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Food retail supply chain resilience and the COVID-19 pandemic: A digital twin-based impact analysis and improvement directions

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ABSTRACT

In this study, we examine the impact of the COVID-19 pandemic on food retail supply chains (SCs) and their resilience. Based on real-life pandemic scenarios encountered in Germany, we develop and use a discrete-event simulation model to examine SC operations and performance dynamics with the help of anyLogistix digital SC twin. The computational results show that food retail SC resilience at the upheaval times is triangulated by the pandemic intensity and associated lockdown/shutdown governmental measures, inventory-ordering dynamics in the SC, and customer behaviours. We observe that surges in demand and supplier shutdowns have had the highest impact on SC operations and performance, whereas the impact of transportation disruptions was rather low. Transportation costs have spiked because of chaotic inventory-ordering dynamics leading to more frequent and irregular shipments. On bright side, we observe the demand growth and utilization of online sales channels yielding higher revenues. We propose several directions and practical implementation guidelines to improve the food retail SC resilience. We stress the importance of SC digital twins and end-to-end visibility along with resilient demand, inventory, and capacity management. The outcomes of our study can be instructive for enhancing the resilience of food retail SCs in preparation for future pandemics and pandemic-like crises.

1. Introduction

Epidemic outbreaks and associated pandemics are specific cases of supply chain (SC) disruptions as they can spread rapidly and disperse worldwide. Recent examples include SARS, MERS, Ebola, swine flu, and most recently, the novel coronavirus (COVID-19/SARS-CoV-2) (Choi, 2020, Govindan et al., 2020, Ivanov, 2020a, Paul and Venkateswaran, 2020, Queiroz et al., 2020, Chowdhury et al., 2021, El Baz and Ruel, 2021, Sodhi et al., 2021). In this study, we analyse the pandemic impacts on food retail SCs in Germany.

The novel coronavirus, first reported in Wuhan, China, in December 2019, expanded rapidly worldwide and was first detected in Germany at the end of January 2020. A pandemic was then declared in March 2020. The COVID-19 outbreak has profoundly impacted human lives and economic activities worldwide, affecting global SCs across many industries by reducing access to markets and materials, leading to significant operational and financial impacts (Dolgui et al., 2020b, Veselovská, 2020, Choi, 2021, Ivanov, 2021c, Nagurney, 2021).

Among others, SCs in the food industry have experienced unprecedented shocks during the COVID-19 pandemic (Chowdhury et al.,

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2020, Loske, 2020, Singh et al., 2021). The crisis has also affected many different sectors in Germany, leading to drastic falls or spikes in demand. Hence, Germany's Gross Domestic Product (GDP) decreased by 6% during 2020 compared to the previous year (IMF, 2020). Retail workers have been significantly affected – many shops have been closed because of pandemic mitigation measures, and as other industries have slowed down, consumption of certain goods has declined. On the other hand, food retailers and grocery store workers have seen a surge in demand as people in confinement buy food and other necessities, often stocking up for long periods of isolation (Chinn et al., 2020, ILO, 2020). In this way, as the COVID-19 pandemic has advanced, particular attention has been given to food retailers. They have had to adapt quickly and respond to the crisis given their critical role in providing daily-life essentials (Ivanov, 2020b, Ivanov and Dolgui, 2021a).

Some of the most visible implications of the pandemic in the food retail industry have included panic buying, changes in food purchasing patterns, food deliveries and digital services, frontline hygiene and preventive measures, logistics and organization of distribution in stores, and supply-side issues due to labour shortages and disruptions to transportation and supply networks (ILO, 2020, PwC, 2020, Rathore et al., 2020, Ivanov, 2021b, Paul and Chowdhury, 2021). Limits on people's mobility have reduced seasonal workers' availability for planting and harvesting in many countries. For example, in the wake of the COVID-19 pandemic, many producers/suppliers could not harvest fruits in the UK primarily because of labour shortages, which led to large-scale food loss and waste (The Guardian, 2020).

Moreover, COVID-19 has led to disruptions in food processing industries, which have been affected by social distancing rules and other measures aiming to contain the spread of the virus, thus reducing operations' efficiency. Similarly, bottlenecks in transport and logistics have disrupted the movement of products – which are transported using three main modes of transportation: bulk (ships and barges), containers (by boat, rail, or truck) and other road transport, and air freight – along SCs (OECD, 2020). At the same time, according to Chinn et al. (2020), food retail in Germany was able to seize new post-crisis opportunities. Thus, the food retail industry has not only faced structural challenges during the COVID-19 crisis, it has also grown during the crisis.

Despite the ongoing research on disruptions management associated with the COVID-19 pandemic, little is known about the impacts of the pandemic on food SCs, the reasons for these impacts, and the most promising directions for SC recovery. Moreover, the partial or even full shutdown of whole industry sectors and regions represents a novel and underexplored setting in SC resilience literature (Ivanov and Das, 2020). While some research has examined the initial impact of the pandemic on food SCs (Chowdhury et al., 2020, Loske, 2020, Singh et al., 2021), the existing literature lacks overarching insights based on real-life pandemic scenario analysis over a longer time scale that includes several pandemic waves and the associated disruptions and recovery phases (Hosseini et al., 2019, Aldrighetti et al., 2021, Hosseini et al., 2020, Ivanov, 2021a). We have developed this study to close these research gaps.

We examine the impact of the COVID-19 pandemic on the food retail SCs. Based on real-life scenarios encountered in German food SCs during the COVID-19 pandemic, we have developed and used a discrete-event simulation model to examine the impact of the pandemic on SC operations and performance. Previous research has provided strong and substantial insights about how to evaluate, measure, and improve resilience in SCs using simulations (Wilson, 2007, Carvalho et al., 2012, Ghadge et al., 2013, Schmitt et al., 2017, Macdonald et al., 2018, Currie et al., 2020, Ivanov and Dolgui, 2021a, Llaguno et al., 2021). For example, Olivares-Aguila and ElMaraghy (2020) have suggested an evaluation framework for SC resilience using system dynamics simulation. In the first phase, their SC simulation model is constructed and used to determine the SC performance in different scenarios. Then, potential disruptions and possible mitigation strategies and configurations are identified. Finally, the disruptions that have the most significant impact on the SC are proposed to build scenarios for analysis. However, neither this nor other works have captured the real-life pandemic scenarios in the food SC over a long period of time or considered two pandemic waves – distinct and substantial contributions made by our study.

Our study makes substantial contributions by uncovering the impact of the COVID-19 disruptions in a food retailer's SC and providing guidelines for recovery actions. Our research outcomes can be instructive for developing SC actions to respond to COVID-19 disruptions and improve SC resilience in the food retail industry. Moreover, we provide generalized recommendations for SC stabilization and recovery that address our two research questions (RQ):

RQ1: How and why has the COVID-19 pandemic impacted food retail SC performance?

The purpose of this question is to analyse the impact of different COVID-19 disruption scenarios and identify concrete impacts on the operations and performance in food retailers' SCs.

RQ2: How can food retail SC resilience be improved?

This question aims to identify SC actions in response to a pandemic that would increase food retailers' SC resilience.

The rest of this paper is organized as follows: In Section 2, the underlying case study, data sources, and simulation model are presented. Section 3 structures the pandemic scenarios for analysis. Our computational results are described in Section 4. Section 5 is devoted to sensitivity analysis. In Section 6, we discuss implications of the simulations and offer guidelines for resilience enhancement in future. Finally, in Section 7, we conclude by summarizing the study's major outcomes and delineating some future research directions.

2. Case study, data, digital twin, and simulation model

2.1. Case study and data

We used anyLogistix SC simulation and optimization software to study a multi-stage SC for a retail company in Germany. This software has been frequently and successfully used for SC resilience analysis (Ivanov, 2017, Ivanov, 2018, Aldrighetti et al., 2020, Dolgui et al., 2020a, Ivanov, 2021c). Without loss of generality, we restricted ourselves to the consideration of ten product categories and 28 supermarket locations in five different countries (Germany, Austria, the Czech Republic, Italy, and Hungary). We selected

product categories that experienced significant changes due to new consumer trends during the COVID-19 pandemic – Fresh Fruits, Fresh Vegetables, Fresh Meat, Fish & Sea Food, Rice, Pasta, Convenience Food, Frozen Meals (ready-to-eat), Wheat Flour, and Confectionary Food. Product demand was calculated by multiplying the annual per capita consumption for each product category by the retail company's market share. The selling prices for each product were taken from Statista data regarding the average price for each product category in 2020.

Next, we created a sample of three suppliers per product category (30 suppliers in total) by analysing supermarket data and manually identifying supplier locations. Three distribution centre (DC) locations were selected, one in east, one in west, and one in south Germany. Fig. 1 shows the SC design.

The suppliers produce and ship their products via trucks to the DCs. We assumed that the costs of shipping the products are already included in the final price agreed with the retailer. Inventory spending corresponds to the expenses for replenishing the inventory. This is the sum of the initial inventory purchase costs and the replenishment costs. This cost is calculated by anyLogistix automatically for suppliers by multiplying initial stock units by the costs for the corresponding product.

2.2. Digital twin and simulation model

Digital SC twins are defined as ‘computerized models that represent the network state for any given moment in time’ (Ivanov and Dolgui, 2021c). The main difference between digital twins and simulation models is comprised of three aspects, i.e., *system complexity*, *real-time connectivity*, and *decision-making integration*. First, the system complexity in digital twins is higher as in simulation models. The digital SC twins are comprised of multiple layers such as network structure, flows, process control algorithms, and operational parameters. Second, data in the digital twins is updated through connectivity with external systems and databases. Third, integration of digital twins into decision-making is much higher as compared to models. Simulation and optimization models are important parts of

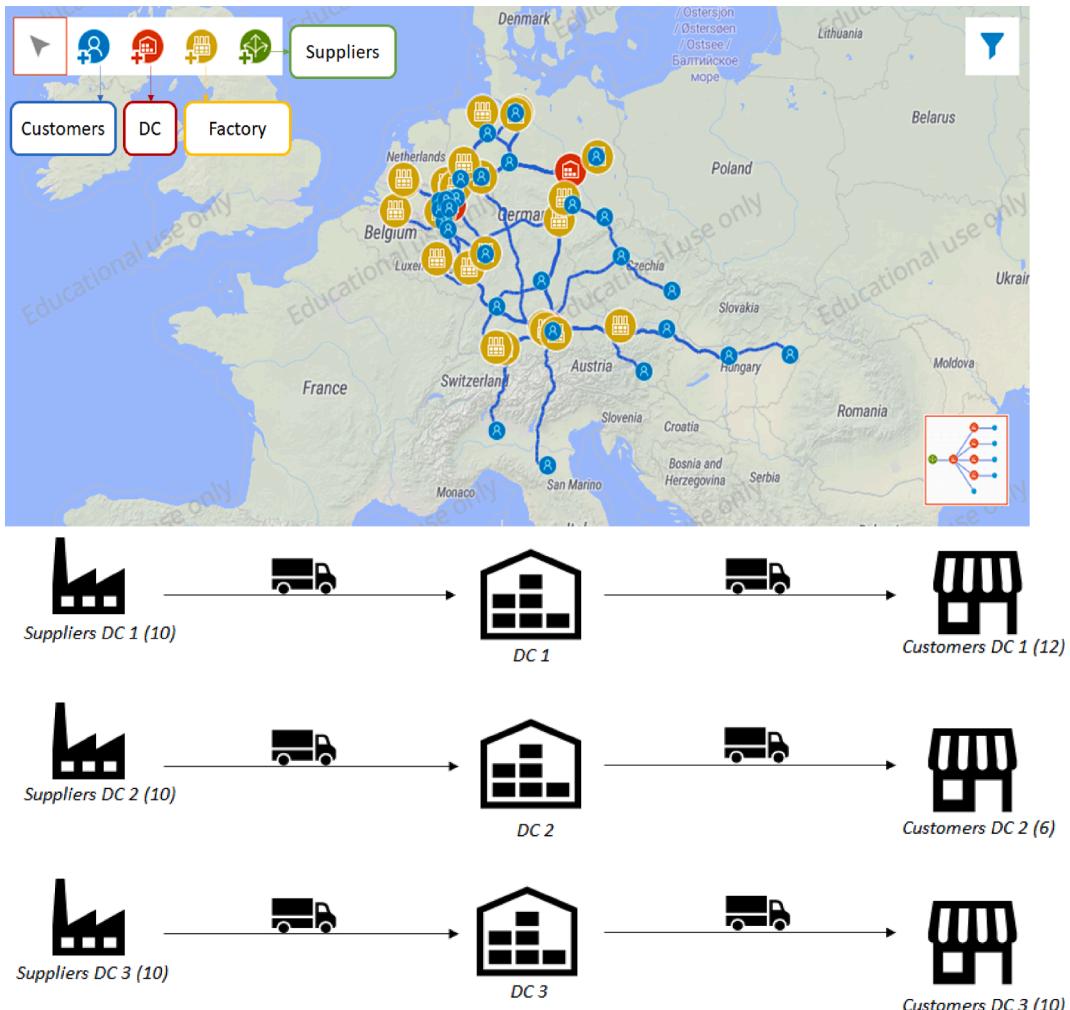


Fig. 1. Supply chain design (interface from anyLogistix Studio Edition).

digital twins whereby digital twins can offer more functions for decision-making support as classical offline modelling, e.g., performance analysis of suppliers, updating SC data in ERP systems, and comparison of the existing processes with the optimal ones. Digital twins allow for both computations of some numerical outcomes and an extended analysis of bottlenecks, comparison of different options, and analysis of resilience investments. A digital SC twin is a part of SC management toolbox, control towers, and decision-making support at strategic, tactical, and operational levels. Besides, data-driven modelling in digital twins allows using artificial intelligence in order to support decision-making by so called dispatch advisors or digital companions. For example, a decision-maker can ask the digital twin to find all current shortages in the SC and suggest possible ways to resolve these problems. In the next step, the shortage data can be used for optimization and simulation to develop most appropriate action plans.

Digital twins can be used for building end-to-end SC visibility, enhancing resilience, and assessing contingency plans. [Cavalcante et al. \(2019\)](#) point out that digital SC twins display the ‘physical SC based on actual transportation, inventory, demand, and capacity data’. Therefore, they can be utilized by decision-makers for planning, monitoring, and supervising. Hence, digital SC twins can improve SC visibility and, as a result, SC resilience. [Ivanov and Dolgui \(2020\)](#) and [Hosseini et al. \(2020\)](#) state that there is an urgent need to visualize SC networks because of the increasing number of SC disruptions.

Digital SC twins enable real-time transparency about important logistics data such as financial key performance indicators (KPIs), inventory level, stock level, service level, capacity, and transportation data. They are powerful data-driven tools and firms’ control towers. Performance-based simulation models help create efficient contingency plans to prevent or recover from disruptions by simulating and creating what-if scenarios that predict the future impact. Digital twins not only visualize SCs and associated risks but also offer supplier performance and risk analysis along with forecasts of SC interruptions and risks. In addition, they can allow to establish and examine detailed backup routes, including *estimated time of arrival* (ETA) calculations. During disruptions, digital twins utilize real-time data to calculate the impact of the disruption, build alternative SC networks and perform KPI analysis to get real-time data about inventory levels, service level, financial parameters and demand ([Ivanov, 2020a](#)). With the help of anyLogistix SC simulation and optimization software, a digital SC can be designed ([Fig. 2](#)).

[Fig. 2](#) shows the structure of a digital SC twin created in this study for disruption analysis. The digital SC twin encompasses three major perspectives—the network, the flows, and the parameters. The SC network can be designed using different location objects, such as customers, DCs, factories, and suppliers. The flows in the network can be flexibly arranged to represent the specifics of different SCs. The flows are associated with some design (i.e., maximum) capacities in production, warehouses, and transportation and controlled by the associated production, inventory, sourcing, and shipment policies. These policies can be flexibly adapted to the specifics of the SC and its management rules. Finally, different operational parameters such as demand, lead time, and control policies’ thresholds (e.g.,

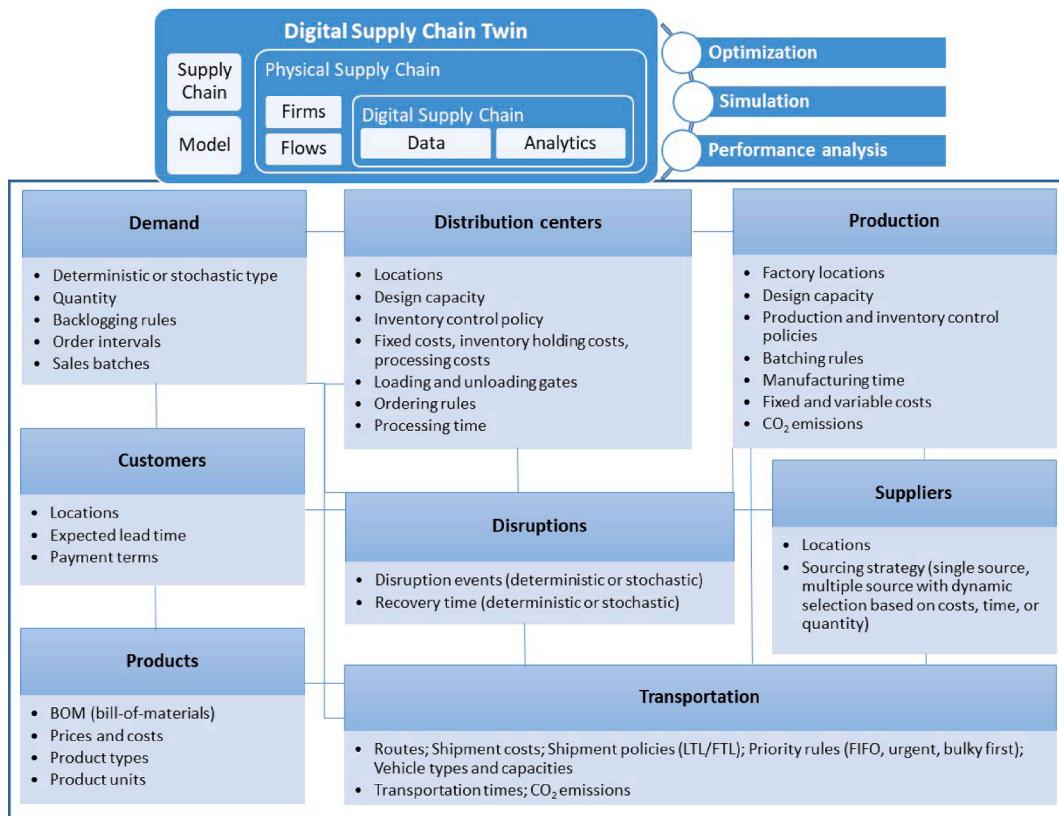


Fig. 2. Digital supply chain design for disruption analysis using anyLogistix (based on [Ivanov and Dolgui, 2021b](#)).

re-order point, target inventory, and minimum vehicle load) can be defined. With that functionality, a digital model of a physical SC (i.e., a digital SC) can be created and used for optimization and simulations to analyse SC operations and performance dynamics under disruptions.

The simulation model structure developed in the anyLogistix digital twin is shown in Fig. 3.

The simulation model is based on production-inventory control with five main components in the control loop (Fig. 3): demand, lead time, continuous inventory control with a re-order point and a target stock setting, production control, and transportation control. It is assumed in this simulation that the DCs follow (s,S) inventory control policy. For this simulation, the re-order point(s) per product per DC equals the daily demand per product at each DC since the lead-time is less than 1 day. Similarly, the target inventory (S) corresponds to twice the value of the re-order point. The computation of target inventory (also known as the baseline stock) is a complex task subject to specific requirements (e.g., a dependence on some service level thresholds) and analysis objectives (Chen and Disney, 2007; Minner and Transchel, 2010; Svoboda et al., 2021)). In this study, we do not pretend to analytically determine optimal re-order points and target inventory for our system. The role of inventory control in our model is to enable dynamic simulation of the SCs. With that in mind, we rely on studies (Ivanov, 2017; Aldrichetti et al., 2020) that used as a target inventory the twice value of the re-order point. Inventory carrying costs for DCs is \$0.22. It is assumed that suppliers have limited inventory. Therefore, an (s,S) inventory policy with the same replenishment logic for the DCs was applied.

The Expected Lead Time (ELT) for each order is 1 day. In other words, if the order is delivered within one day, it is considered on-time delivery. Otherwise, the order is counted as a delayed delivery. The delayed deliveries have a negative impact on the ELT service level (i.e., on-time delivery), which is defined as a ratio of on-time delivered orders to the total number of orders. The facilities have some processing costs, which can be classified as inbound and outbound costs. These costs correspond to the expenses incurred in receiving shipments from a supplying site and from sending shipments to a receiving site, respectively.

The pandemic is modelled by setting some disruption and recovery events for supply and capacities along with surges in demand. The results of the simulations are evaluated through the following KPIs (following studies by Ivanov, 2017, Ivanov, 2018, Singh et al., 2021, Dolgui et al., 2020a):

- **Financial indicators:** Statistics related to this group provide detailed information on generated revenue and incurred expenses during the simulation experiment for the specified scenario. They include profit, revenue, and costs (inventory carrying costs, transportation costs, inventory spending, inbound processing costs, outbound processing costs, and other costs).
- **Expected lead time:** It displays statistics on the delivery time of every ordered product item. It is updated each time a shipment containing the order is delivered (all delivered orders are considered whether they are on time or delayed).
- **Average daily available inventory:** It shows statistics on the daily integral mean of the available volume of products in stock.
- **Demand (product backlog):** It illustrates the quantity of processed products for incomplete orders (orders that currently lack the required number of products).
- **Fulfillment (late orders):** It shows statistics on the number of orders that failed to arrive within the specified ELT (e.g., the orders that are still being delivered after the ELT has expired).
- **ELT service level by orders:** It shows the service level based on the ratio of on-time orders to the overall number of outgoing orders.

We validated the model in several ways. First, we tested the model on the ideal (i.e., business-as-usual) scenario (see Fig. 5). Second, we compared the results of our simulations with statistical data for German retail in 2020, which confirmed the trends identified in our

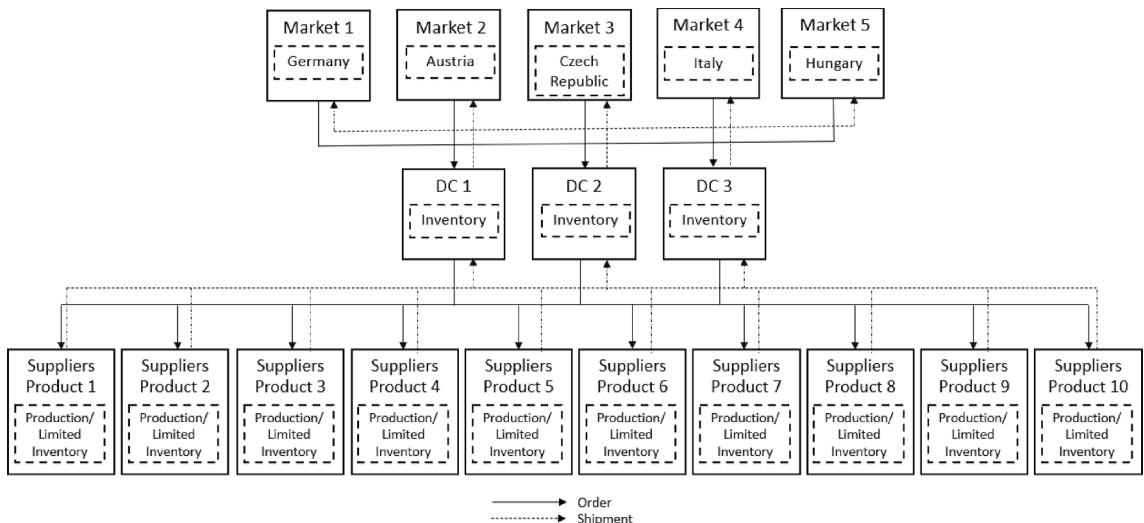


Fig. 3. Simulation model design.

experiments (e.g., growing demand and increasing transportation costs). Third, we visually checked the dynamics of material flows through the simulations jointly with two retail SC managers, who confirmed the correlation between our simulation and performance dynamics and real-life settings. Fourth, we performed a set of variation experiments with different parameters (e.g., re-order point and demand). They confirmed the model's sensitivity. The sensitivity analysis with individual parameters did not reveal any interesting or novel managerial implications, so we have omitted the presentation of these test computations and focussed on the managerial implications of our experimental results. However, another set of sensitivity analyses with consideration of time-to-recovery provided interesting insights which are discussed in [Section 5](#). Finally, we used the output data analysis in the log files and replication tests for the validity proof. We selected the timing of disruptions to avoid the 'noise' at the start of the simulation experiment.

3. COVID-19 pandemic scenarios

Our analysis aimed to investigate the impact of COVID-19 on German food retail SC performance. Therefore, different disruptions resulting from policies adopted to contain the spread of COVID-19 were examined. For analysis purposes, the timeline of the COVID-19 outbreak in Germany was used.

The first coronavirus case was reported in Germany in January 2020. By mid-February 2020, Germany's COVID-19 cases had been contained. However, on 25 and 26 February, multiple cases were detected in the country, and the virus began spreading ([WHO, 2020](#)). To contain the spread of the coronavirus, numerous restrictions to public life – including rules for reduced contact in daily life, the closing of non-essential businesses, and temporary border controls – were imposed.

In May 2020, an initial lifting of border controls, a gradual relaxation of the containment measures, and a return to public life started to occur. However, a second wave of increased coronavirus cases began around 20 October. A partial lockdown was imposed on 1 November and continued until the end of the year.

We created the following timeline as a guideline for the simulation experiments ([Deutschland.de., 2020](#)) ([Fig. 4](#)).

3.1. Scenario 0. Disruption-free (baseline) scenario

This simulation analyses the performance of the food retail SC in a scenario free of COVID-19 disruptions. We consider it as a baseline scenario. The results serve as a basis for comparing and analysing the food retail SC performance during COVID-19 pandemic-induced disruption events.

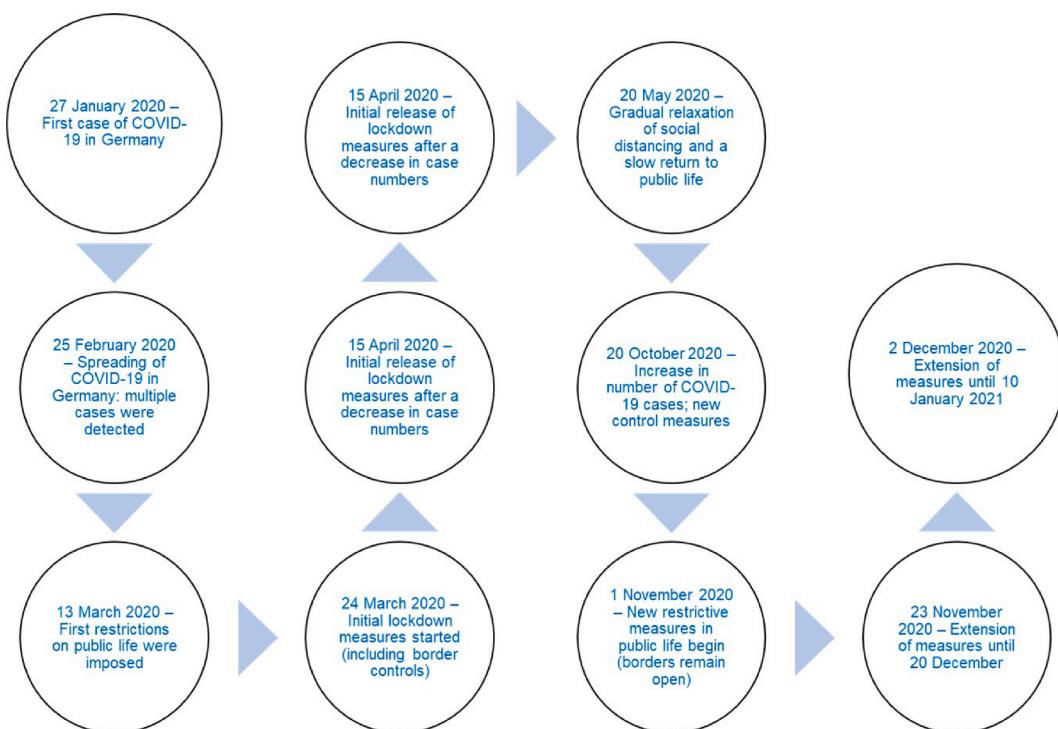


Fig. 4. Timeline of simulation experiments following the real-life COVID-19 control dynamics Based on the timeline shown in [Fig. 4](#), we developed several simulation scenarios.

3.2. Scenario 1. Increase in demand

Four fixed periods that are distinct in demand are simulated ([Table 1](#)).

The demand disruptions belong to the most important vulnerabilities in SCs ([Shen and Li, 2017](#)). The logic of this experiment is as follows. Base demand (i.e., 100%) corresponds to a business-as-usual scenario. This period corresponds to the beginning of 2020, when COVID-19 was not yet widespread in Germany. The base demand increase by 75% corresponds to the first lockdown period. It starts when the first restrictions on public life were imposed and ends when social distancing restrictions were relaxed and a slow return to public life began (following the timeline described above). During this period, panic buying increased the demand enormously in different product categories, which is reflected in our scenarios ([Paul and Chowdhury, 2021](#)). Next, a period of 10% increase in the base demand is introduced. This period corresponds to the time when coronavirus control measures were relaxed. Finally, the third period of base demand increase (of 35%) corresponds to Germany's second lockdown period, which impacted the demand to a lesser extent than the first lockdown. The objective of this scenario is to simulate the impact of increasing demand over the whole year. The results are analysed using the KPIs explained in [Section 4.1](#).

3.3. Scenario 2. Shutdown at suppliers' factories

The pandemic has caused temporary shutdowns of factories, which in turn has resulted in a sharp decline in production. Limits on people's mobility have reduced seasonal workers' availability for planting and harvesting in many countries. In addition, food processing industries have been affected by social distancing rules and other measures aiming to contain the virus's spread, which have reduced operations' efficiency ([OECD, 2020](#)). Thus, we simulate a shutdown at three factories (i.e., suppliers) to analyse the impact of their closure on food retailers. [Table 2](#) shows the experimental setup for the event simulation and the period when the shutdown occurs.

The shutdown period for each site is consistent with the German government's period of restrictions to contain the coronavirus spread (explained in the timeline above). The objective of this scenario is to simulate the impact of closing the factories of two major suppliers during a fixed period of 10 days in March and one supplier's factory during a 15-day fixed period in April.

3.4. Scenario 3. Bottlenecks in transport

Bottlenecks due to increased border controls are simulated in this experiment according to real-life scenarios encountered in spring 2020 ([BMI, 2020](#)). Although no border closures for the transportation of goods were imposed, traffic jams at the border and long queues occurred because of the temporary border controls during the first lockdown in Germany. This limited the normal flow of transports into the country. Bottlenecks in transport due to border control delays are simulated for six different periods. This scenario simulates an interruption of material flows over a period of 2 days in each experiment. [Fig. 5](#) shows the interrupted paths with their respective durations.

The disruption period for each route is consistent with the period during which the German government's restrictions to stop the coronavirus spread were in effect, as explained in the timeline above. The purpose of this scenario is to simulate the impact of closing paths from suppliers to DCs and from DCs to customers during short periods of 2 days in March and April.

3.5. Scenario 4. COVID-19: Increase in demand, shutdown of suppliers' factories, and transport bottlenecks

This scenario simulates the impact of COVID-19 on the food retail industry SC by combining scenarios 1, 2, and 3. This simulation aims to reflect the overall food SC performance during two pandemic waves in 2020.

4. Results and analysis

4.1. Impact of COVID-19 in Germany's food retail SC performance

This section aims to respond to RQ1: How and why has the COVID-19 pandemic outbreak impacted food retail SC performance? This section presents the simulation results and analysis of the simulation experiments. First, the performance of a disruption-free scenario will be described. Subsequently, the disruption scenarios will be evaluated using four simulation experiments. Additionally, a cross-comparison analysis of the scenarios and generalizations of the COVID-19 impact in the food SC will be provided.

Table 1
Experiment description: Demand levels.

Event	Period	Coefficient
Base demand	01/01/2020–14/03/2020	1
Base demand increase 75%	15/03/2020–31/05/2020	1.75
Base demand increase 10%	01/06/2020–31/10/2020	1.1
Base demand increase 35%	01/11/2020–31/12/2020	1.35

Table 2
Experiment description: Supplier's factories shut down.

Event type	Shutdown period
Shutdown factory: Frozen Meals supplier	01/04/2020–15/04/2020
Shutdown factory: Fresh Fruits supplier	16/03/2020–27/03/2020
Shutdown factory: Fresh Vegetables supplier	16/03/2020–27/03/2020

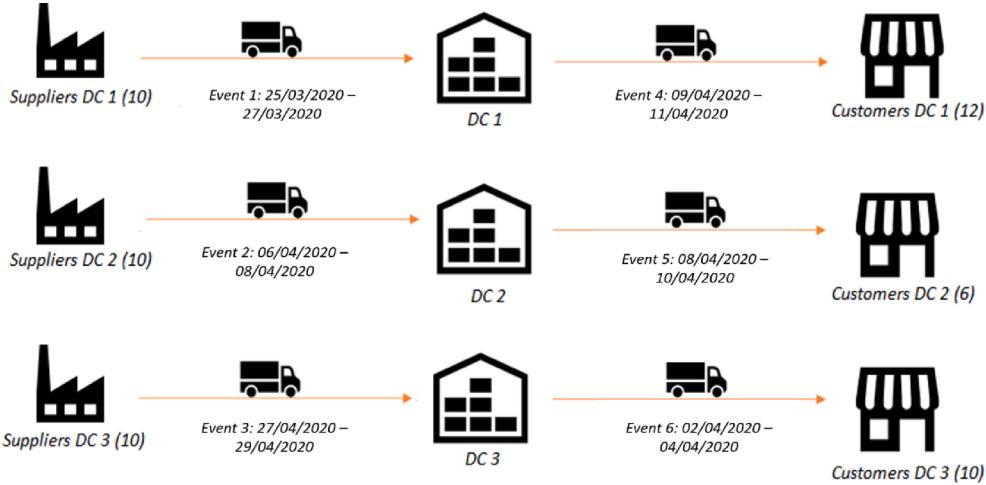


Fig. 5. Experiment description: Bottlenecks in transport.

4.1.1. Scenario 0. Disruption-free (baseline) scenario

This section describes the SC performance of the food retail industry in Germany in a pandemic-free (i.e., baseline) scenario. Fig. 6 shows the simulation results.

Regarding *Lead Time*, Fig. 6 shows a histogram of the daily lead time, representing the delivery time for each product item ordered. The x-axis shows the lead-time in days, and the y-axis indicates the number of occurrences of orders with a particular lead-time. Products are delivered within a time interval of 0 and 12 h, but most of the products are delivered within a 2-hour timeframe. Thus, the customer's ELT of 1 day is met for all product categories. This case suggests that lead times in the food retail industry are usually short because of recurring orders and high inventory rotation in DCs.

With respect to the *Average Daily Available Inventory*, the simulation outcome shows the inventory levels in DCs for all product categories. The order-up-to-level policy (s, S) allows ordering quantities up to level S when reaching the re-order point s . This policy prevents excessive inventory levels and shortages and considers some situational demand fluctuations. From the results, it is evident that there is enough stock availability from day 1 in all scenarios, which allows for high flexibility to match demand. Small fluctuations with low amplitude can also be seen for all products. Moreover, inventory levels do not fall to the 0 level during the year, which means that the inventory policy allows the retailer to satisfy demand across the SC.

Demand satisfaction can be measured in terms of *Product Backlog*, which indicates the number of processed products for orders that lack the required number of products. In Fig. 6, a backlog of 0 can be observed, meaning that all orders are completely delivered.

Fulfilment (Late Orders) shows the number of orders that fail to arrive within the specified ELT. As the ELT is one day, every order delivered within a frame greater than 1 is considered a late delivery. In Fig. 6, it can be seen that all products are delivered on time because the number of late orders is 0. Therefore, the number of on-time orders equals the total number of orders.

Finally, the *ELT Service Level* analyses the ratio of on-time orders to the overall number of outgoing orders. Hence, late deliveries have a negative impact on ELT service. Results show a service level of 1, which means that customers receive 100% of their orders without delays and within the expected lead time.

4.1.2. Scenario 1. Increase in demand

Scenario 1 shows the impact on the food SC performance after an increase in demand resulting from the COVID-19 pandemic outbreak. Fig. 7 illustrates the results for each KPI.

This scenario reveals that an increase in demand positively influences the revenues because a higher volume of products is sold, which increases the profits. Additionally, inventory levels decrease because of demand growth. Consequently, lead time increases, as well as the number of late orders, reducing the ELT service level. An increase in the product backlog can also be seen because of a rise in the number of incomplete orders.

Lead Time for most orders in scenario 1 is between 0 and 10 days. Under normal conditions, lead time is a maximum of half a day. Also, with a lower frequency, some orders can take up to 50 days to be delivered to the customer. It can be inferred from these results

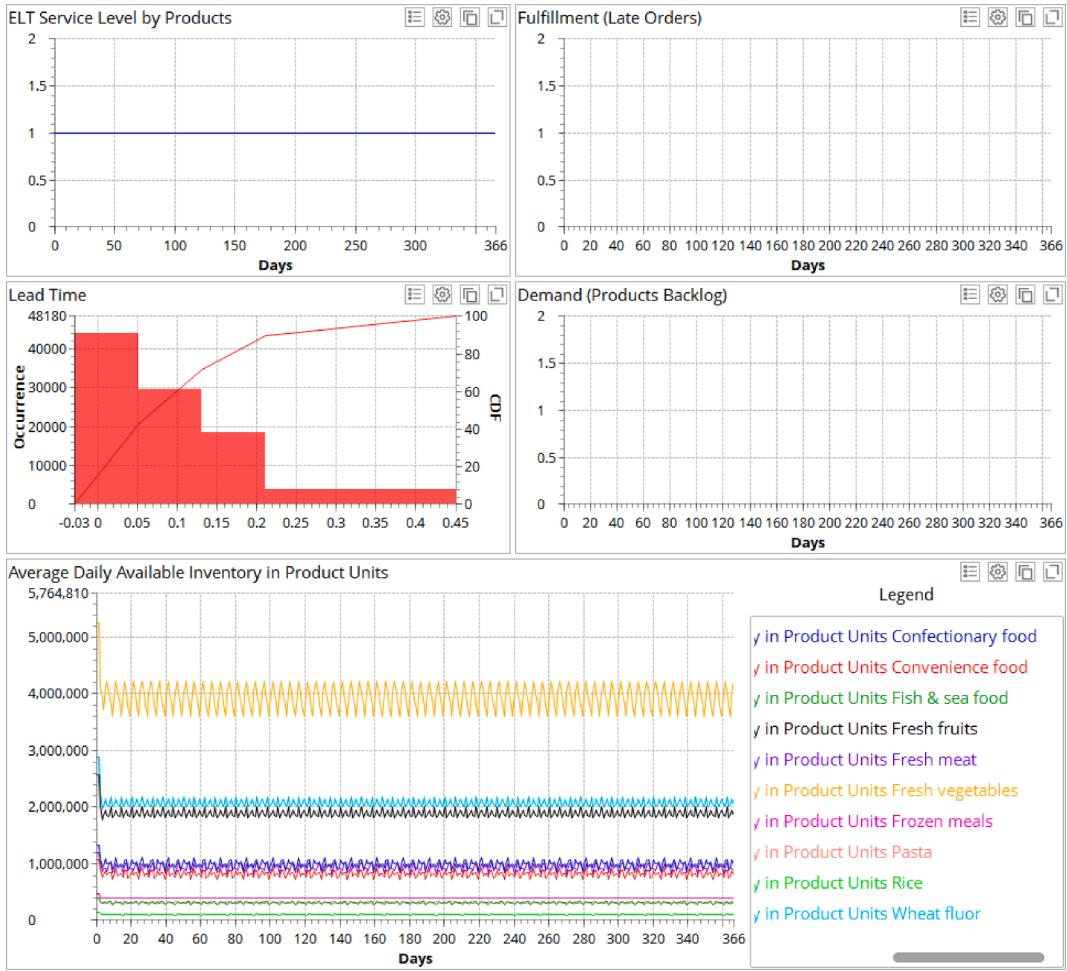


Fig. 6. Experiment results: Disruption-free (baseline) scenario.

that as the demand increases, procuring the quantities required to meet it takes longer because the available inventory is insufficient to satisfy the growing demand. Delays in delivery occur until the stock is replenished. The results also show that the Average Daily Available Inventory dramatically decreases because of the increased demand. Fluctuations throughout the year can be seen in the ‘Average Daily Available Inventory’ graph in Fig. 7. When demand increases by 75% (corresponding to Germany’s first lockdown), there is a sharp drop in inventory. Inventory levels do not recover to a level similar to that in the initial scenario throughout the year. On the other hand, during the second lockdown, a slight decrease in inventory can be seen for some product categories, but this decrease is not as abrupt as the decrease during the first lockdown. An increase in the demand for all products simultaneously over a relatively long period causes delays and unattended orders.

In addition, concerning the *Product Backlog*, the results show that orders are not completely delivered, and thus demand is not 100% satisfied. The ‘Demand (Product Backlog)’ graph in Fig. 6 shows a sharp increase in the product backlog during the first lockdown period, when demand for all products increases by 75% compared to their initial level (in the disruption-free scenario). Then, beginning on day 150 of the year, there is a decrease in the backlog as demand decreases compared to the first lockdown period but remains 10% higher than in a disruption-free scenario. An increase in the backlog appears again on day 300 – which corresponds to Germany’s second lockdown period – representing an increase in demand of 35% compared to its initial level. According to the simulation results, the accumulated backlog throughout the year is 32.1 million kg, while the total demand for all products is 1.157 trillion kg. Therefore, 2.7% of the total demand is not satisfied after an increase in demand due to the COVID-19 pandemic.

The results also indicate that when there is an increase in lead time, the *Fulfillment (Late Orders)* indicator is affected. In the ‘Fulfillment (Late Orders)’ graph in Fig. 7, a growing line over time indicates the number of orders that are not delivered on time for all products in all customer locations. According to the results, 3,949 orders are delivered late throughout the year, representing 3.7% of the total number of orders placed by the customers.

Similarly, Fig. 7 shows that the *ELT Service Level* for all products is 100% from the start of the year until the beginning of the first lockdown period in mid-March. Then, the average service level falls to 87.2% and remains at this level throughout the rest of the year. The increasing number of late orders is the reason for these ELT service level dynamics.

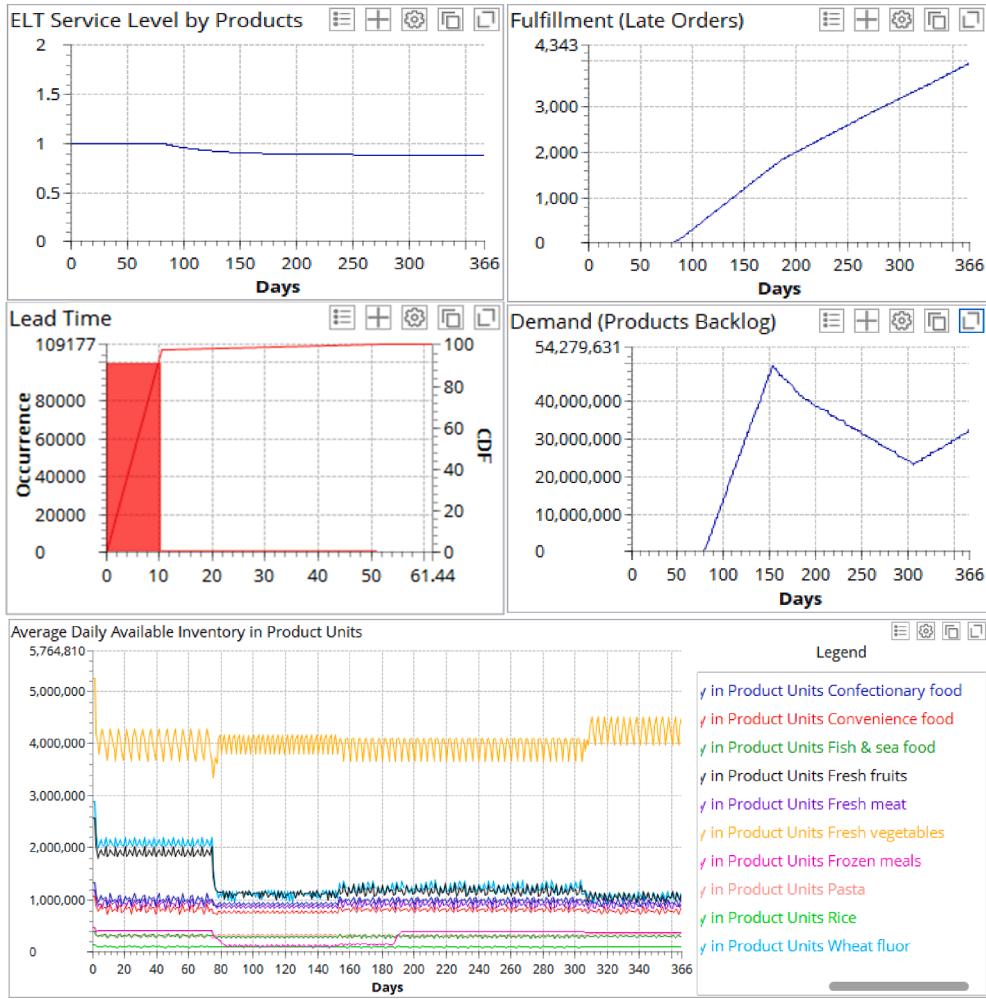


Fig. 7. Experiment results: Increase in demand.

4.1.3. Scenario 2. Shutdown in suppliers' factories

Scenario 2 shows the impact on the food SC performance after a shutdown in suppliers' factories due to the COVID-19 pandemic outbreak. We simulated a shutdown for three different product categories over periods of 10 and 15 days. This yielded the results depicted in Fig. 8. According to these results, a temporary production shutdown at three suppliers' factories slightly reduces profit as total costs increase. Moreover, a reduction in inventory levels at DCs occurs as suppliers stop delivering the products during the disruption period. Additionally, there is a high increase in inventory when the factories are reopened. This effect can be explained by disruption tails – that is, a destabilization of production-ordering dynamics in the post-disruption period due to a lack of adaptability in the production-inventory control policies when transitioning from the disruption to the recovery period (Ivanov, 2019, Ivanov and Rozhkov, 2020). Consequently, lead time (as well as the number of late orders) increases, which decreases the ELT service level over an extended period. Furthermore, the number of incomplete orders also grows, generating product backlog in some product categories.

After an outage of products, incoming quantities accumulate in DCs. Thus, stock levels grow, causing an increase in inventory carrying costs. Also, during a supply outage, incomplete orders are transported from DCs to customers, decreasing the vehicle capacity utilization. Then, when products become available after the suppliers' factories re-open, the number of trips escalates to deliver the missing quantities. Therefore, transportation costs increase. Inbound and outbound costs remain the same. Other administrative costs do not vary, as they are fixed costs. The ELT service level falls to an average of 88.2% as the minimum value and improves throughout the year, reaching a level close to 100% at the end of the year.

4.1.4. Scenario 3. Bottlenecks in transport

Scenario 3 shows the impact on the food SC performance of multiple transport bottlenecks due to the COVID-19 pandemic outbreak. Six bottleneck events are simulated for 2-day periods in different paths from suppliers to DCs and from DCs to customers. The results are depicted in Fig. 9.

According to the results of scenario 3, transport bottlenecks have a small impact on profit performance. There is a minor reduction

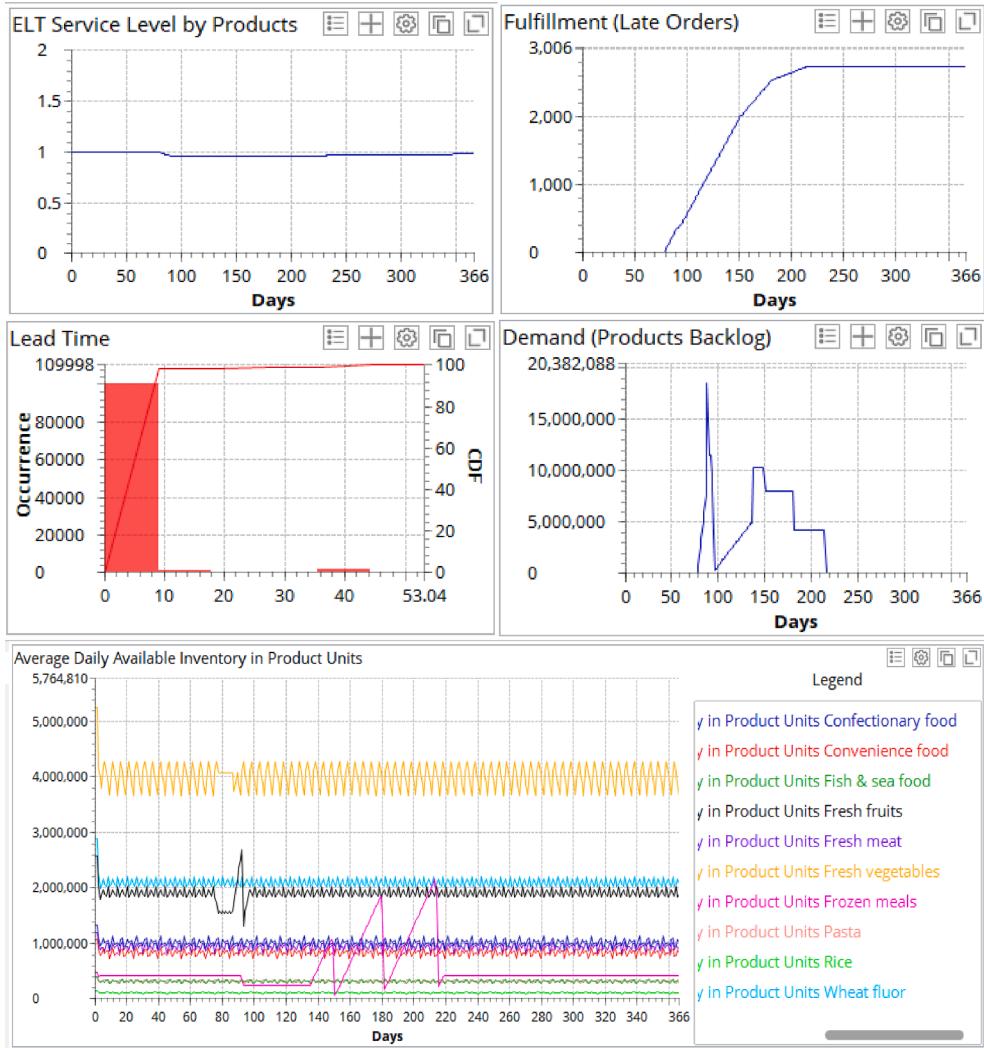


Fig. 8. Experiment results: Suppliers' factories shutdown.

in inventory levels at DCs during the disruption as suppliers stop delivering the products within short time periods. Therefore, the number of late orders increases, although in minimal quantities compared to the total number of orders. Moreover, the number of incomplete orders rises but only slightly, resulting in a very low backlog. As a result, the service level remains close to 100% within the entire period, indicating demand satisfaction.

In terms of *Fulfillment (Late Orders)*, a growing line that stabilizes over time can be observed. 30 orders are delivered late throughout the year, representing approximately 0.03% of the total number of orders placed (102,280). Finally, the *ELT service level* is approximately 100% during the whole period. This number can be explained by the small number of late deliveries as most orders were delivered on time. Thus, the demand during the year is satisfied overall despite the transport disruptions.

With regard to scenario 3, we can conclude that the magnitude of the disruption impact is significantly lower as compared to scenarios 1 and 2. The short-term bottleneck in transport lasts for two periods, with a lead time of one period and can be considered rather an operational risk event and not as a disruption. Fig. 8 confirms that there is no significant SC performance impact.

4.1.5. Scenario 4. Full impact of COVID-19 pandemic through two waves in 2020 – A combination of all scenarios

Scenario 4 shows the impact on the food SC performance after experiencing a combination of the three disruptive scenarios explained above: an increase in demand, a shutdown in suppliers' factories, and transport bottlenecks. Fig. 10 shows the results of the experiment through the selected KPIs.

This simulation illustrates the SC performance in the food retail industry during the COVID-19 pandemic outbreak in Germany. In this scenario, synergistic effects of adding different negative events can be observed. Interestingly, the aggregation of events results in a positive impact on SC financial performance. Increased revenues and decreased total costs have a positive impact on profit. Nevertheless, delays occur, and a considerable percentage of products are not delivered on time or are incompletely delivered (reflected in

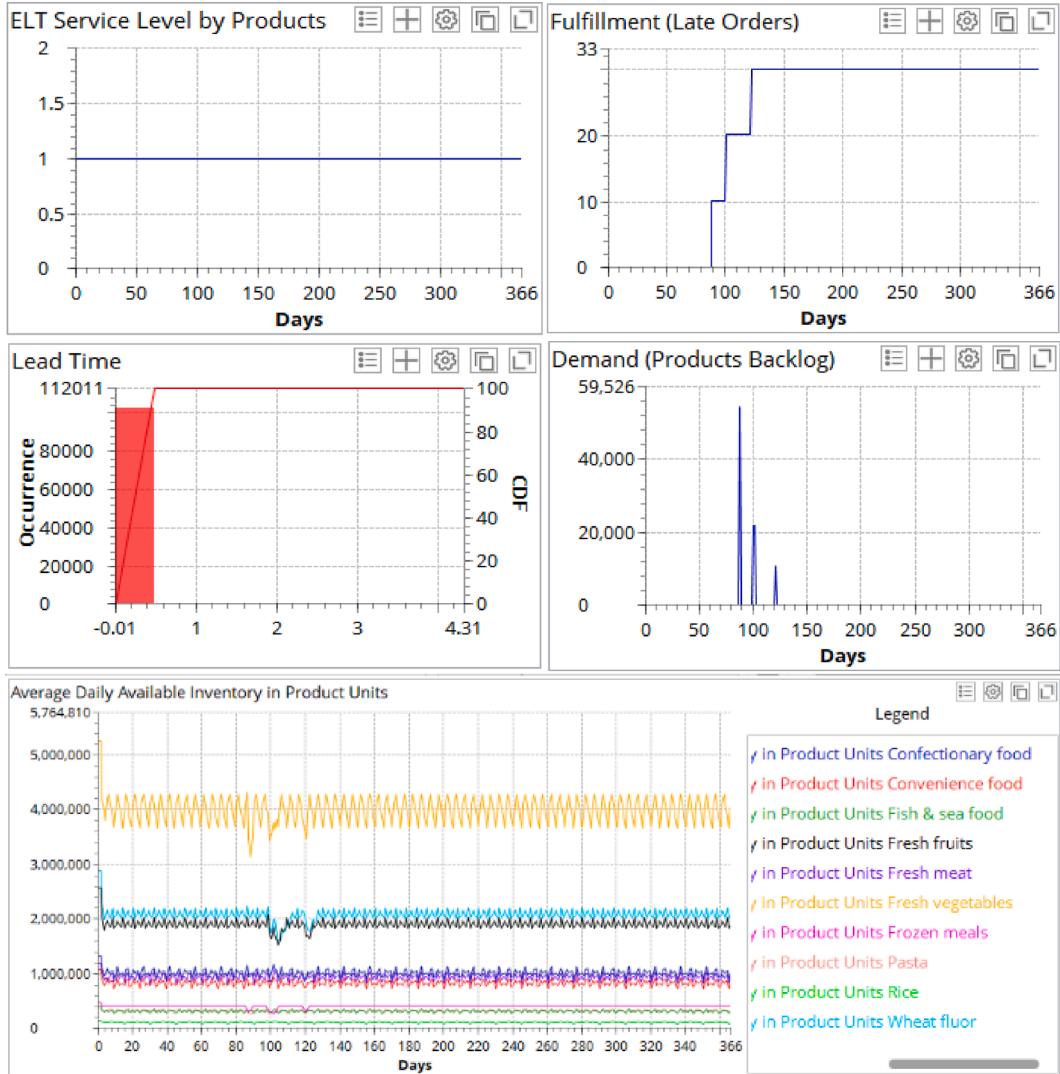


Fig. 9. Experiment results: Bottlenecks in transport.

the fulfilment (late orders) and demand (products backlog) graphs, respectively). These outcomes lead to out-of-stock products, especially during the first lockdown period. Moreover, a decrease in inventory followed by a considerable increase after the government relaxes the lockdown measures is apparent in the average daily available inventory graph.

The second wave of COVID-19 impacts the industry to a lower extent than the first wave as inventory levels do not drop significantly and a smaller backlog is accumulated. Furthermore, the late orders curve is flattened, which implies a smaller number of delayed orders. The accumulated disruptions result in a drop in the service level to 80%, demonstrating that a significant percentage of the demand is still satisfied despite the pandemic outbreak. Therefore, in general terms, the simulation suggests that the food retail industry can benefit from the pandemic in terms of financial performance and growth opportunities.

Transportation costs increase in the COVID-19 scenario because a higher quantity is shipped in response to higher demand during the pandemic. However, there are inefficiencies in transport as incomplete orders are shipped from the warehouse to customers when suppliers' factories are shut down, leading to lower vehicle capacity utilization. In addition, transportation costs increase because there is an increase in the average number of vehicles used to transport the requested amounts. Inbound and outbound costs also increase because increasing demand leads to more goods needing to be processed at warehouses. Other costs do not vary as they are fixed administrative costs.

The *Lead Time* graph shows that a considerable number of orders are delivered to the customer within a range of 0 to 10 days, but under normal conditions, this takes a maximum of half a day. Less frequently, orders may take up to 70 days to be delivered. Thus, the disruptions resulting from the coronavirus outbreak affect the lead time, so providing customers with the required quantities of goods within the expected time becomes a challenge for food retailers.

Moreover, *Average Daily Available Inventory* levels are affected by the COVID-19 disruption. Initially, a sharp drop in inventory

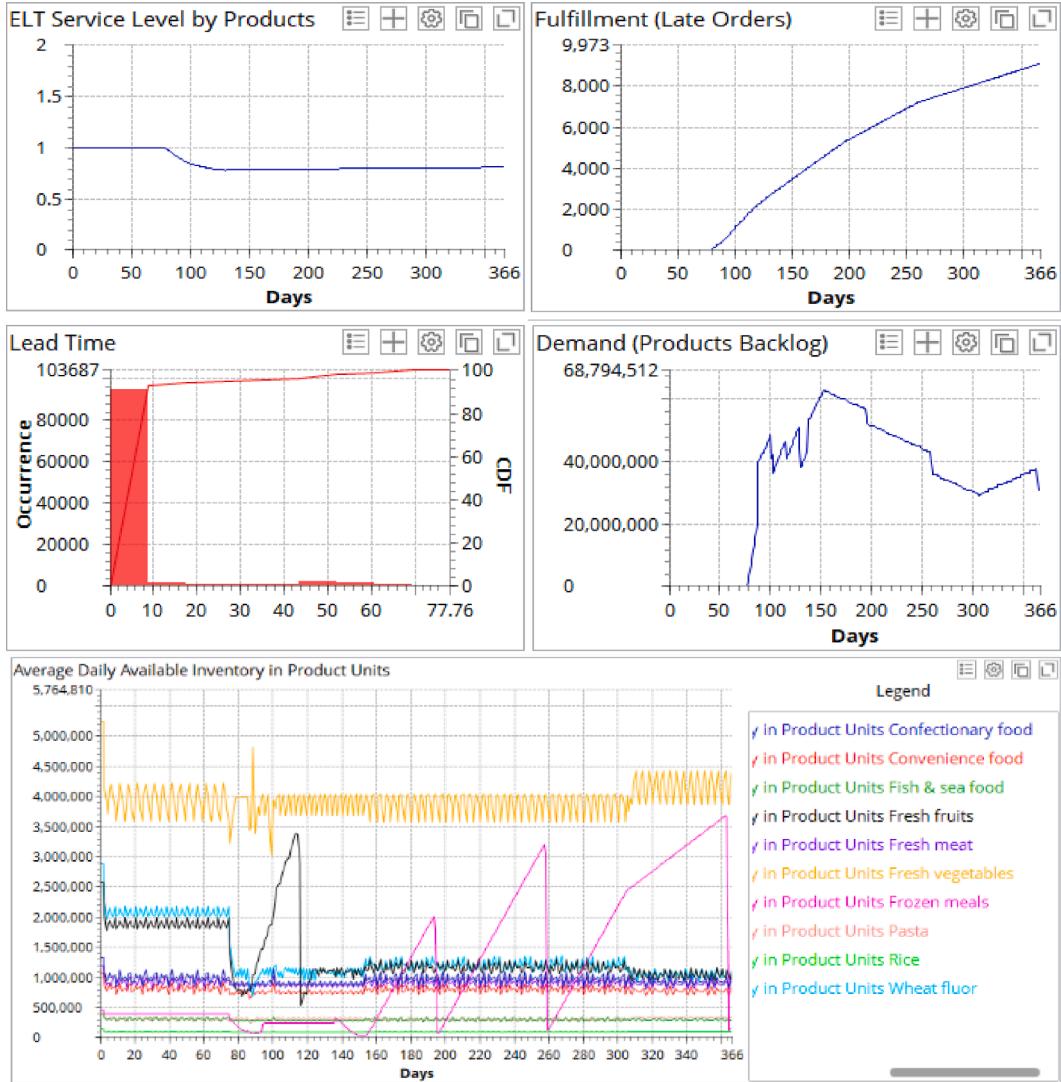


Fig. 10. Experiment results: COVID-19 scenario.

occurs because of the increased demand along with factory shutdowns and bottlenecks in transport during Germany's first lockdown. During the second lockdown, a slight decrease in inventory can be observed; however, it is not as abrupt as that in the first lockdown. Also, alterations in stock at the end of the period can be observed inducing the *ripple effect* (Ivanov et al., 2014, Dolgui et al., 2018, Li et al., 2021) of the first lockdown. For some product categories, inventory levels recover to a level similar to that in a disruption-free scenario throughout the remaining part of the year.

Regarding *Product Backlog*, the results show that some orders are not entirely delivered because of a lack of the required number of products, and thus demand is not 100% satisfied. The graph starts with a sharp increase in the product backlog, which results from the 75% increase in demand, disruptions in transport, and shutdowns in the suppliers' factories during the first lockdown. Then, beginning on day 150, a decrease in the backlog can be observed. This result occurs as coronavirus regulations are softened, and the country begins a gradual return to normality. As a result, demand decreases compared to the first lockdown period, suppliers' factories reopen, and transport operates under normal conditions. At the end of the year, a slight increase in product backlog can be explained by the increased demand during Germany's second lockdown period.

The pandemic outbreak negatively impacted the *Fulfillment (Late Orders)* indicator, which shows a growing line over the whole period beginning on day 80, which coincides with the first lockdown. This line indicates the number of orders that fail to be delivered on time in all customer locations. According to the results, 9,067 orders are delivered late throughout the year, representing approximately 8% of the total number of orders (102,290). Finally, this scenario shows that the *ELT service level* is 100% from the start of the year until the first lockdown period in mid-March, when the service level falls to 80% and remains at this level throughout the rest of the year.

4.2. Cross-comparison analysis

After evaluating each simulation scenario separately, we used a cross-comparison analysis of all scenarios to evaluate the results and create generalizations. A summary of the computational results is presented in [Table 3](#).

The overview in [Table 3](#) allows for analysing the effects of the COVID-19 outbreak in the food SC for the selected KPIs. It serves as a guide for addressing the main SC issues in Germany's food retail industry resulting from the pandemic.

Regarding financial performance in the scenarios, [Table 3](#) displays detailed information on generated revenue and incurred expenses during the initial scenario simulation experiment. Revenue includes the income generated from selling products to customers. Total costs include inventory carrying costs, transportation costs, processing costs (inbound and outbound), inventory spending, and other costs. Profits are calculated by subtracting total costs from revenues. The baseline scenario shows profitability, leading to outstanding performance. Total costs add up to USD 2.750bn and represent 90% of the revenue (USD 3.057bn). Given that companies in the retail industry do not usually produce, but rather purchase, inventory, inventory spending (i.e., 84.6%) typically represents the highest costs in their SC. Inventory carrying costs represent 12.8% of the total costs. As many of the products are perishable, they rotate quickly – typically on a daily basis. Thus, DCs do not accumulate excessive stock, leading to relatively low inventory costs.

For scenario 1, the results suggest that an increase in demand in different periods throughout the year shows a positive impact on sales as profit increases because of increased revenues. The total costs add up to USD 2.723bn and represent around 71% of the revenue (USD 3.825bn). Transportation costs increase and represent 6.2% of the total costs (see [Table 3](#)). This increase results from a growth in the number of shipping vehicles as larger quantities are transported from the DCs to customers. Inbound and outbound costs also increase because more goods must be processed to meet demand.

In scenario 2, financial performance is not strongly affected throughout the year after experiencing a stoppage in supply for a certain period. Profit decreases by approximately 1% compared to a disruption-free scenario. Although revenues are not impacted, total costs are affected by increased inventory and transportation costs. Thus, total costs add up to USD 2.753bn and represent 90% of the revenue (USD 3.057bn). Inventory levels are readjusted to satisfy the demand because the min-max policy allows variable order quantities, thus preventing inventory shortages.

In scenario 3, the financial performance shows only a minimum change as compared to the baseline scenario. The COVID-19 scenario (no. 4) has a positive impact on revenues and profits. The increasing demand throughout the year is the principal reason for revenue generation. Total costs add up to USD 2.707bn and represent approximately 71% of the revenue (USD 3.816bn). Regarding inventory costs, the min-max policy allows adjusting the inventory levels to satisfy demand, preventing inventory shortages. Thus, inventory levels change to cope with the multiple disruptions faced. Nevertheless, available inventory is rapidly consumed, leading to lower stock levels at DCs. As a result, inventory carrying costs decrease by 17% in the COVID-19 scenario compared to the disruption-free scenario.

Analysis of the results from the different scenarios yields several important observations. As the overall demand increases (scenario 1) at different levels during the selected period, inventory levels decrease. Also, the number of total shipping vehicles rises as more orders need to be dispatched. At the same time, longer lead times can be observed, leading to an increase in the late-orders ratio, which in turn reduces the service level. Backlogs due to incomplete orders also occur, but they are low when compared to the total demand. From a financial point of view, an increase in demand positively impacts revenues, leading to growing profits.

A shutdown in three suppliers' factories (scenario 2) for 10 or 15 days generates increased inventory levels and a higher number of shipping vehicles used when inventory accumulates at DCs after the factories are reopened. This growth in the number of shipping vehicles used leads to decreased transport efficiency because some vehicles are not fully utilized during the shutdown. Longer lead times can be observed, leading to an increased late-orders ratio and a reduced service level. Backlogs due to incomplete orders are

Table 3
Summary of computational results.

Performance impact	Baseline scenario 0. Disruption-free	Scenario 1. Demand increase	Scenario 2. Shutdown at supplier's factories	Scenario 3. Bottlenecks in transport	Scenario 4. COVID-19
Revenue (USD)	3,057,962	3,825,920	3,057,962	3,045,062	3,816,148
Total costs (USD)	2,750,695	2,723,818	2,753,020	2,759,776	2,707,307
Profit (USD)	307,266	1,102,101	304,941	285,286	1,108,840
Mean lead time (days)	0.10	1.03	0.86	0.10	3.112
Average daily available inventory (kg)	11,858	10,748	12,018	11,996	10,579
Total shipped vehicles	39,697	47,089	40,764	39,766	49,387
Average number of vehicles used	6,008	7,391	6,217	6,037	7,935
Total demand by customer (kg)	918,006	1157,252	918,006	918,006	1,157,252
Total product backlog (kg)	0	32,194,785	0	0	30,885,163
Backlog % of total demand by customer	0.00%	2.78%	0.00%	0.00%	2.67%
Demand placed (orders) by customers	102,280	102,280	102,280	102,280	102,280
Late orders	0	3,949	2,733	30	9,067
Fulfillment rate (ratio of on-time orders to total orders), %	100	96	97	100	92
ELT service level (%)	1.00	0.87	0.98	1.00	0.80

evident.

Multiple short-time bottlenecks in transport (scenario 3) have a small impact on the KPIs selected. The inventory levels and the number of shipping vehicles used slightly increase. The mean lead time remains low, within the expected lead time of 1 day, and the number of late orders rises, although in a small quantity compared to the total demand. This leads to a high service level, close to 100%. Backlogs due to incomplete orders occur in small quantities such that the approximate value of backlogs is 0. Profits slightly decrease because of increased total costs and declined revenues. A combination of the disruptions mentioned above is simulated in the COVID-19 scenario, providing insights regarding the synergistic effects. Since disruptions coincide along the simulation period, a more substantial impact on SC performance and operations can be observed. Inventory levels decrease because of a rapid demand increase at the beginning of the first coronavirus wave, which is intensified when products stop being received because of production stoppages and transport barriers. In turn, the inventory decrease leads to higher lead times and unattended orders, generating an increase in the mean lead time and late orders rate, and entailing an overall reduced ELT service level.

5. Sensitivity analysis

In this section, we discuss the design and results of sensitivity analysis using the Time-to-Recover (TTR) approach proposed by Simchi-Levi et al. (2015) and extended by Kinra et al. (2020) for the purpose of validation and derivation of additional managerial insights.

The Simchi-Levi et al. (2015) model introduced the TTR notion as the time it would take for a particular node in the SC network to be restored to some required functionality after a disruption. Kinra et al. (2020) extended the optimization-based TTR approach through the lens of simulation. They used service level (SL) (i.e., the ratio of on-time orders to the overall number of outgoing orders) as an indicator of disruption and recovery in the SC and computed the TTR based on Eq. (1):

$$TTR = t_{failureSL} - t_{recoveredSL}, \quad (1)$$

where $t_{failureSL}$ is the point of time at which the SL drops to a level which is considered as a failure, and $t_{recoveredSL}$ is the point of time at which the service level returns to a level which is considered as a recovery.

We run a series of the sensitivity experiments for different values of $SL_{failureSL}$ and $SL_{recovered}$ in the range between 50% and 100% (or 0.5 and 1). Two results are presented in Figs. 11 and 12 considering scenario no. 4 (i.e., full impact of COVID-19 pandemic). The TTR has been analysed for all 10 product groups involved with our case-study.

It can be observed in Figs. 11 and 12 that the model is sensitive to the selection of SL failure and recovery thresholds. In Fig. 11, the TTR for the thresholds $SL_{failure} = 0.9$ and $SL_{recovered} = 0.98$ are presented. The average TTR is between 0 and 1.5 weeks for 3 product groups, between 3.2 and 4.8 weeks for 6 other product groups, and between 14.7 and 16.3 weeks for another product group. In Fig. 12, the TTR for the thresholds $SL_{failure} = 0.7$ and $SL_{recovered} = 0.9$ are presented. The average TTR is between 0 and 0.72 weeks for 3 product groups, between 3.2 and 4 weeks for 6 other product groups, and between 5.65 and 6.47 weeks for another product group.

The results displayed in Figs. 11 and 12 show the sensitivity of TTR to the selected SL thresholds. This sensitivity analysis has several managerial implications. First, through the analysis of the results, one can identify the products with longer TTR which would require more attention, and develop measures to strengthen their resilience. Second, the TTR analysis allows for understanding of SL

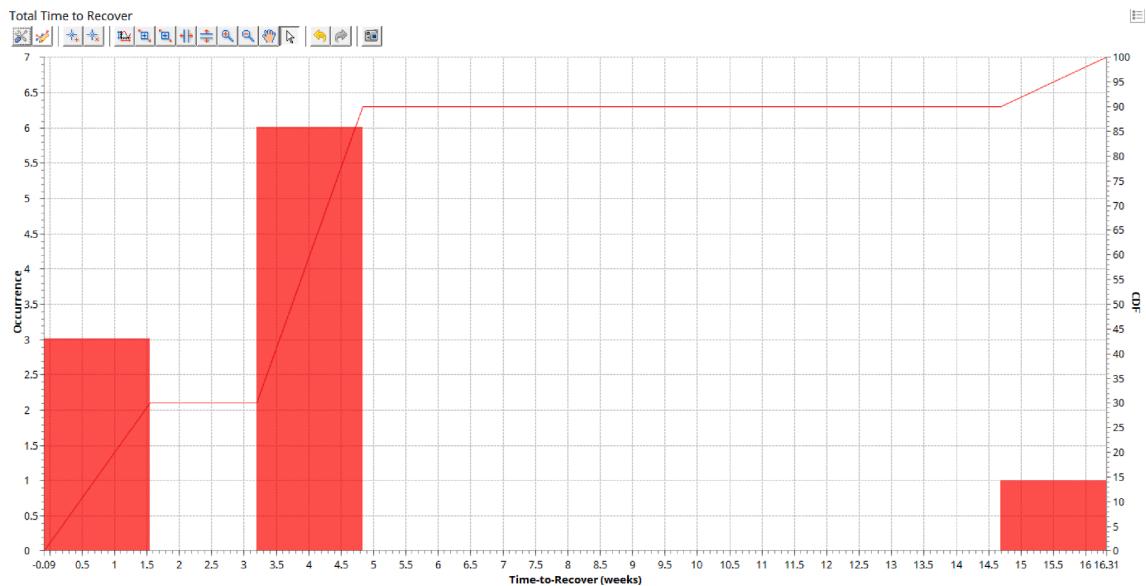


Fig. 11. Time-to-recover for service level $SL_{failure} = 0.9$ and $SL_{recovered} = 0.98$.

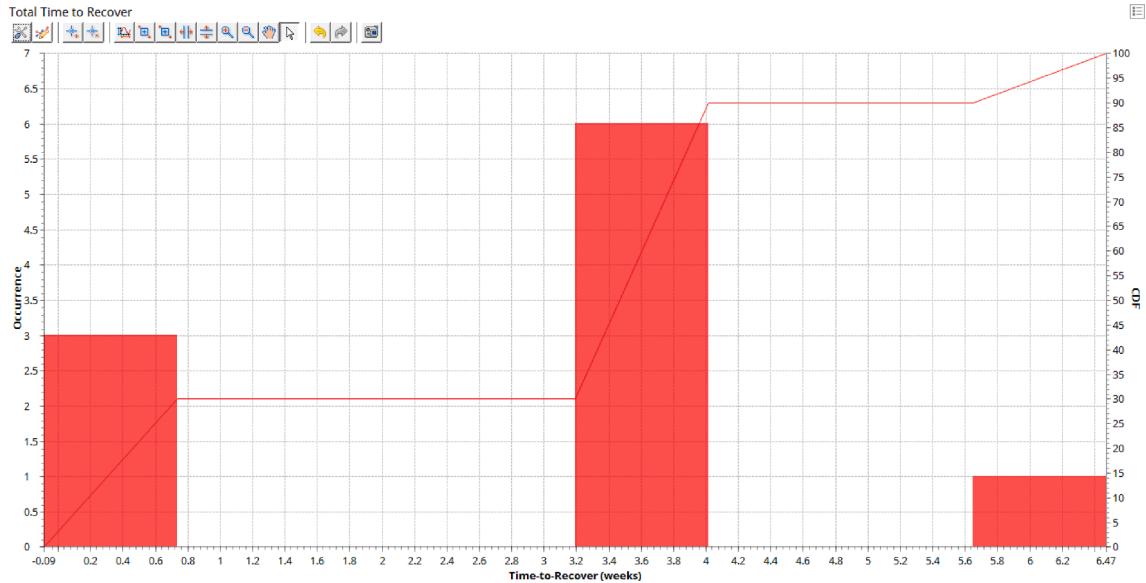


Fig. 12. Time-to-recover for service level $SL_{failure} = 0.7$ and $SL_{recovered} = 0.9$.

thresholds to be associated with SC operations and performance dynamics according to different disruption scenarios.

6. Discussion and implications

This section aims to respond to RQ2: How can food retail SC resilience be improved? In particular, we discuss what companies should do to increase resilience during a pandemic and how these measures can be implemented.

The COVID-19 pandemic has brought both challenges and opportunities to the food retail industry in Germany. Customers have modified their shopping behaviour and increased their home consumption. Thus, the demand for food has seen a rapid and unprecedented growth that has impacted Germany's food SC. Nevertheless, the increased demand has introduced significant pressure on the SC, creating many immediate challenges. It has caused alterations in inventory levels, which have led to simultaneous surpluses for producers and shortages for consumers. Hence, food retailers experienced a sharp reduction in inventory, increased product backlog,

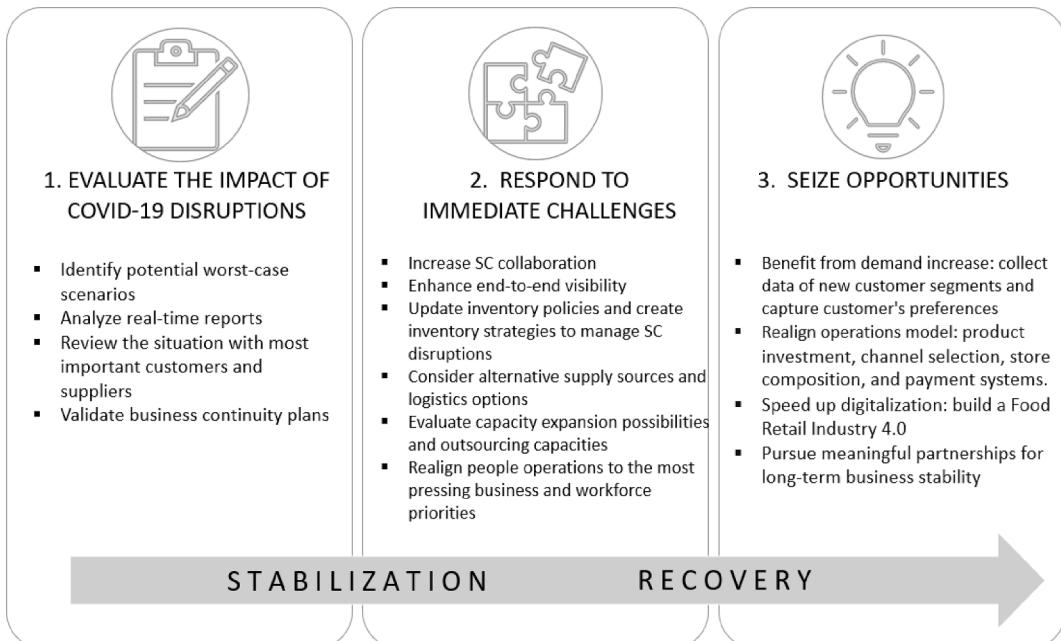


Fig. 13. Post-disruption framework to increase SC resilience in the food retail industry.

and late orders during the first lockdown period. Some product categories presented delays and did not arrive within the expected lead times. In short, empty shelves in supermarkets were seen at the beginning of the COVID-19 outbreak in Germany.

Furthermore, food processing plants experienced shutdowns or were forced to operate at reduced capacity because of Germany's measures to contain the coronavirus's spread during the first lockdown. Transport bottlenecks have disrupted the movement of goods along the food SC. Although the simulation carried out was limited to land transport by truck, the effects of an interruption in the road that connects suppliers with DCs and DCs with customers was evidenced. Additionally, on-time deliveries and service levels also decreased. In sum, this section's results, combined with the examined literature review, identify the following SC issues in Germany's food retail SC due to the COVID-19 pandemic: (1) change in the quantity demanded, (2) change in the demand patterns and market composition, (3) suppliers' output reduction due to partial or total capacity shutdown, (4) inventory shortages and surpluses at DCs, (5) transport and logistics backlogs, (6) adoption of new distribution channels (e.g., a shift to online sales), (7) capacity constraints at DCs, (8) increased lead times, (9) increased number of non-fulfilled orders, and (10) increased hygienic regulations and traceability requirements. When these changes and challenges occur, the food retail industry should adjust its SC to increase its resilience. In this section, we discuss some directions and actions that food retail companies can take to increase their SC resilience, and how these measures can be implemented in practice (Fig. 13).

In the context of the COVID-19 outbreak, the first step we recommend is that companies in the food retail industry evaluate the impact of COVID-19 disruptions on their business. Companies must assess and address the effect of disruptions in their SCs by carrying out a rapid evaluation of their current situation and those of their most important partners. During this phase, we also recommend that companies identify potential worst-case scenarios that may emerge from the outbreak and analyse real-time reports to develop measures to stabilize these situations.

The second step we recommend aims to respond to SC challenges resulting from COVID-19 disruptions. Food retailers should increase communication and collaboration across their SCs to design alternative plans and supply allocations, aiming to minimize the disruption's impact on SC operations and performance. Thus, contact with key suppliers to make decisions that could prevent stockouts or other potential problems for the end customer is essential. Food retailers should also enhance end-to-end visibility to enable them to better understand disruptions and conduct specific actions based on existing priorities. Visibility should extend beyond tier 1 suppliers along the entire SC. Through visibility, access to the real status of inventory at suppliers' locations, production schedules, and shipment status can be gained, which may help food retailers respond accordingly. End-to-end visibility can be achieved by utilizing a variety of available digital technologies, such as big data analytics, blockchain, and collaborative SC platforms (Cavalcante et al., 2019, Dubey et al., 2019, Ivanov et al., 2019, Lohmer et al., 2020, Wamba and Queiroz, 2020, Dubey et al., 2021). Furthermore, end-to-end visibility can enable mapping of the SC beyond the first or second tiers (e.g., using digital twins) (Ivanov and Dolgui, 2021c, Frazzon et al., 2021).

Securing additional stock and redefining inventory strategies is another recommendation for companies in the food retail industry. Along with alternative supply sources and logistic transport options, food retail companies can maintain the required inventory levels and respond quickly to COVID-19 disruptions such as demand changes, transport disruptions, or factory shutdowns. Additionally, expanding DCs' capacity or outsourcing DCs can help respond to pandemic challenges related to increasing demand and an accelerated shift to online sales. Finally, food retailers should restructure operations to be in line with essential SC priorities in the presence of disruptions.

As the third step, we recommend that food retailers leverage opportunities from the COVID-19 outbreak. Food retail is one of the few sectors in Germany that faces new opportunities as a result of the pandemic. Although the food retail SC may suffer short-term challenges, the food retail industry has the potential to grow during the crisis. Companies in this industry should benefit from demand increase and assess the market by collecting data on new customer segments, capturing customers' evolving preferences. This would help food retailers adjust their SCs to respond to changes in demand patterns, improve operations, and increase their market share and revenues. We also suggest that food retailers transform their operations model and SC to adapt to permanent changes in the industry such as the shift to home deliveries, online sales, and increasing digital payments. As a result, companies must decide on product investment, channel selection, store composition, and payment systems to respond to these changes.

In addition, food retailers can seize new opportunities through digitalization. Building a Food Retail Industry 4.0, which completely digitalizes (e.g., through cloud-based services) the entire food SC, will become necessary in a post-pandemic environment. Artificial intelligence, blockchain and T&T technologies, robotics and automation, and smart data for predictive analytics can be implemented to increase resilience and grow opportunities in the industry by increasing productivity and reducing costs (Brinstrup et al., 2020, Winkelhaus and Grosse, 2020, Fürstenhans et al., 2021). Digital technologies can also help address the safety and hygienic concerns enabling the 'contactless concept'.

In sum, to grow and take advantage of new opportunities, food retailers must seek meaningful partnerships that can become a critical component of their SCs to build redundancies, thus enhancing customer experience and ensuring long-term business stability.

7. Conclusion

The research on disruptions management and resilience in light of the COVID-19 outbreak has become an essential field in SC management. Post-disruption recovery analysis amid the COVID-19 pandemic outbreak is relevant for organizations seeking to respond to disruptions and create new growth opportunities.

We contribute to the existing literature on this topic by examining the COVID-19 pandemic's impact on food retail SCs with the help of a discrete-event simulation methodology and secondary data support. We examined the impact of multiple scenarios of the COVID-19 disruptions (i.e., temporary bottlenecks in transport, shutdown in suppliers' factories, and increasing demand) to determine (i) the

overall impact on food retailers' SC performance and (ii) SC actions that increase resilience in response to the identified problems. Our simulation results showed how the COVID-19 pandemic impacted the food retail SC operations and performance but also created growth opportunities. Although food retailers' SCs have experienced adverse effects from the pandemic – specifically in terms of demand backlogs and delayed orders, long lead times, decreased service levels, and increased total costs – opportunities have also arisen because of the increased demand.

A cross-comparison analysis of the examined scenarios suggested a positive relationship between the duration of the disruption and its SC impact. Moreover, this analysis provided insights regarding the events' synergetic effects and the impact of the sequence of disruptions during the pandemic on the SC performance.

We have suggested potential improvements and SC actions in response to the identified challenges. Furthermore, we have created a framework containing structured recommendations for stabilization and recovery in a post-disruption environment, which can be used as a guideline for the main SC actors in the food retail business. This framework identified the following five main directions for food SC resilience improvement: digitalization, inventory management, SC flexibility, SC collaboration, and end-to-end SC visibility.

As for the limitations of this study, it should be noted that the simulations were performed using data from certain secondary sources, which may lead to misleading generalizations and generate inaccuracy. Another limitation is related to the restricted timeline available for observing the effects of implementing potential improvements in the disruption scenarios. Our improvement suggestions have been developed from a qualitative point of view and require quantitative validation in the post-pandemic future. In addition, the study has limitations due to reduced complexity because our analyses of the scenarios were confined to a limited number of variables and SC locations. Finally, as COVID-19 is an outgoing event, restrictions on data access should be noted.

Nevertheless, our study suggests a number of directions for further research. One exciting research path would investigate SC policies to address and improve control of the ripple effect in case of pandemic outbreaks. Responding to COVID-19 disruptions and creating a long-term recovery strategy is becoming a priority for companies facing enormous challenges in their SC due to the pandemic outbreak (Ivanov and Dolgui, 2021c; Ruel et al., 2021). Hence, another interesting future research avenue would create generic actions to recover from the pandemic through digital technologies that enhance end-to-end visibility along the SC. For the specific case of food retailers, it would be interesting to analyse how the use of robotics and automation at distribution centres can help the transition to online sales, which is one of the biggest challenges the industry faces because of the pandemic (Azzi et al., 2011, Winkelhaus and Grosse, 2020, Fragapane et al., 2021). With regards to the specific scenarios, it would be interesting to include some other features of real-life scenarios encountered through the COVID-19 pandemic such as shortages of packaging materials and boxes in food SCs (Battini et al., 2016). Another promising research path would analyse how predictive analytics can help food retailers be prepared for new customer patterns and market composition, adjusting their SC accordingly. Finally, research should be conducted on the next steps to enhance SC resilience in a post-pandemic environment in the food retail industry.

CRediT authorship contribution statement

Diana Burgos: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Writing - original draft, Visualization. **Dmitry Ivanov:** Conceptualization, Methodology, Validation, Resources, Writing - review & editing, Supervision.

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