

Figure 13. (Color online) Comparison of Simulated and Actual Numbers of Finished Orders

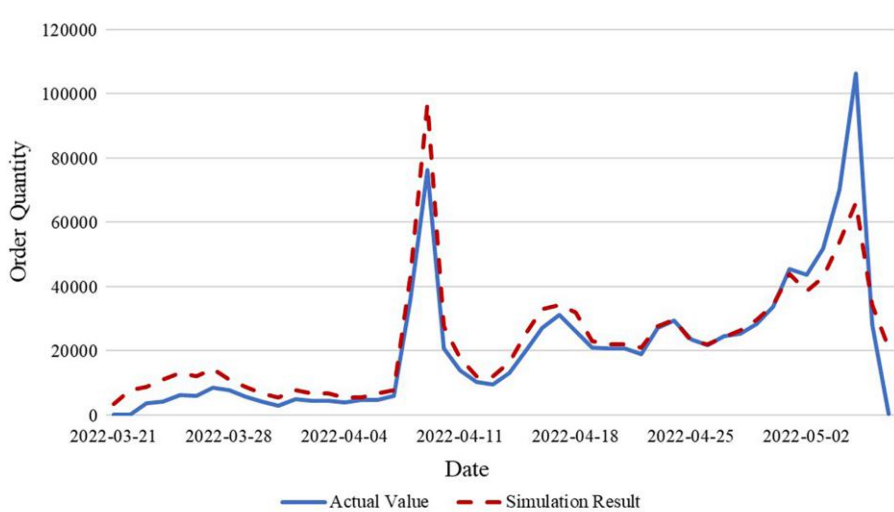
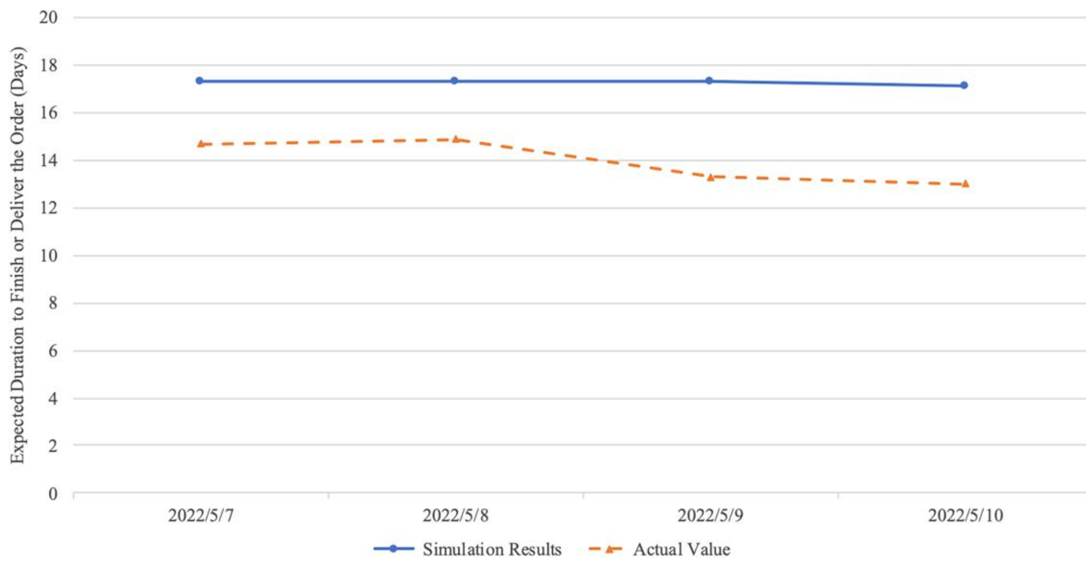


Figure 14. (Color online) Comparison of Simulated and Actual Delivery Duration



the C2M generated US$43 million in service revenues. The launch cycle time for new products was reduced by more than 67% on average. In regard to identifying target consumers, the intelligent algorithms significantly improved the likelihood that consumers would purchase a given product compared with the traditional approach that manufacturers used previously. During 2021, JD.com distributed 28.78 million trial products, and the transition rates (i.e., the percentage of consumers making purchases after the trial program) of new and existing consumers were 3.9% and 6.7%, respectively. In 2022, JD.com handled more than 60 million trial items, and transition rates of new and all consumers further improved to 4.5% and 7.9%, respectively. The C2M platform has significantly promoted the retail ecosystem's growth and innovations.

Conclusion

Grounded in advanced analytical techniques, JD.com has built an intelligent, integrated, and resilient supply chain to create value for consumers and all participants within the retail ecosystem. Despite challenges in the complex and sophisticated retail supply chain, JD.com has strengthened its supply chain agility, and attained shared value by focusing on supply chain efficiency, supply chain resilience, and customer-demand intelligence. By implementing an end-to-end inventory management methodology based on a dynamic programming model and an RNN model, the company significantly reduced inventory holding costs and improved its operational efficiency. In response to major disruptions such as COVID-19, JD.com used its intelligent techniques, including a simulation model and a precise indicator system, to strengthen collaboration with its supply chain partners and attain the necessary resilience. By incorporating state-of-the-art AI algorithms like DSSM and GATNE, the C2M system has enabled JD.com to accurately identify customer preferences and helped manufacturers design and produce products that are more responsive to these preferences, hence creating value for the entire retail ecosystem.

The techniques described in this paper have high transportability and can be applied to a wider range of supply chain management scenarios. JD.com will expand the scope of these techniques and continue to enhance their capabilities in the future. It is trying to generalize the end-to-end inventory management model to include more general inventory management settings, such as multiechelon cases and inventory allocation problems. JD.com will also work to increase the efficiency and accuracy of the simulation module of the Intelligent Risk Management system in various disruption cases. To fully use the C2M system, JD.com is trying to create new product categories by combining features from different products, hence bringing more product variety to consumers. With its advanced technologies and future plans, JD.com's supply chain aspires to be the best in the industry and to continue enhancing the welfare of all ecosystem participants and consumers.

Acknowledgments

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University for the support in writing this paper; and colleagues at JD.com, including Lei Chen, Peng Xu, Yang Feng, Jianshen Zhang, Ruoxing Zhang, Juxin Li, Zhilong Qin, Hao Dong, Xin Wang, Zijiang Liu, Zhe Chen, Yixin Li, and Xuhong Wang, for providing the data. The opinions expressed in this paper are those of the authors and do not necessarily represent the views of JD.com.

Appendix. Mathematical Details of the End-to-End Dynamic Programming Model

The mathematical details of the dynamic programming model in the first step of the end-to-end model are as follows. Suppose that over a planning horizon of T periods, the sequence of random demands were d_t, $\forall t \in \{1, \ldots, T\}$, and the inventory level at the beginning of period t was I_t. The inventory level can be positive if we have inventory excess on hand or negative if we have an inventory shortage and, hence, backorders. Moreover, using a periodic review policy, the firm placed M orders over T periods, and each order $m \in \{1, \ldots, M\}$ had a stochastic VLT of L_m. That is, if the firm placed an order at period t_m, then the order would arrive at period $v_m = t_m + L_m$. Suppose $V_m(I_{v_m})$ denotes the optimal cost over interval $[v_m, v_{m+1} - 1]$ with starting inventory I_{v_m}. Then the following dynamic programming model can be obtained:

$$V_m(I_{v_m}) = \min_{a_m \geq 0} \sum_{s=v_m}^{v_{m+1}-1} h[I_{v_m} + a_m - d_{[v_m,s]}]^+ + b[d_{[v_m,s]} - I_{v_m} - a_m]^+ + V_{m+1}(I_{v_m} + a_m - d_{[v_m, v_{m+1}-1]}), \tag{A.1}$$

where h is the unit holding cost, b is the unit penalty cost for unsatisfied demand, $[\cdot]^+$ denotes $max\{0, \cdot\}$, a_m denotes the order quantity, and $d_{[i,j]}$ is defined as $d_{[i,j]} = \sum_{t=i}^{j} d_t$. Qi et al. (2023) derived the closed form of the optimal solution of Equation (A.1) as

$$a_m^* = max\{d_{[v_m, s^*]} - I_{v_m}, 0\},$$

where

$$s_m^* = v_m + \left\lfloor \frac{b(v_{m+1} - v_m)}{h + b} \right\rfloor.$$

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Verification Letters

Lei Xu, Chief Executive Officer, JD.com, No. 18 Kechuang 11 St., BDA, Beijing, China, writes:

"This letter is to verify that the paper entitled 'Socially Responsible Planning Strengthens Supply Chain Capability for JD.com' by Hao Hu, Yongzhi Qi, Hau L. Lee, Zuo-Jun Max Shen, Curtis Liu, Weimeng Zhu, and Ningxuan Kang describes a real-life project of JD.com for optimizing the supply chain.

"JD.com aims to build an intelligent, integrated supply chain that not only benefits its own company but also the partners, consumers, and the whole ecosystem. JD.com has implemented end-to-end inventory management method to reduce the inventory cost and improve the efficiency, with which the automatic replenishment system is built. Since 2020, the system has saved the inventory cost of 663 million RMB yuan. To fast react to the disruptions during COVID-19 and natural disasters, JD.com has built the intelligent risk management system, provides service to various internal departments, like logistics and customer service, and coordinates response strategies in unified rules. It has contributed to a revenue increase of 318 million RMB yuan since the implementation of the system. With the application of C2M system, JD.com helps manufacturers design and produce more popular products, which both benefits the manufacturers and consumers. JD.com has applied C2M model to more than 2000 brands and manufacturers, and the total revenue of C2M products hatched by JD.com has reached 20.8 billion RMB yuan since 2020.

"As a supply chain-based technology and service enterprise, JD.com will continue to create more commercial and social value by building a "responsible supply chain" with intelligent operations research and AI-based techniques. JD.com will endeavor to provide high-quality service to customers and partners with an efficient supply chain."

Shuyang Huang, Purchase Manager, Pet Supply Department, JD Retail, No. 18 Kechuang 11 St., BDA, Beijing, China, writes:

"End-to-end optimization technology has been applied to a wide range of product categories across JD.com, including pet supplies, beverages, electronics, home appliances, etc. Based on a combination of end-to-end concept and deep learning, AI, Big Data, and other technologies, different business units are able to make faster and more accurate inventory management decisions by using this highly automated system.

"End-to-end technology not only saves time for me because of its automatic learning and execution capability, but also facilitates us making high-quality replenishment decisions since it reduces the bull-whip effect caused by forecasting errors. Since the implementation of end-to-end inventory optimization, we have achieved a better stock-out rate and inventory turnover rate.

"JD.com will continue to expand the use of end-to-end optimization technology for more categories of SKUs, and the end-to-end concept is having an influence on other kinds of supply chain operations beyond inventory management."

Meng Gao, Labor Union Secretary, Guangdong Second Provincial General Hospital, No. 466 Xin'gang East Rd., Haizhu District, Guangzhou, China, writes:

"During the postpandemic era, supply chain resilience and collaborations become even more important, acting like a shield to protectoperations under continuous disruptions, JD.com has always devoted itself to creating values for different parties in the society. Regarding to intelligent risk management, JD.com takes the initiative to bring together different departments including procurement, logistics and fulfillment, marketing and sales and more to collaborate seamlessly, and by take advantage of operations research method, the risk management system can simulate and predict upcoming risks, produce possible solutions and adjustments, and guide related departments to take actions. Thus, JD.com can better prepare and deal with emergencies with improved resilient supply chain.

"During the COVID-19 outbreak in Guangzhou, necessities of life were in a state of highly shortage, disrupted supply chain flow seriously influenced normal operations of hospitals. Thanks to JD.com that they helped fulfill related necessities in time despite of disruptions, which helped us better serve our patients.

"Leveraging the intelligent risk management system, JD.com was able to help not only hospitals, but also consumers, suppliers, and other parties in the society to be more resilient in fighting the virus and other emergencies."

Ricky, CMO, Market Center, MOMENTPLUS, No. 83 Hongxiangbei Rd., Pudong District, Shanghai, China, writes:

"We really appreciate that JD.com has used C2M technology to help us develop our new laptop products, and achieve a more efficient operation model. We all know that the laptop market is already a 'red ocean,' and with the impact of COVID-19, the demand has further been influenced, even as the cost for developing and producing new products has risen. As a relatively new player in the laptop market, we have to use limited resources to figure out a new efficient way to develop and operate our new products—and that is where C2M comes into the picture.

"By collaborating with JD.com and implementing C2M technology, we have shortened our product launch cycle time; better arranged our production plan, inventory positioning, and sales and promotion plans; and become more competitive in a rapidly changing market. More importantly, by successfully launching two new laptops, which were sold out in only 3 minutes during presales, we finally have achieved a better cash flow under the impact of COVID-19.

"In the future we plan to continuously collaborate with JD.com on C2M technology, to cover more categories of products and further integrate supply chain operations."

Hao Hu is the president of the Department of Intelligent Supply Chain Y, JD.com. He is devoted to building a data-driven intelligent supply chain system by using technology in combination with JD business scenarios for many years. Leading his team, he continuously promotes intelligence, automation, technology middle office construction of supply chain and other system innovations including category management, retail plan, dynamic pricing, intelligent fulfillment and inventory optimization.

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Curtis Liu was the vice president of JD.com, Beijing, China. He has devoted himself to the retail industry for 20 years. He has extensive expertise in the utilization of digitalization capabilities to construct efficient and superior supply chains in various businesses including brands, traditional retail, B2B/B2C e-commerce, and omnichannel retail.

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