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Assessing last-mile distribution resilience under demand disruptions

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ABSTRACT

The COVID-19 pandemic led to a significant breakdown of the traditional retail sector resulting in an unprecedented surge in e-commerce demand for the delivery of essential goods. Consequently, the pandemic raised concerns pertaining to e-retailers' ability to maintain and efficiently restore level of service in the event of such low-probability high-severity market disruptions. Thus, considering e-retailers' role in the supply of essential goods, this study assesses the resilience of last-mile distribution operations under disruptions by integrating a Continuous Approximation (CA) based last-mile distribution model, the resilience triangle concept, and the Robustness, Redundancy, Resourcefulness, and Rapidity (R4) resilience framework. The proposed R4 Last Mile Distribution Resilience Triangle Framework is a novel performance-based qualitative-cum-quantitative domain-agnostic framework. Through a set of empirical analyses, this study highlights the opportunities and challenges of different distribution/outsourcing strategies to cope with disruption. In particular, the authors analyzed the use of an independent crowdsourced fleet (flexible service contingent on driver availability); the use of collection-point pickup (unconstrained downstream capacity contingent on customer willingness to self-collect); and integration with a logistics service provider (reliable service with high distribution costs). Overall, this work recommends the e-retailers to create a suitable platform to ensure reliable crowdsourced deliveries, position sufficient collection-points to ensure customer willingness to self-collect, and negotiate contracts with several logistics service providers to ensure adequate backup distribution.

1. Introduction

The retail sector, traditionally dominated by brick-and-mortar stores, has witnessed an increasing presence of e-commerce in the past few years. At the turn of the 21st century, e-commerce barely accounted for 1 % of total retail sales, yet by the end of the last decade (i.e., 2020), more than a tenth of all retail sales came from online channels (U.S. Census Bureau,2021). This steady 15 % annual growth in e-commerce sales, in contrast to 4 % annual growth in total retail sales in the past decade, came about due to a consistently improving online shopping experience for the consumer (cheaper shipping, expedited deliveries, free returns, etc.) and improved proximity to the market for the e-retailer (digital omnipresence). Yet, despite the ease of online shopping, the wide-range of product

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availability online, and the lucrative offers available on e-commerce platforms, traditional in-store shopping continued to be the dominant channel for daily purchases (Jaller and Pahwa, 2020), until the COVID-19 pandemic enforced a sudden and significant shift in consumer shopping behaviors (Jaller and Dennis, 2023; Leatherby and Gelles, 2020).

On 11th March 2020, the World Health Organization (WHO) declared the novel coronavirus (SARSCoV2) outbreak causing the coronavirus disease (COVID-19) as a global pandemic (World Health Organization, 2020). A level of panic ensued among buyers; the local brick-and-mortar stores witnessed opportunistic purchase behaviors resulting in long queues and hoarding of daily essentials (Knoll, 2020; Rivera-Royero et al., 2022). Concomitantly, governments around the world enforced aggressive virus containment measures to build capacity to test, trace, and treat the infected. Following suit, the California State Government issued a stay-at-home order on 19th March 2020, which was lifted eventually on 15th June 2020 (Office of Governor Gavin Newsom, 2020a, b). These measures led to a total meltdown of the retail sector. Retailers that largely relied on physical stores faced the brunt of the crisis, while other retailers who had some online presence managed through the crunch, though usually at the expense of significant cost cutting from reduced workforce and operations (Maheshwari and Corkery, 2020b). The e-retailers on the other hand, particularly those selling essential goods, daily consumables, groceries, medications, and health-care products witnessed an unprecedented surge in demand (Jones, 2020). This shift in consumer shopping behaviors was consistently evident during periods of aggressive containment across different parts of the world [Germany: Koch et al. (2020), India: Awasthi and Mehta (2021), New Zealand: Hall et al. (2021), Nigeria: Adunchezor and Akinade (2020)]. Fig. 1 showcases this shift in consumer shopping behavior due to the COVID-19 pandemic in the US in the form of increase in e-commerce transactions for the first half of 2020.

Typically, e-retailers observe steady year-on-year growth in demand with a few high-probability low-severity fluctuations through the year, such as around the holiday season. To contend with such market dynamics, e-retailers regularly monitor and manage their distribution operations, which can include the redesign of vehicle delivery routes (short-term operational management), procurement or disposal of resources, e.g., staff and equipment (medium-term tactical management), or even reconfiguration of the distribution structure (long-term strategic management). However, the surge in e-commerce demand that ensued with the coronavirus outbreak gave e-retailers little time to reassess and reconfigure decision-making concerning tactical but especially strategic operational management. Thus, constrained to a pre-pandemic level of resources, the e-retailers coped with the surge in demand while operating at a much lower level of service than usual by outsourcing last-mile operations in a range of ways: either to crowdsourced fleets for delivery, or to customers for pickup at collection-points, or to logistics service providers (LSP) for distribution (Creswell, 2018; Maheshwari and Corkery, 2020a); as well as by prioritizing the delivery of essential goods at the cost of delayed service for other goods (Weise, 2020). Beyond providing last-mile delivery service to the typical customer, some e-retailers also received demand from frontline healthcare services for delivery of personal protective equipment such as gowns, masks, and gloves (Weise, 2020). Considering the role of e-commerce last-mile distributions in ensuring the supply of essential goods during the COVID-19 pandemic, it is pertinent to assess the resilience of last-mile distribution operations in terms of e-retailers' ability to maintain and efficiently restore level of service in the event of such low-probability high-severity disruptions. Thus, for the purpose of the analyses, the authors 1) model e-retailer's last-mile distribution operations using Continuous Approximation (CA) techniques, 2) develop the e-retailer's operational, tactical, and strategic decision-making to model its behavior pre-, peri-, and post- disruption and 3) evaluate its response to disruptions through a novel performance-based qualitative-cum-quantitative domain-agnostic resilience assessment framework proposed here. This assessment framework is developed by integrating a Continuous Approximation (CA) based last-mile distribution model, the resilience triangle concept, and the Robustness, Redundancy, Resourcefulness, and Rapidity (R4) resilience framework.

In the next section, the authors summarize the literature pertaining to resilience with a review of the various definitions and frameworks developed to assess resilience. The section also discusses literature on the impacts of COVID on goods distribution, and e-commerce. The authors then present the Continuous Approximation (CA) framework modeling e-retailer's last-mile distribution operations, develop the logic to model the e-retailers' decision-making, and then introduce the R4 Last Mile Distribution Resilience Triangle Framework, followed by a description of the case study. The study then discusses the results establishing the dynamics of last-

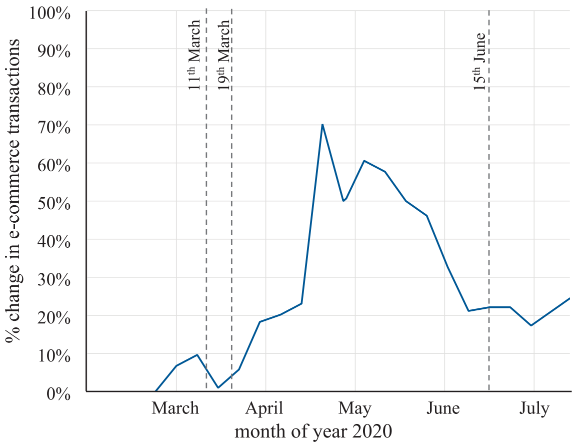

Fig. 1. E-commerce demand surge in the early months of the COVID-19 pandemic.

mile distribution for not only the market disruption that ensued with the COVID-19 pandemic but also for other market disruptions in general with varying characteristics, before concluding with a discussion of the key findings and logistics implications.

2. Literature review

In recent years, the research and development of sustainable systems that are economically viable, environmentally efficient, and equitable has garnered a lot of academic interest. Nonetheless, designing resilient systems that can resist, respond to, and recover from the consequences of disruptions is equally important for long-term system performance. In fact, a system that is not resilient to disruptions cannot be sustainable (Abadi and Ioannou, 2014; Ivanov, 2020; Novak et al., 2021). To be precise, resilience is "… the ability of social units (e.g., organizations, communities) to mitigate hazards, contain the effects of disaster when they occur, and carry out recovery activities in ways that minimize social disruption and mitigate the effects of future disasters" (Bruneau et al., 2003). In the context of transportation systems, the literature (Fletcher and Ekern, 2016; Janić, 2019; Serulle et al., 2011; Ta et al., 2009) has generally characterized a resilient transportation system to be one that can maintain and efficiently restore network functionality (passenger mobility and/or freight flows) in the event of a disruption (Cantillo et al., 2019; Rivera-Royero et al., 2022). The resilience literature offers a wide-range of such domain-specific interpretations. Yet, across domains, the literature has emphasized the need for organizational, social, economic, and engineering units of the system to consistently perform pre-disruption mitigation, appropriately respond during the disruption, and efficiently carry out post-disruption analysis and recovery, to build systemic resilience (Hosseini et al., 2016; Ivanov, 2019). Moreover, the various definitions and interpretations of resilience serve as foundations to develop robust frameworks to analyze and evaluate a system's response to disruptions.

To this end, the literature has developed many qualitative and quantitative frameworks (Faturechi and Miller-Hooks, 2015; Hosseini et al., 2016). The qualitative frameworks typically guide long-term decision-making for strategic management of systems. For instance, the Resilience Capacity framework, one such qualitative framework, highlights the need for developing and maintaining absorptive, adaptive, and restorative capacities to establish a resilient system (Biringer et al., 2013). Similarly, the R4 resilience framework underscores four salient properties for resilient operations, namely, robustness, the ability of the system to withstand disruption; redundancy, the extent to which the elements of the system are substitutable; resourcefulness, the ability to diagnose and prioritize problems as well as initiate solutions; and rapidity, the ability to restore functionality in a timely manner (Bruneau et al., 2003). The quantitative frameworks, on the other hand, offer precise assessments of a system's response to disruptions and in turn allow for operational, tactical, and strategic management of the system. To do so, these quantitative frameworks employ attribute-based methods that measure the properties of the system that bolster its resilience, or performance-based methods that gauge the system's performance under disruption (Zhou et al., 2019). The use of resilience triangle(s) introduced by Tierney and Bruneau (2007) to depict and characterize the loss in a system's performance in the event of a disruption is one of the most widely employed performance-based quantitative frameworks (Adams et al., 2012; Sahebjamnia et al., 2015; Zobel, 2011; Zobel and Khansa, 2014). Fig. 2 presents typical use of resilience triangle(s) for a system witnessing disruption (between disruption start and end day) resulting

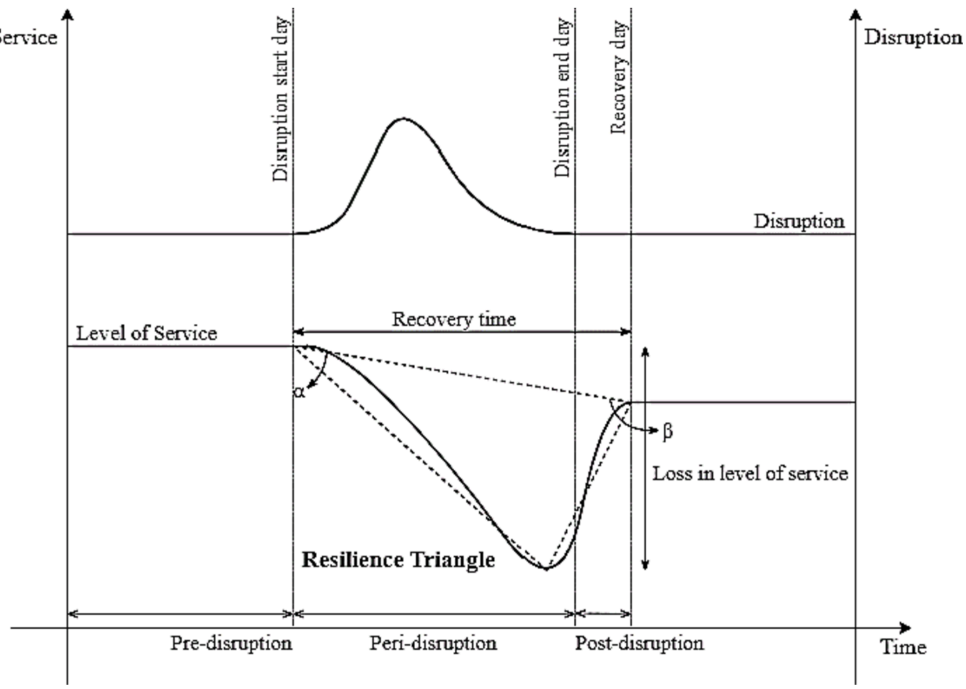

Fig. 2. Use of resilience triangle to assess system's response to disruption.

in a loss of service (until recovery day) which is characterized by the shape and size of triangle(s) pivoted at pre-disruption initial -, peri-disruption nadir -, and post-disruption recovered - level of service. While these attribute- and performance- based methods typically use domain-agnostic indicators, the resilience literature has also developed domain-specific indicators such as topological metrics used for network analysis (Rivera-Royero et al., 2022; Zhou et al., 2019).

The last-mile literature has extensively analyzed the sustainability of distribution operations under stochastic delivery environments with high-probability low-severity fluctuations in the delivery environment (Oyola et al., 2017, 2018). Research on transportation system resilience in the event of low-probability high-severity disruptions is limited to disaster management, humanitarian logistics, and relief operations for earthquakes, tsunamis, hurricanes, terrorist attacks, etc. (Chen and Miller-Hooks, 2012; Hallegatte and Rentschler, 2018; Stamos et al., 2015; Vugrin et al., 2011). However, the total breakdown of global supply-chains and the consequent surge in e-commerce demand witnessed for months after the initial SARSCoV2 outbreak was unlike any other low-probability high-severity disruption (considering the magnitude, duration, and physical manifestation of the disruption), and therefore warrants dedicated research. Thus, the past couple of years since the outbreak have garnered fresh interest in the resilience literature across varying domains. In the context of freight distribution, Hobbs (2020) provided an early assessment of the impact of the pandemic on food supply-chains, and projected a wider adaptation of online grocery and meal delivery services during the course of the pandemic. A year later, Hobbs (2021) provided another assessment and argued for a sustained shift in demand for such online services even after the pandemic. And while the pandemic has indeed created new opportunities for e-commerce, Ali et al. (2021) and Herold et al. (2021) emphasized the need for mitigation strategies (ex-ante) and ad hoc responses (post-ante) to protect the core functionality of the distribution structure (Rivera-Royero et al., 2022). In particular, Burgos and Ivanov (2021) underscored the importance of resolving transport/logistics bottlenecks to improve the level of service, and thus suggested that retailers secure additional stock or backup supplies to tackle demand surges. To this end, Moosavi and Hosseini (2021) evaluated the increase in costs and improvement in resilience from such ex-ante measures, and thereby recommended retailers with critical supply-chains to secure additional stock for significant improvement in network resilience albeit at a high cost, while retailers with non-essential product distribution also secure a backup supply. Taking lessons from the pandemic, Singh et al. (2021) and Srinivas and Marathe (2021) proposed the use of drones/robots from a delivery truck functioning as a mobile warehouse carrying high-demand products in anticipation of customer requests (anticipatory shipping) to limit product shortages and reduce customer lead time in future disruptions. Guthrie et al. (2021) in fact showcased the use of the react-cope-adapt framework to predict the evolution of consumer shopping behaviors during the course of the pandemic, thus enabling retailers to fine-tune and manage inventory for anticipatory shipping. These studies highlight the newfound interest in understanding the impact of disruptions to better prepare for and respond to future disruptions.

Thus, considering the role of e-commerce last-mile distribution in ensuring the delivery of essential goods not only to the typical customer, but also to frontline healthcare services during the COVID-19 pandemic, the objective of this work is to assess resilience of last-mile distribution operations in terms of e-retailers' ability to maintain and efficiently restore service levels in the event of such low-probability high-severity disruptions. While conventional last-mile distribution entails door-to-door deliveries via diesel trucks operating from an e-retailer's warehouse, alternate delivery strategies includes outsourcing last-mile to a crowdsourced fleet for delivery (Akeb et al., 2018; Pourrahmani and Jaller, 2021; Wang et al., 2016), to the consumers for pickup at collection-points (curbside, lockers, or stores) (Arnold et al., 2017; Halldórsson and Wehner, 2020; Park et al., 2016), or to a 3rd party logistics service provider with delivery consolidation at micro-hubs (Isa et al., 2021; Janjevic and Ndiaye, 2017; Perboli et al., 2021). In comparison to the conventional distribution strategy, use of micro-hubs coupled with light-duty low-pollution vehicles allows for low-cost low-pollution distribution, while use of collection-points or crowdsourced fleet allows for low-cost expedited delivery (Pahwa and Jaller, 2022). Beyond these last-mile strategies, more recent innovations include the use of robots/drones from a delivery truck functioning as a mobile consolidation facility operating in dense urban environments carrying high-demand goods in anticipation of purchase (anticipatory shipping) for expedited (within minutes) and contactless delivery (Goodchild and Toy, 2018; Moshref-Javadi et al., 2020; Stolaroff et al., 2018). Thus, to cope with the disruption, this study assumes that the e-retailer will make use of one of the many outsourcing channels at its disposal, while delaying any demand beyond the distribution capacity for a late delivery. These outsourcing channels include delivery via a crowdsourced fleet, customer pickup via collection-points, or distribution via a logistics service provider (LSP) operating from its micro-hubs using cargo-bikes. To this end, the authors propose the R4 Last Mile Distribution Resilience Triangle Framework, integrating the R4 resilience framework (Bruneau et al., 2003) and resilience triangle concept (Tierney and Bruneau, 2007) with a Continuous Approximation (CA) based last mile distribution model. Further, unlike in the previous studies that quantify resilience by the area of the resilience triangle, in this framework, the authors present a more nuanced use of the resilience triangle to quantify the qualitative properties of resilience, i.e., robustness, redundancy, resourcefulness, and rapidity. With this, the study aims to develop a holistic understanding concerning the capability of e-retailers' last-mile distribution operations to maintain and efficiently restore service levels under disruption.

3. Methodology

In this section, the authors create a framework to model an e-retailer's last-mile distribution operations and assess its response to disruption building on the Continuous Approximation based last-mile delivery model developed by Pahwa and Jaller (2022). Note, conventional discrete formulation methods offer a precise yet flexible model but require complex solution techniques necessitating significant computational effort, which is justified when a precise plan is needed. However, the continuous approximation method renders a sound compromise between accuracy and feasibility, estimating parameters and decision variables with continuous density functions which enables decision-making when operating costs may be needed but the precise plan cannot be established.

This study analyzes an e-retailer making deliveries in a service region of size A, using a homogenous fleet of delivery trucks operating from an e-commerce fulfillment facility located at (ρ_x, ρ_y) relative to the center of this service region. The authors assume the e-retailer to organize its distribution structure for low-cost just-in-time deliveries. While such a distribution structure can cope with minor disruptions, a severe unforeseen disruption can put the e-retailer at risk of operating at a much lower level of service than usual. Thus, to assess the last-mile distribution resilience of an e-retailer against a low-probability high-severity disruption, the authors develop the response of this e-retailer to the kind of market disruption witnessed in the early months of the COVID-19 pandemic. In particular, the authors model the market disruption depicting the impact of inhibited public movement in the form of reduced traffic congestion (ϕ_t) and increased e-commerce demand (N_t). To cope with this market disruption, the e-retailer may outsource some operations either via a crowdsourced fleet for delivery, or via N^{cp} collection-points for customer pickup, or via a logistics service provider (LSP) for distribution from N^{mh} micro-hubs using cargo-bikes. Below is a list of notations specific to the e-retailer's distribution channel, but when used with a prime superscript these notations refer to the outsourcing channel.

Indices

t: Subscript for time (in days)
e: Subscript for emissions

Distribution structure

Parameters
A: Size of the service region
ϕ_t: Congestion factor (speed relative to free-flow speed) on day t
N_t: Customer demand on day t
N^{cp}: Number of collection-points
N^{mh}: Number of micro-hubs
δ_t: Customer density on day t
δ^{cp}: Collection-point density
δ^{mh}: Micro-hub density
V: Collection-point capacity
$\overline{N}_t$: Distribution structure capacity on day t
Decision variables
ρ_x, ρ_y: E-commerce fulfillment facility location relative to center of service region

Distribution operations

Parameters
L_t: Delivery tour length on day t
T_t: Delivery tour time on day t
ρ: Long-haul length
Λ_t: Long-haul travel time on day t
k: Continuous Approximation (CA) constant
θ: Number of customers served per delivery stop
p_u: Maximum permissible outsourcing share
Decision variables
f: Fleet size
m: Number of delivery tours per vehicle
C_t^c: Number of customer visits per delivery tour on day t
C_t^{cp}: Number of collection-point visits in a delivery tour on day t
C_t^{mh}: Number of micro-hub visits in a delivery tour on day t
p_t: Share of customers served via outsourcing channel on day t

Vehicle parameters

VC: Vehicle capacity
v_{out}: Vehicle free-flow speed outside the service region
v_{in}: Vehicle free-flow speed inside the service region
τ_{sF}: Service time loading/unloading packages at a facility (per customer)
τ_{sC}: Service time delivering packages to a customer
r_f: Rate of fuel consumption
r_e: Rate of emissions

Cost parameters

Π_t: Distribution cost on day t
F_{fc}: Facility fixed cost
PC: Vehicle purchase cost
π_d: Driver cost
π_f: Maintenance cost
π_e: Emission cost

Other parameters

t_o: Day 1
t_s: Disruption start day
t_r: Recovery day
t_e: Disruption end day
W: Working hours in a day
η: Amortization factor
ψ^{cs}: Binary variable ($\psi^{cs} = 1$ if outsourcing via the crowdsourced fleet)
ψ^{cp}: Binary variable ($\psi^{cp} = 1$ if outsourcing via the collection-points)
ψ^{mh}: Binary variable ($\psi^{mh} = 1$ if outsourcing via the logistics service provider)
$\bar{f}$: Fleet size limit

3.1. Modeling last-mile distribution operations using Continuous Approximation (CA)

To model the distribution and outsourcing operations, this work builds on a continuous approximation (CA)-based last-mile delivery model (Pahwa and Jaller, 2022), which unlike conventional discrete formulation methods enables long-term strategic decision-making, especially when operating costs may be needed but the precise plan cannot be established. *Equations 1–16* detail this last-mile delivery model in the context of this work and how the different phases of the disruption are considered.

3.2. Pre-disruption ($t \in [t_o, t_s)$) distribution operations:

Prior to the surge in demand ($t \in [t_o, t_s)$), this work assumes the e-retailer to operate independently with its fleet of delivery trucks making all the delivery tours. This delivery tour comprises of the long-haul, the journey from the e-commerce fulfillment facility to the first customer-stop and likewise from the last customer-stop back to the facility; and the last-mile, the journey between the first and last customer-stops. Hence, the length of this delivery tour (*equation (1)*) is the sum of back-and-forth long-haul distance (ρ) and the last-mile distance, represented by each term in the equation, respectively. And the delivery tour time (*equation (2)*) is the sum of the service time loading packages at the facility (τ_{sF} per package), the long-haul travel time (Λ_t), the last-mile travel time, and the service time delivering packages at customer-stops (τ_{sC} per customer), represented by each term in the equation, respectively. Note, the long-haul is estimated by the average distance between the e-commerce fulfillment facility and the customers, considering the location of this facility (refer to *equations (15) and (16)*), while the last-mile is continuously approximated proportional to the number of stops in the

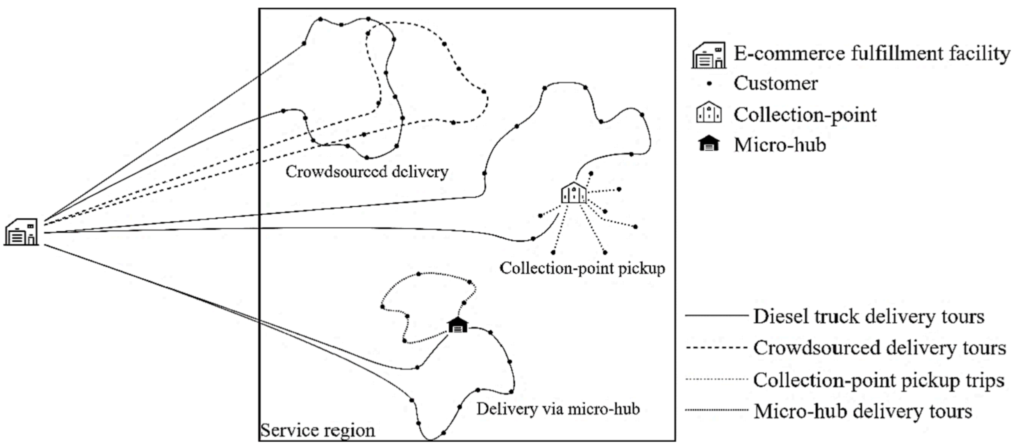

Fig. 3. Distribution operations of e-retailer plus outsourcing channel combined.

delivery tour - $[C_t^c/\theta]^+$, and inversely proportional to the square root of stop density (δ_t/θ) (Daganzo, 1984; Pahwa and Jaller, 2022). Here, θ represents the number of customers consolidated per stop. Note, in typical last-mile delivery environments, these distribution operations are constrained by vehicle capacity, working-hours, and service constraints (detailed in section 3.2) affecting delivery tour length and tour time.

$$L_t = 2\rho + \frac{k[C_t^c/\theta]^+}{\sqrt{\delta_t/\theta}} \tag{1}$$

$$T_t = C_t^c\tau_{sF} + 2\Lambda_t + \frac{k[C_t^c/\theta]^+}{v_{in}\phi_t\sqrt{\delta_t/\theta}} + C_t^c\tau_{sC} \tag{2}$$

3.3. Peri-disruption ($t \in [t_s, t_e]$)/Post-disruption ($t \in (t_e, t_r]$) distribution operations:

To cope with a low-probability high-severity surge in demand ($t \in [t_s, t_r]$), this work assumes that the e-retailer will choose to outsource p_t share of its operations, either via a crowdsourced fleet for delivery, collection-points for customer pickup, or via a LSP for distribution from its micro-hubs using cargo-bikes (Fig. 3). *equations 3–16* model the distribution operations for the e-retailer and outsourcing channel combined distribution structure.

Crowdsourced delivery - The crowdsourced operations in this study take their inspiration from the Amazon Flex program (Amazon.com Inc.). Much like the e-retailer's delivery trucks, the crowdsourced drivers collect packages at the e-commerce fulfillment facility before embarking on e-retailer designed tours. The length of this delivery tour (*equation (3) and (5)*) is the sum of long-haul and last-mile distances, represented by each term in the equations, respectively. And the delivery tour time (*equations (4) and (6)*) is the sum of the service time loading packages at the facility, the long-haul travel time, the last-mile travel time, and the service time delivering packages to the customers, represented by each term in the equations, respectively. Note, *equations (3) and (4)* model the e-retailer's delivery truck tour, while *equations (5) and (6)* model the delivery tour of the crowdsourced vehicle. As described previously, the long-haul is estimated by the average distance between the e-commerce fulfillment facility and the customers, considering the location of this facility (refer to *equations (15) and (16)*), while the last-mile is continuously approximated proportional to the number of stops in the delivery tour (delivery truck delivery tour - $[C_t^c/\theta]^+$, crowdsourced vehicle delivery tour - $[C_t^{c'}/\theta]^+$), and inversely proportional to the square root of stop density (delivery truck delivery tour - $\delta_t(1-p_t)/\theta$, crowdsourced vehicle delivery tour - $\delta_t p_t/\theta$). Note, these distribution operations are constrained by vehicle capacity, working-hours, and service constraints (detailed in section 3.2) affecting delivery tour length and tour time.

$$L_t = 2\rho + \frac{k[C_t^c/\theta]^+}{\sqrt{\delta_t(1-p_t)/\theta}} \tag{3}$$

$$T_t = C_t^C\tau_{sF} + 2\Lambda_t + \frac{k[C_t^c/\theta]^+}{v_{in}\phi_t\sqrt{\delta_t(1-p_t)/\theta}} + C_t^c\tau_{sC} \tag{4}$$

$$L_t^{'} = 2\rho + \frac{k[C_t^{c'}/\theta]^+}{\sqrt{\delta_t p_t/\theta}} \tag{5}$$

$$T_t^{'} = C_t^{C'}\tau_{sF}^{'} + 2\Lambda_t^{'} + \frac{k[C_t^{c'}/\theta]^+}{v_{in}^{'}\phi_t\sqrt{\delta_t p_t/\theta}} + C_t^{c'}\tau_{sC}^{'} \tag{6}$$

Customer pickup at collection-points – Unlike crowdsourcing, where the outsourcing channel operates independently, here the e-retailer must fulfill the collection-points using its fleet of delivery trucks before customers can travel to one of the collection-points to collect their packages. Note, the model assumes that the e-retailer has located N^{cp} collection-points randomly and uniformly in the service region, each with a capacity to hold V packages. Thus, the e-retailer's delivery truck tour comprises of long-haul and last-mile, with the latter including visits to the customers and collection-points. Therefore, the delivery tour length (*equation (7)*) is the sum of the long-haul and last-mile distances, represented by each term in the equation, respectively. And the delivery tour time (*equation (8)*) is the sum of the service time loading packages at the e-commerce fulfillment facility, the long-haul travel time, the last-mile travel time, the service time delivering packages at customer-stops, and the service time unloading packages at the collection-points, represented by each term in the equation, respectively. Again, the long-haul is estimated by the average distance between the e-commerce fulfillment facility and the customers, considering the location of this facility (refer to *equations (15) and (16)*), while the last-mile is continuously approximated proportional to the number of stops in the delivery tour - $[C_t^c/\theta]^+ + [C_t^{cp}]^+$, and inversely proportional to the square root of stop density - $\delta_t(1-p_t)/\theta + \delta^{cp}$. On the other hand, the customer's collection-point visit (trip) is estimated by the average distance from customer-stop to the nearest collection-point (*equations (9) and (10)*). Note, these distribution operations are constrained by vehicle capacity, working-hours, and service constraints (detailed in section 3.2) affecting delivery tour length and tour time.

$$L_t = 2\rho + \frac{k\left(\left[C_t^c/\theta\right]^+ + \left[C_t^{cp}\right]^+\right)}{\sqrt{\delta_t(1-p_t)/\theta + \delta^{cp}}} \tag{7}$$

$$T_t = \left(C_t^C + V\right)\tau_{sF} + 2\Lambda_t + \frac{k\left(\left[C_t^c/\theta\right]^+ + \left[C_t^{cp}\right]^+\right)}{v_{in}\phi_t\sqrt{\delta_t(1-p_t)/\theta + \delta^{cp}}} + C_t^c\tau_{sC} + V\tau_{sF} \tag{8}$$

$$L_t^{'} = 2\left(\frac{2}{3}\sqrt{A/N^{cp}}\right) \tag{9}$$

$$T_t^{'} = \frac{2\rho^{'}}{v_{in}^{'}\phi_t} + \tau_{sC}^{'} \tag{10}$$

Distribution via micro-hubs operated by a logistics service provider (LSP) - The authors assume this LSP to operate from N^{mh} identical micro-hubs located randomly and uniformly in the service region, each with a fleet of cargo-bikes or other small/light delivery vehicles. The e-retailer must fulfill the LSP's micro-hubs using its fleet of delivery trucks before the cargo-bikes from these micro-hubs can embark for last-mile deliveries. Thus, the delivery truck's delivery tour comprises of long-haul and last-mile, with the latter including visits to the customers and micro-hubs. The delivery truck's delivery tour length (*equation (11)*) is therefore the sum of the long-haul and the last-mile distances, represented by each term in the equation, respectively. And the delivery truck's delivery tour time (*equation (12)*) is the sum of the service time loading packages at the e-commerce fulfillment facility, the long-haul travel time, the last-mile travel time, the service time delivering packages at the customer-stops, and the service time unloading packages at the micro-hubs, represented by each term in the equation, respectively. As described previously, the long-haul is estimated by the average distance between the e-commerce fulfillment facility and the customers, considering the location of this facility (refer to *equations (15) and (16)*), while the last-mile is continuously approximated proportional to the number of stops in the delivery tour - $\left[C_t^c/\theta\right]^+ + \left[C_t^{mh}\right]^+$, and inversely proportional to the square root of stop density - $\delta_t(1-p_t)/\theta + \delta^{mh}$. On the other hand, a cargo-bike's delivery tour is comprised of long-haul, the journey from the micro-hub to the first customer-stop and likewise from the last customer-stop back to the micro-hub; and last-mile, the journey between the first and last customer-stops. The cargo-bike's delivery tour length (*equation (13)*) is therefore the sum of the long-haul and the last-mile distances, represented by each term in the equation, respectively. And the cargo-bike's delivery tour time (*equation (14)*) is the sum of the service time loading packages at the micro-hub, the long-haul travel time, the last-mile travel time, and the service time delivering packages at the customer-stops, represented by each term in the equation, respectively. Again, the long-haul is estimated by the average distance between the micro-hubs and the customers, while the last-mile is continuously approximated proportional to the number of stops in the delivery tour - $\left[C_t^c/\theta\right]^+$, and inversely proportional to the square root of stop density - $\delta_t p_t/\theta$. Note, these distribution operations are constrained by vehicle capacity, working-hours, and service constraints (detailed in section 3.2) affecting delivery tour length and tour time.

$$L_t = 2\rho + \frac{k\left(\left[C_t^c/\theta\right]^+ + \left[C_t^{mh}\right]^+\right)}{\sqrt{\delta_t(1-p_t)/\theta + \delta^{mh}}} \tag{11}$$

$$T_t = \left(C_t^C + 2C_t^{mh}\frac{Np_t}{N^{mh}}\right)\tau_{sF} + 2\Lambda_t + \frac{k\left(\left[C_t^c/\theta\right]^+ + \left[C_t^{mh}\right]^+\right)}{v_{in}\phi_t\sqrt{\delta_t(1-p_t)/\theta + \delta^{mh}}} + C_t^c\tau_{sC} \tag{12}$$

$$L_t^{'} = 2\left(\frac{2}{3}\sqrt{A/N^{mh}}\right) + \frac{k\left[C_t^{c'}/\theta\right]^+}{\sqrt{\delta_t p_t/\theta}} \tag{13}$$

$$T_t^{'} = C_t^{C'}\tau_{sF}^{'} + \frac{2\rho^{'}}{v_{in}^{'}\phi_t} + \frac{k\left[C_t^{c'}/\theta\right]^+}{v_{in}^{'}\phi_t\sqrt{\delta_t p_t/\theta}} + C_t^{c'}\tau_{sC}^{'} \tag{14}$$

Where,

$$\rho = \begin{cases} |\rho_x| + |\rho_y| & \text{if}|\rho_x|\text{and}|\rho_y| \geq \sqrt{A}/2 \\ |\rho_x| + \rho_y^2/\sqrt{A} + \sqrt{A}/4 & \text{if}|\rho_x| \geq \sqrt{A}/2, |\rho_y| < \sqrt{A}/2 \\ \rho_x^2/\sqrt{A} + \sqrt{A}/4 + |\rho_y| & \text{if}|\rho_x|\langle\sqrt{A}/2, |\rho_y| \geq \sqrt{A}/2 \\ \rho_x^2/\sqrt{A} + \rho_y^2/\sqrt{A} + \sqrt{A}/2 & \text{if}|\rho_x|\text{and}|\rho_y| < \sqrt{A}/2 \end{cases} \tag{15}$$

$$\Lambda_t = \frac{1}{\phi_t}\begin{cases} \frac{\rho}{v_{out}} + \sqrt{A}\left(\frac{1}{v_{in}} - \frac{1}{v_{out}}\right) & \text{if}|\rho_x|\text{and}|\rho_y| \geq \sqrt{A}/2 \\ \frac{\left(|\rho_x| - \sqrt{A}/2\right)}{v_{out}} + \frac{\left(\rho_y^2/\sqrt{A} + 3\sqrt{A}/4\right)}{v_{in}} & \text{if}|\rho_x| \geq \sqrt{A}/2, |\rho_y| < \sqrt{A}/2 \\ \frac{\left(\rho_x^2/\sqrt{A} + 3\sqrt{A}/4\right)}{v_{in}} + \frac{\left(|\rho_y| - \sqrt{A}/2\right)}{v_{out}} & \text{if}|\rho_x| \langle \sqrt{A}/2, |\rho_y| \geq \sqrt{A}/2 \\ \frac{\rho}{v_{in}} & \text{if}|\rho_x|\text{and}|\rho_y| < \sqrt{A}/2 \end{cases} \tag{16}$$

3.4. Developing e-retailer's decision-making in the pre-, peri-, and post- disruption phase

In the pre-disruption phase ($t \in [t_o, t_s)$), the model assumes that the e-retailer observes a stable daily demand of N_o customers. With the e-retailer having complete knowledge of the delivery environment, the e-retailer organizes its distribution structure to offer low-cost just-in-time delivery service. Thus, in a static and deterministic pre-disruption phase, the e-retailer minimizes the total distribution cost - Π_t (*equation (17)*) by considering the location of e-commerce fulfillment facility (ρ_x,ρ_y), fleet size (f_t), number of delivery tours per vehicle (m_t), and number of customers served per delivery tour (C_t^c), subject to vehicle capacity (*equation (18)*), working hours (*equation (19)*), and service constraints (*equation (20)*). This total cost includes amortized fixed costs - facility fixed costs and fleet purchase costs; operational costs - driver, maintenance, and fuel costs; and emission costs. To this end, let $\left(\rho_{x_o}, \rho_{y_o}\right)$ denote the optimal e-commerce fulfillment facility location and let f_o be the optimal e-retailer's delivery truck fleet size resulting from minimizing the pre-disruption distribution cost.

$$\min_{\{\rho_x, \rho_y, f_t, m_t, C_t^c\}} \Pi_t = \left(F_{fc} + PCf_t\right)/\eta + m_t f_t\left(T_t\pi_d + L_t\left(\pi_m + r_f\pi_f + \Sigma_e r_e\pi_e\right)\right) \tag{17}$$

Subject to,

$$C_t^c \leq VC \tag{18}$$

$$T_t m_t \leq W \tag{19}$$

$$C_t^c m_t f_t = N_o \tag{20}$$

$$\forall t \in [t_o, t_s)$$

In the peri-/post- disruption phase ($t \in [t_s, t_r]$), to serve the daily demand of N_t customers ($N_t > N_o$) plus previous unmet demand of N_{t-1}^u customers, the model assumes that the e-retailer will outsource some of its operations via the outsourcing channels at its disposal. Unlike in the pre-disruption phase, in the peri-/post- disruption phase, the e-retailer has no information on future demand. In particular, at the start of on any given day $t \in [t_s, t_r]$, the e-retailer has information only on N_t customers ($N_t > N_o$) received since the start of the previous day, requesting delivery service by the end of this day, and previous unmet demand of N_{t-1}^u customers. To this end, the e-retailer can only optimize for its operational decision variables and not for its strategic or tactical choices here. Thus, in a semi-dynamic and deterministic peri-/post- disruption phase, if the combined e-retailer and outsourcing channel distribution structure capacity of $\overline{N}_t$ customers *(equation (21))* is sufficient to cater to the increased e-commerce demand of $N_t + N_{t-1}^u$ customers, then the e-retailer minimizes the distribution cost - Π_t (*equation (22)*) outsourcing deliveries for $\left(N_t + N_{t-1}^u\right)p_t$ customers while serving the remaining using its available fleet of delivery trucks, optimizing for the share of operations to outsource (p_t), operational parameters of the outsourcing channel (f_t',m_t',$C_t^{c'}$), and operational parameters of its delivery tours (m_t,C_t^c), subject to vehicle capacity (*equations (24) and (25)*), working hours (*equations (26) and (27)*), service (*equations (28) and (29)*), and resource constraints (*equations (30) and (31)*). However, if the combined distribution capacity of $\overline{N}_t$ customers falls short of the increased e-commerce demand, then the combined distribution structure caters to the $\overline{N}_t$ customers, while delaying delivery for $N_t^u = N_t + N_{t-1}^u - \overline{N}_t$ customers to the next day. Note, the distribution cost here includes fixed, operational, and emissions costs for the combined distribution structure.

$$\max_{\{m_t, C_t^c, f_t', m_t', C_t^{c'}, p_t\}} \overline{N}_t = C_t^C m_t f_o + C_t^{C'} m_t' f_t' \tag{21}$$

$$\begin{aligned} \min_{\{m_t, C_t^c, f_t', m_t', C_t^{c'}, p_t\}} \Pi_t = \quad & \left(F_{fc} + PCf_t\right)/\eta + \left(F_{fc}' + PCf_t'\right)/\eta + \\ & m_t f_o\left(T_t\pi_d + L_t\left(\pi_m + r_f\pi_f + \Sigma_e r_e\pi_e\right)\right) + \\ & m_t' f_t'\left(T_t'\pi_d' + L_t'\left(\pi_m' + r_f'\pi_f + \Sigma_e r_e'\pi_e\right)\right) \end{aligned} \tag{22}$$

Subject to,

$$N = \begin{cases} \overline{N}_t & \text{if the objective is to maximize distribution capacity} \\ N_t + N^u_{t-1} & \text{if the objective is to minimize distribution cost} \end{cases} \tag{23}$$

$$\left(C^c_t + \psi^{cp} V + \psi^{mh} C^{mh}_t N p_t / N^{mh}\right) \leq VC \tag{24}$$

$$C^{c'}_t \leq VC' \tag{25}$$

$$T_t m_t \leq W \tag{26}$$

$$T'_t m'_t \leq W \tag{27}$$

$$C^c_t m_t f_o = N(1 - p_t) \tag{28}$$

$$C^{c'}_t m'_t f'_t = N p_t \tag{29}$$

$$f'_t \leq \overline{f'} \tag{30}$$

$$p_t \leq p_u \tag{31}$$

$$\forall t \in [t_s, t_r]$$

All decision variables are constrained to be non-negative. In addition, all decision variables except for facility location and outsourcing share are constrained to be integers.

Finally, *equation (32)* shows facility fixed cost (per sq. ft.) in the service region as a function of facility location, developed using CoStar (2020) sales and lease data for industrial facilities in southern California. To estimate the size of the distribution facility, this work assumes a consolidation of 0.2 customers per sq. ft based on interviews and field study experience.

$$F_{fc} = \$356.37\left(\rho_x^2 + \rho_y^2\right)^{-0.116} / sq.ft. \tag{32}$$

To solve the above optimization problems, the authors employ Frontline Solver (Frontline Systems Inc) which first solves a relaxed version of the problem ignoring the integer constraints, using the Generalized Reduced Gradient (GRG) non-linear method (Lasdon et al., 1978). The solver then uses the Branch and Bound technique to branch the relaxed problem into subproblems for every integer decision variable in the original problem with appropriate binding constraints, each of which is solved using the GRG non-linear method. This process is repeated until the integer decision variables take integer values subject to a tolerance level.

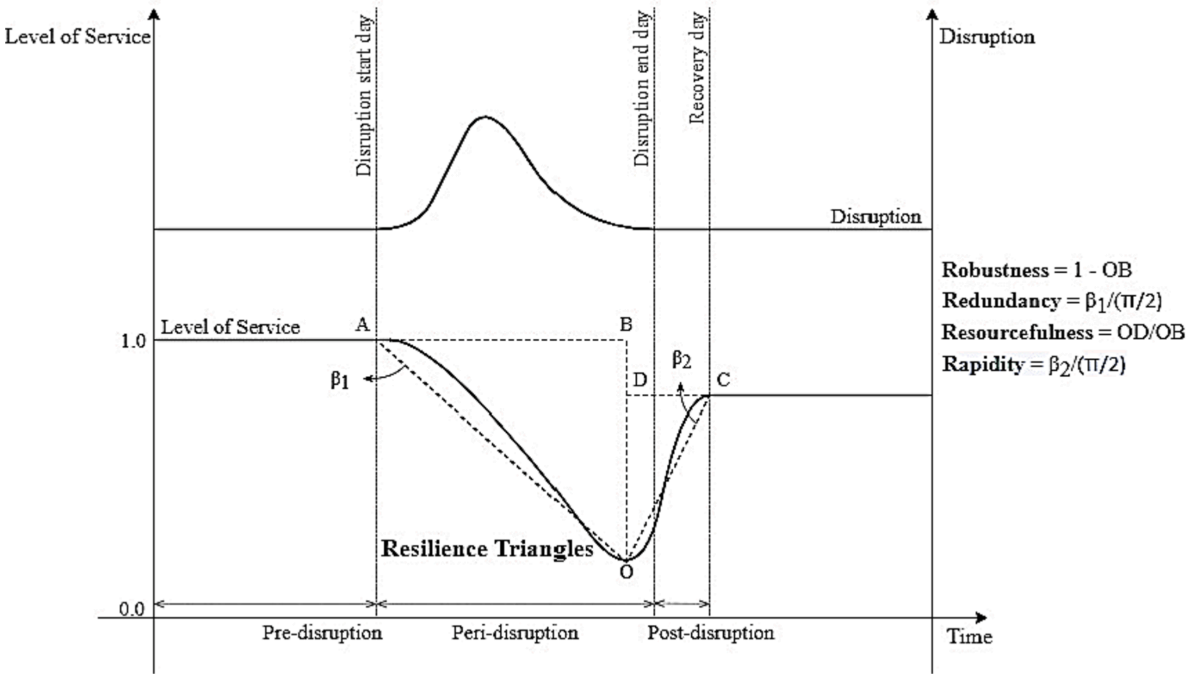

Fig. 4. Characterizing system's level of service under disruption using resilience triangles.

3.5. Evaluating e-retailer's response to disruption

Here, the authors further develop the framework to assess the e-retailer's response to disruption in the form of level of service. Fig. 4 presents use of resilience triangles in this work for an e-retailer witnessing disruption (between disruption start and end day) resulting in a loss of service (until recovery day) which is characterized by the shape and size of triangles pivoted at pre-disruption peak, peri-disruption nadir, and post-disruption recovered level of service. The level of service (*equation (33)*) in this study is a performance indicator defined as the ratio of demand served to total demand evaluated by solving the optimization models described in the previous subsection (*equations 17–32*). The authors then characterize the drop in level of service as a consequence of the disruption using the proposed Robustness, Redundancy, Resourcefulness, and Rapidity (R4) Last Mile Distribution Resilience Triangle Framework (Fig. 4). In particular, the authors quantify robustness, the ability of the system to withstand disruption, as the gap between the nadir and zero level of service line (*equation (34)*). Redundancy, the extent to which the elements of the system are substitutable, is the average downward slope towards the nadir (*equation (35)*). Resourcefulness, the ability to diagnose and prioritize problems as well as initiate solutions, is quantified as the ratio of recovered level of service to the drop in level of service at nadir (*equation (36)*). And rapidity, the capability to restore functionality in a timely manner, is the average upward slope towards recovery from nadir (*equation (37)*).

$$r(t) = 1 - N_t^u/(N_t + N_{t-1}^u) \tag{33}$$

$$Robustness = r(t_n);\, t_n = \text{argmin}\, r(t) \tag{34}$$

$$Redundancy = \tan^{-1}((t_n - t_s)/(r(t_s) - r(t_n)))/(\pi/2) \tag{35}$$

$$Resourcefulness = (r(t_r) - r(t_n))/(r(t_s) - r(t_n)) \tag{36}$$

$$Rapidity = \tan^{-1}((t_r - t_n)/(r(t_r) - r(t_n)))/(\pi/2) \tag{37}$$

This performance-based qualitative-cum-quantitative framework allows for assessing the resilience of last-mile distribution operations under any disruption. Moreover, the integrated R4 and Resilience Triangle component of this assessment framework is not specific to last-mile logistics or transportation systems, but is domain-agnostic, and thus can be employed across domains to assess resilience of any system under disruption.

In addition to the resilience metrics, the authors evaluate the e-retailer's response with operational metrics that quantify the extent of delayed deliveries, as well as economic metrics that evaluate the direct, indirect, and total loss to the e-retailer from the disruption. These metrics are further detailed in Section 5.1.2.

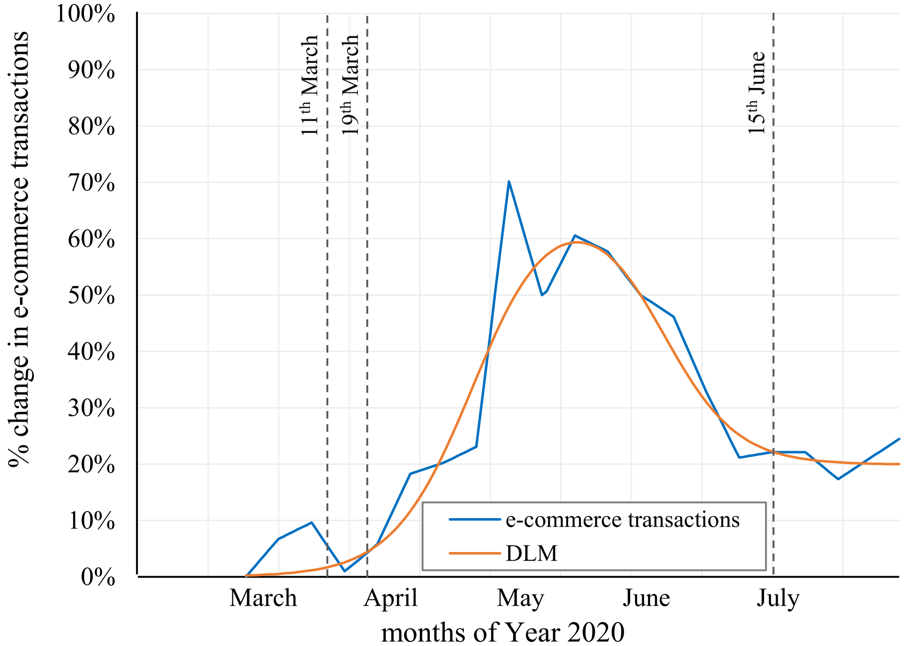

Fig. 5. Modeling e-commerce demand surge instigated by the COVID-19 pandemic.
DLM: Double Logistic Model $y_t = 0.685/(1+\exp(-(t-49.373)/8.447)) - 0.486/(1+\exp(-(t-89.512)/7.885)); R^2 = 0.937$

4. Case study

This study develops analyses for a fairly large-sized e-retailer with a market share of ~ 20 %, serving the city of Los Angeles, a 475 sq. mi. service region with ~ 150,000 pre-disruption daily online customers located randomly and uniformly in the region (Jaller and Pahwa, 2020; Pahwa and Jaller, 2022). Using the daily internet transactions data (Fig. 5), the authors model the pandemic-instigated surge in demand as a double logistic model (*equation (39)*) commonly deployed to model COVID-19 spread and associated second-order effects (Liu et al., 2020; Shen, 2020; Triambak et al., 2021), rendering a peri-disruption peak demand for the e-retailer of 47.8 k customers and a post-disruption demand of 36 k customers (Fig. 5). Thus, in the pre-disruption stage, the e-retailer organizes its distribution structure for low-cost just-in-time service to deliver 30 k packages daily, and in the peri-/post- disruption stage, the e-retailer must then outsource part of its operations to a crowdsourced fleet for delivery, or to customers for pickup at collection-points, or to logistics service providers (LSP) for distribution, to cope with the surge in demand. Note, for simplicity, the authors assume no direct impact on the e-retailer's distribution capacity with continued availability of resources (staff and drivers) during the course of the pandemic.

$$y_t = (Q_t/Q_o - 1)*100 \tag{38}$$

$$y_t = \frac{\alpha_1}{1+\exp\left(\frac{-(t-\mu_1)}{\theta_1}\right)} - \frac{\alpha_2}{1+\exp\left(\frac{-(t-\mu_2)}{\theta_2}\right)} \tag{39}$$

where

Q_t : e-commerce transactions.
y_t : percentage change in e-commerce transactions.
α_1 : growth factor (% increase to peak disruption).
α_2 : decay factor (% decrease from peak disruption).
μ_1 : growth half-life (days to half the increase to peak disruption).
μ_2 : decay half-life (days to half the decrease from peak disruption).
θ_1 : Inverse growth rate (inverse of the rate of increase to peak disruption).
θ_2 : Inverse decay rate (inverse of the rate of decrease from peak disruption).

To begin with, the authors design these outsourcing channels and plan the available resources such that the e-retailer can just about cope with the pandemic-instigated surge in demand, i.e., without any loss in level of service.

To be more precise, for delivery via the crowdsourced fleet, the authors assume 565 crowdsourced drivers with their light-duty trucks to be available at the disposal of the e-retailer. The e-retailer remunerates the crowdsourced drivers on an hourly basis only, and not for their fuel costs or vehicle maintenance expenses, consistent with the Amazon Flex Program, wherein Amazon hires drivers on an on-demand basis and gives them a dispatch plan to make deliveries using their personal vehicles. Note, due to such limited incentives, the analysis here assumes the crowdsourced drivers to make only one delivery tour for the e-retailer. For customer-pickup at the collection-points, the authors assume the e-retailer to ship packages from its e-commerce fulfillment facility to 200 such lockers

Table 1
Vehicle characteristics.

Vehicle characteristics		Class-5 DT	LDT	PC	ECB
Purchase cost [a] ($)	PC	80 k	–	–	9.5 k[*]
Capacity (customers per tour)	VC	360	30	1	30
Speed outside the service region (mph)	v_{out}	55	60	60	10
Speed inside the service region (mph)	v_{in}	20	25	25	10
Service time at facility (mins per customer)	τ_{sF}	0.3	0.5	–	0.3
Service time at customer (mins)	τ_{sC}	1.0	0.5	1.0	0.5
Driver cost [b] ($/hour)	π_d	35	35	–	35
Maintenance cost [b] ($/mi)	π_m	0.20	–	–	0.02
Fuel cost [c] ($/gal, $/kWh)	π_f	3.86	–	–	0.12
Fuel consumption rate [a] (mi/g, mi/kWh)	r_f	0.1	0.05	0.03	0.29
Range (mi)	R	–	–	–	30
CO_2 emission rate [d] (g/mi)	r_{CO_2}	1049.38	386.1	303	0
CO emission rate [d] (g/mi)	r_{CO}	0.77	1.77	1.09	0
NO_x emission rate [d] (g/mi)	r_{NO_x}	4.1	0.17	0.08	0
PM emission rate [d] (g/mi)	r_{PM}	0.132	0.0026	0.002	0

DT – Diesel Truck, ECB – Electric Cargo Bike, LDT – Light Duty Truck (crowd-sourcing vehicle), PC – Passenger Car.
[a] Jaller et al. (2021).
[b] Caltrans (2016).
[c] AAA (2019).
[d] California Air Resource Board (2018).
[*] Charging infrastructure cost included.

(located randomly and uniformly in the region) each with a capacity of 50 packages, from where the customers finally collect the packages. Note, the analysis assumes that at most 85 % of the customers would be willing to collect packages from the nearest collection-point. Considering that prior to the pandemic, e-commerce witnessed as many as 37 % of customers willing to collect package at an alternate location, i.e. other than the customer's home or office (UPS, 2018), an 85 % willingness could be justified if the alternate option for the customer is to shop in-store during the pandemic. And for distribution via a logistics service provider, the authors assume the e-retailer to ship packages from its e-commerce fulfillment facility to 10 such micro-hubs (located randomly and uniformly in the region) from where the LSP delivers packages using its fleet of electric cargo-bikes. Note, the analysis assumes the LSP to equip each micro-hub with 22 cargo-bikes and as many Level 2 chargers (priced at $3k each).

With this, the e-retailer can just about cope with the pandemic-instigated surge in demand without any loss in level of service. Nonetheless, the authors then limit the resources available to the e-retailer from these outsourcing channels to elicit reduced distribution capacity to evaluate e-retailer's ability to maintain and restore level of service from the pandemic-instigated disruption. This study also performs a sensitivity analysis on disruption characteristics to further evaluate the e-retailer's ability to maintain and restore level of service under disruptions in general.

Table 1 shows the relevant features for each of the vehicle-type deployed in the distribution process. For the analyses, this study assumes a consolidation of 3 deliveries per stop ($\theta = 3$). To evaluate emissions costs, this work accounts for CO_2, CO, NO_x, and PM emissions from last-mile distribution, valued at $0.066, $0.193, $76.97, and $630.3 per kilogram of emissions, respectively (Caltrans, 2017; Marten and Newbold, 2012). In addition to the surge in demand, the authors also model reduced traffic congestion - observed as a consequence of inhibited public movement owing to the various virus containment measures, as a double logistic model similar to the surge in demand.

5. Empirical results

The empirical results detail the e-retailer's response and assess the resilience of last-mile distribution operations against the market disruption instigated by the COVID-19 pandemic (Section 5.1). In the first part of this analysis (Section 5.1.1), the authors detail the distribution operations under the market disruption that ensued with the COVID-19 pandemic. Recall that the authors have designed these outsourcing channels and planned the available resources such that the e-retailer can just about cope with the pandemic-instigated surge in demand. Thus, in the second part (Section 5.1.2), the authors limit the distribution capacity of the outsourcing channels to evaluate e-retailer's response and therefore to assess the resilience of its last-mile distribution operations under the pandemic-instigated market disruption. In addition to the primary analysis, the authors perform a sensitivity analysis (Section 5.2) to assess the e-retailer's response to disruptions (in general) with varying characteristics to guide the e-retailer's decision-making against future disruptions.

5.1. *Primary analysis - market disruptions instigated by the COVID-19 pandemic*

As discussed in the Case Study, prior to the COVID-19 pandemic, the e-retailer serves a total of 30 k customers daily, delivering just-in-time to minimize its distribution cost (*equation 17–20*). This minimization renders a pre-disruption distribution cost of $50.35 k for the e-retailer operating from an e-commerce fulfillment facility optimally located at 6.45miles from downtown LA, with an optimal fleet size of 98 class-5 diesel trucks loaded with a less-than-truckload number of packages at 85 % load utilization to comply with driver working-hours. However, with the onset of the COVID-19 pandemic, the local authorities impose aggressive virus containment measures which significantly inhibit public movement and thus trigger a market disruption with a 2-week lag ($t_o = 1, t_s = 14, t_e = 118$) including a surge in e-commerce demand (*equation (40)*) and a reduction in traffic congestion (*equation (41)*). In particular, the e-retailer observes a peak peri-disruption demand of 47.8 k customers and a stable post-disruption demand of 36 k customers daily, with traffic conditions improving to almost as good as free-flow conditions in the peri-disruption stage before returning back to pre-disruption levels after the disruption (Fig. 6).

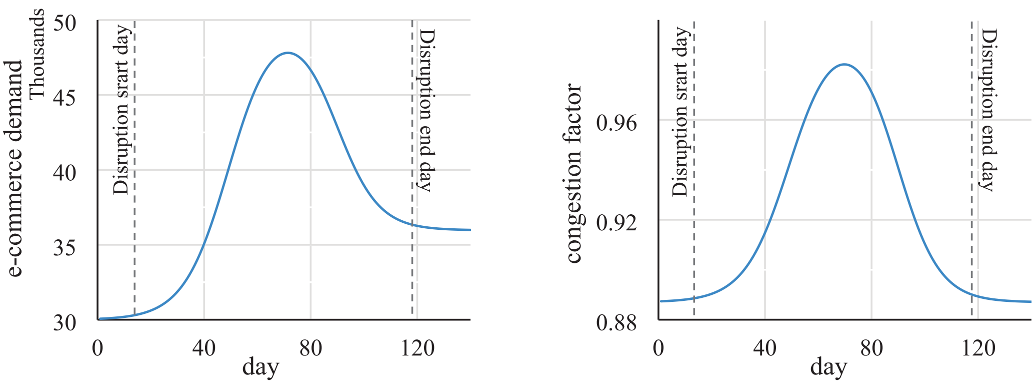

Fig. 6. Modeled market disruption instigated by the COVID-19 pandemic.

$$N_t = N_o\left(1 + \frac{0.685}{\left(1 + \exp\left(\frac{-(t-49.373)}{8.447}\right)\right)} - \frac{0.486}{\left(1 + \exp\left(\frac{-(t-89.512)}{7.885}\right)\right)}\right) \tag{40}$$

$$\phi_t = \phi_o\left(1 + \frac{0.1274}{\left(1 + \exp\left(\frac{-(t-49.373)}{8.447}\right)\right)} - \frac{0.1274}{\left(1 + \exp\left(\frac{-(t-89.512)}{7.885}\right)\right)}\right) \tag{41}$$

$$\forall t \in t \geq t_s; t_s = 14, t_e = 118, N_o = 30000, \phi_o = 0.887$$

5.1.1. Detailing last-mile distribution operations under the COVID-19 disruption

5.1.1.1. without outsourcing. Due to low-cost just-in-time delivery practices, the e-retailer's distribution structure has little slack capacity (Fig. 7). The e-retailer thus continues to serve ~ 30 k customers daily while completely dropping more than a 5th of all demand in the peri-disruption stage. This renders an out-of-pocket distribution cost of ~$50.35 k (equivalent to $1.68 per package; Fig. 8) but also an unobserved cost of unmet demand to the e-retailer. Thus, to cope with this surge in demand, the e-retailer could outsource part of its operations via one of the three outsourcing channels while delaying excess demand beyond the combined distribution capacity for a delivery on a later date.

5.1.1.2. with delivery via crowdsourced fleet. Last-mile delivery via a fleet of crowdsourced vehicles offers one such outsourcing option. This crowdsourced fleet operates independently of the e-retailer's distribution channel as the crowdsourced drivers collect packages from the e-commerce fulfillment facility before embarking on a delivery tour. Hence, crowdsourcing delivery renders flexible and on-demand deployment, with the e-retailer catering to 30 k customers using its fleet of class-5 diesel trucks and outsourcing the remaining via the crowdsourced fleet. Altogether, the 565 crowdsourced light duty trucks, each with a capacity to serve 30 customers in a delivery tour, augment the distribution capacity by 16.95 k customers, taking it to ~ 47.9 k customers, which is sufficient to serve the peak disruption demand of 47.8 k customers (Fig. 7). Thus, as the demand rises in the peri-disruption stage, the e-retailer gradually employs more crowdsourced drivers (from the 565 crowdsourced drivers at its disposal) for last-mile deliveries on an on-demand basis, with at most 35.2 % packages crowdsourced at peak disruption, resulting in a distribution cost of $82.97 k, equivalent to $1.74 per package (Fig. 8). In the post-disruption stage on the other hand, the e-retailer observes a daily demand of 36 k customers, of which the e-retailer serves 30 k customers using its fleet of diesel trucks and crowdsources deliveries for the remaining 6 k customers (16.6 % packages), with a total distribution cost of $1.76 per package.

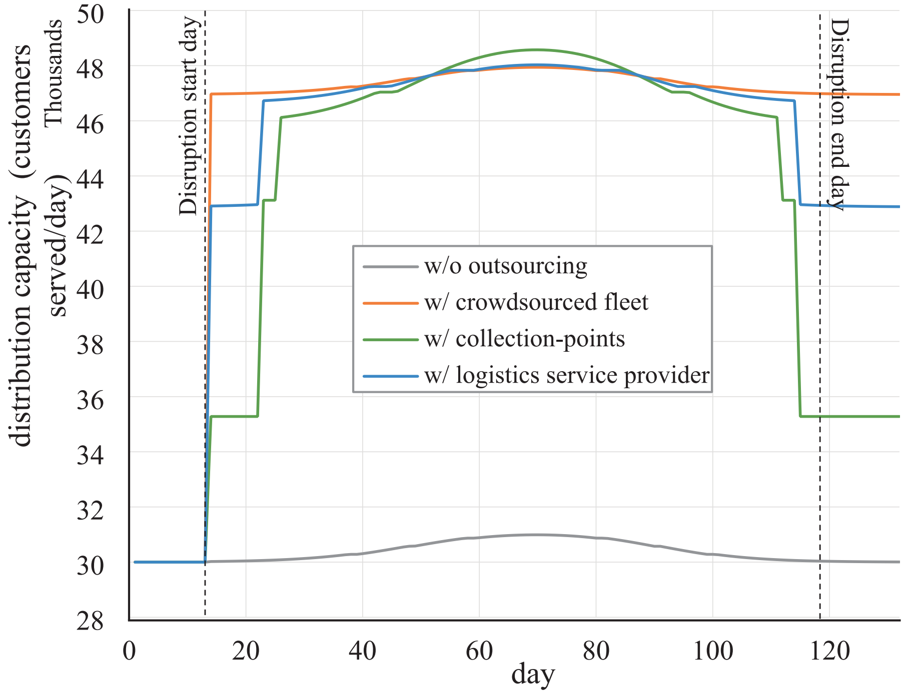

Fig. 7. Distribution capacity with/without outsourcing.

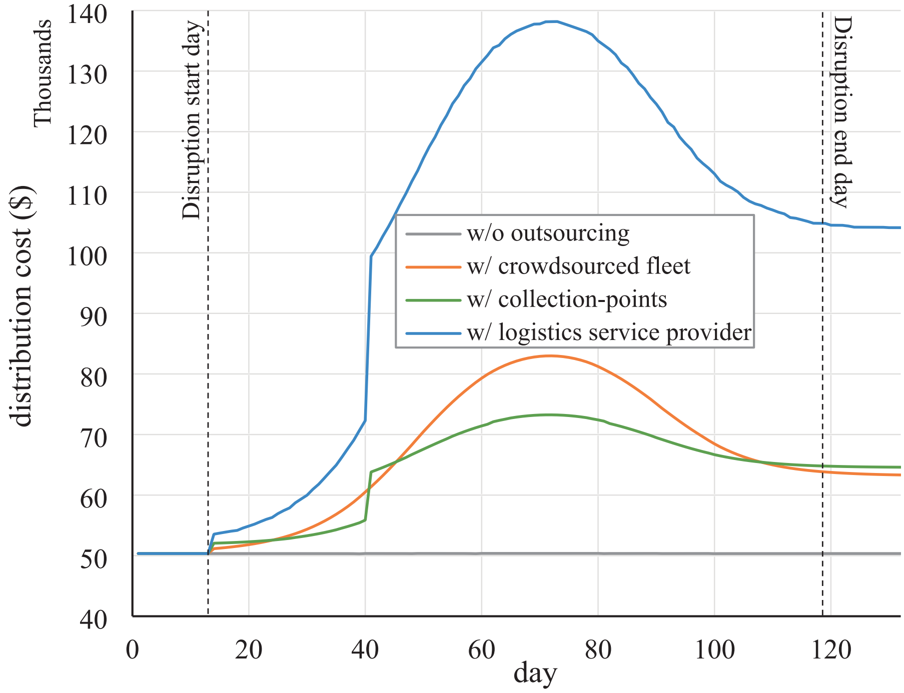

Fig. 8. Distribution cost with/without outsourcing.

These results showcase the flexibility of crowdsourced last-mile deliveries in coping with a surge in demand. However, it is important to note that the effectiveness of a crowdsourced service is sensitive to the availability of drivers willing to deliver packages. Thus, to ensure reliable last-mile operations, the e-retailer can offer better incentives to crowdsource, whether with higher hourly remuneration, reimbursement of maintenance and fuel costs, and/or a start-on bonus. Nonetheless, delivery via a crowdsourced fleet can be challenging, more so in the context of the COVID-19 pandemic, wherein virus containment measures such as stay-at-home orders inhibit public movement and may further limit the availability of crowdsourced drivers.

5.1.1.3. with customer pickup at collection-points. Alternatively, the e-retailer can outsource the last-mile for customer pickup at collection-points. However, unlike with crowdsourced deliveries, outsourcing via collection-points is dependent on the e-retailer's distribution channel. In particular, the e-retailer must fulfill the collection-points before customers can collect their packages. Thus, as the demand rises in the peri-disruption stage, the e-retailer gradually loads its underutilized delivery trucks with additional packages (recall, 85 % load utilization in pre-disruption), which are eventually unloaded at collection-points for customer pickup. This demand consolidation at collection-points, along with the reduced traffic congestion in the peri-disruption stage, enables the e-retailer to continue complying with driver working-hours despite loading its delivery trucks with more packages. As the demand rises to 35.28 k customers, the delivery trucks reach full-truckload with a large share of packages consolidated for collection-point pickup. As the demand further surges beyond this level, the delivery trucks make an additional delivery tour to cater to this increased demand, adding non-negotiable long-haul travel time, and therefore to comply with driver working-hours, the e-retailer reduces delivery trucks' time spent traveling in the last-mile by outsourcing and consolidating an even larger share of packages for collection-point pick-up. This is evident by the sharp jump in distribution costs depicted in Fig. 8. Thus, at peak disruption, the e-retailer consolidates 84 % of packages for collection- point pickup, resulting in a distribution cost of $73.24 k, equivalent to $1.53 per package (Fig. 8). In the post-disruption stage then, the e-retailer observes a daily demand of 36 k customers, beyond the 35.28 k customer threshold, and therefore continues to operate and depend heavily on the outsourcing channel, delivering 83.7 % of all its packages via collection-points at a distribution cost of $1.79 per package. At this point, the e-retailer can acquire 2 additional class-5 diesel trucks to increase the volume capacity of its fleet to 36 k and thereby reduce its dependence on the outsourcing channel with only as much as 26.7 % of the total demand routed for collection-point pick-up, resulting in a distribution cost of $1.61 per package. Alternatively, the e-retailer can purchase 19 additional class-5 diesel trucks and completely eliminate the use of collection-points for a distribution cost of $1.59 per package.

While these results present the cost-effectiveness of collection-points to cope with a surge in demand, the success of collection-points is nonetheless contingent on the willingness of customers to collect their packages. In fact, in the context of the COVID-19 pandemic, customer's willingness to self-collect a package could be sensitive to the individual's perceived susceptibility to the virus. Moreover, it is important to account for the increased externalities, i.e., vehicle miles traveled and emissions from individuals traveling to collect packages at collection-points, when discussing the use of collection-points in general.

5.1.1.4. with distribution via micro-hubs using cargo-bikes operated by logistics service provider. Similar to collection-points, outsourcing via micro-hubs requires that the e-retailer fulfill the micro-hubs before the LSP's cargo-bikes can embark for last-mile deliveries. Thus, in the peri-disruption stage, as the demand rises, the e-retailer gradually loads its delivery trucks with additional packages consolidated for the LSP to distribute. In doing so, the e-retailer complies with the driver working-hours until the demand surges beyond the 35.28 k customer threshold. To cater to the demand beyond this threshold, the delivery trucks make an additional delivery tour, adding non-negotiable long-haul travel time. At this point, to comply with driver working-hours the e-retailer reduces the time spent by the delivery trucks traveling in the last-mile by consolidating a much larger share of packages for distribution via the LSP. This again is evident by the sharp jump in distribution cost depicted in Fig. 8. Thus, at peak disruption, the e-retailer consolidates 82.1 % of packages for distribution via the LSP resulting in a distribution cost of \$138.1 k, equivalent to \$2.89 per package (Fig. 8). In the post-disruption stage then, the e-retailer observes a daily demand of 36 k customers, yet still beyond the 35.28 k customer threshold. To cater to this post-disruption demand, the e-retailer routes as much as 59.2 % of its packages via the LSP, amounting to a distribution cost of \$2.88 per package. As with the collection-points, at this stage the e-retailer can acquire 2 additional class-5 diesel trucks, which increases the volume capacity of its fleet to 36 k and thereby reduces its dependence on the outsourcing channel with only as much as 26.2 % of the total demand distributed via the LSP, resulting in a distribution cost of \$2.10 per package. Alternatively, the e-retailer can purchase 19 additional class-5 diesel trucks and completely eliminate the dependance on logistics service providers for a distribution cost of \$1.59 per package.

It is important to note that the LSP could itself be constrained for resources due to the disruption, nonetheless, the results highlight the need for prior contracts with multiple such logistics service providers to efficiently reroute distribution in the event of disruptions. Moreover, unlike either of the two previously discussed outsourcing channels, outsourcing via a 3rd party LSP offers the least potential for uncertainty in the distribution process.

5.1.2. Evaluating e-retailer's response to the COVID-19 disruption

The results developed above, and the related discussion offer salient insight into the last-mile distribution operations of the e-retailer using different outsourcing channels under the market disruption instigated by the COVID-19 pandemic. Recall, the authors designed the outsourcing channels and planned the available resources such that the e-retailer can just about serve the increased demand, thereby rendering resilient last-mile distributions with the e-retailer operating at a full level of service. However, to assess the capability of the e-retailer's distribution operations to maintain and efficiently restore level of service under the same pandemic-instigated market disruption, the authors assume the outsourcing channels to be resource constrained and therefore limit the share of packages they can service, implicitly or explicitly, in the form of a (maximum) permissible outsourcing share (p_u). For instance, a crowdsourced fleet implicitly limits the number of customers it can deliver to in the form of driver availability, while customer willingness to self-collect package indicates the share of packages that the e-retailer can deliver via collection-point for customer pickup, and the LSP can explicitly express the maximum share of packages it is willing to distribute considering its own internal resource constraints. Such constraints effectively limit the distribution capacity and force the e-retailer to operate at a lower level of service. Note, below a certain permissible level of outsourcing share (lower threshold), the e-retailer and outsourcing channel combined distribution capacity would fall short of the post-disruption stable demand of 36 k customers, resulting in last-mile distributions at a near zero level of service post the disruption. On the other hand, above a certain permissible level of outsourcing share (upper threshold), the combined distribution structure sufficiently large distribution capacity, enough to serve the peak peri-disruption demand of 47.8 k customers, thereby enabling last-mile distribution at a full level of service throughout the disruption. The discussion hereon assesses the reponse of the e-retailer constrained for the values of maximum permissible outsourcing share between the two thresholds under the COVID-19 instigated disruption (see Table 2).

The analysis employs resilience metrics to evaluate robustness, redundancy, resourcefulness, and rapidity on the e-retailer's level of service; operational metrics to evaluate total and average delay; and economic metrics to measure direct, indirect, and total loss. The resilience metrics of robustness and redundancy reflect the magnitude and rate of loss in the e-retailer's level of service, while resourcefulness and rapidity assess the magnitude and rate of recovery, respectively. The operational metrics characterize the delay in service, in particular, the total delay expresses cumulative delay in terms of number of package-days of delayed service, while the average delay evaluates the average number of additional packages delayed on any day, and the average number of days a package is delayed, assuming that packages are delivered on a first-come-first-served basis. The economic metrics, namely direct loss, evaluates the change in distribution cost relative to pre-disruption distribution cost (\$50.35 k), and indirect loss accounts for the loss from delayed service penalizing late delivery (unmet demand) at \$5 per package for every day of delayed service, while the total loss is the sum of direct and indirect loss, and thereby reflects the explicit and implicit costs to the e-retailer.

To begin, a permissible outsourcing share beyond the lower threshold renders distribution capacity that functions as slack capacity as the disruption fades away, thus enabling the e-retailer to restore the level of service and limit the disruption loss. In fact, an increase in permissible outsourcing share increases the distribution capacity which - increases the slack capacity building robustness and redundancy, enables faster recovery improving rapidity, and reduces service delays limiting the disruption loss to the e-retailers.

Table 2
Lower and upper threshold for permissible outsourcing share.

Outsourcing	Lower threshold	Upper threshold
w/ crowdsourced fleet	16.7 %	35.2 %
w/ collection-points	60.0 %	83.6 %
w/ logistics service provider	59.5 %	82.0 %

Resourcefulness remains constant at 1.0 since any amount of slack capacity ensures recovery. These dynamics are evident in Figs. 9, 10, and 11, which highlight the variation in resilience, operational, and economic metrics, respectively, for last-mile distribution operations with the e-retailer outsourcing distribution via the LSP constrained to a maximum permissible outsourcing share in the range of 0.60 to 0.82. Further, Table 3, 4, and 5 quantify these dynamics in the form of resilience elasticity, operational sensitivity, and economic sensitivity, respectively. Note, elasticity measures the % change in the value for a % increase in permissible outsourcing share, while sensitivity measures the absolute change in the value for a % increase in permissible outsourcing share. For instance, a % increase in customer's willingness to self-collect package from a collection-point increases the distribution slack capacity, rendering a 7.4 % improvement in robustness, a 2.9 % improvement in redundancy, and a 9.5 % improvement in the rapidity of last-mile distribution operations, with reduction in shipping time by 16 days resulting in a $3.19b (18.9 %) fewer disruption loss to the e-retailer. Similarly, a 2.8 % increase in number of drivers available for crowdsourcing (or a % increase in permissible outsourcing share) increases the slack capacity, improving robustness by 3.6 %, redundancy by 1.7 %, and rapidity by 3.2 %, with on average 6 k fewer packages delayed per day, resulting in a $0.67b (8.1 %) fewer disruption loss.

These tables also highlight the differences between the different outsourcing channels. For instance, Table 3 shows the improvement in last-mile distribution resilience with crowdsourced delivery to be relatively modest in comparison to the other two outsourcing channels. Because every crowdsourced driver only makes one delivery tour given the incentives on offer, the increase in distribution capacity is only marginal as more crowdsourced drivers are employed. In fact, a % increase in permissible outsourcing share renders only 132 m (11.0 %) fewer package-day delays for last-mile distribution with packages outsourced for crowdsourced delivery, in contrast to 322 m (27.0 %) fewer package delays with packages outsourced for distribution via the LSP, and 628 m (24.0 %) fewer package delays with packages outsourced for customer pickup at collection-points (see Table 4). However, the differences in direct loss sensitivity are contingent on the cost structure. In particular, operating a crowdsourced fleet with drivers remunerated only for hourly wages renders significantly low last-mile operational costs; similarly, customer pickup from collection-points saves the e-retailer on last-mile operational costs for its fleet of delivery trucks, whereas the LSP charges high operational costs in the form of hourly driver wages, as well as cargo-bike energy and maintenance costs. Hence, a % reduction in permissible outsourcing share limits consolidation benefits (economy of scale benefits) for the outsourcing channel, rendering as much as a $81.4 m (4.70 %) increase in direct loss for last-mile distributions with packages outsourced for distribution via the LSP in contrast to a $46.8 m (6.19 %) increase with packages outsourced for collection-point pickup, and only a $17.4 m (2.95 %) increase with packages outsourced for crowdsourced delivery (Table 5). While the cost structure employed in this work is consistent with real-world examples, it is important to note that modeling certain parameters is outside the scope of this work, such as crowdsourced driver availability as a function of delivery incentives, customer willingness to self-collect considering their value of time, and the cooperation and collaboration dynamics between the e-retailer and the LSP.

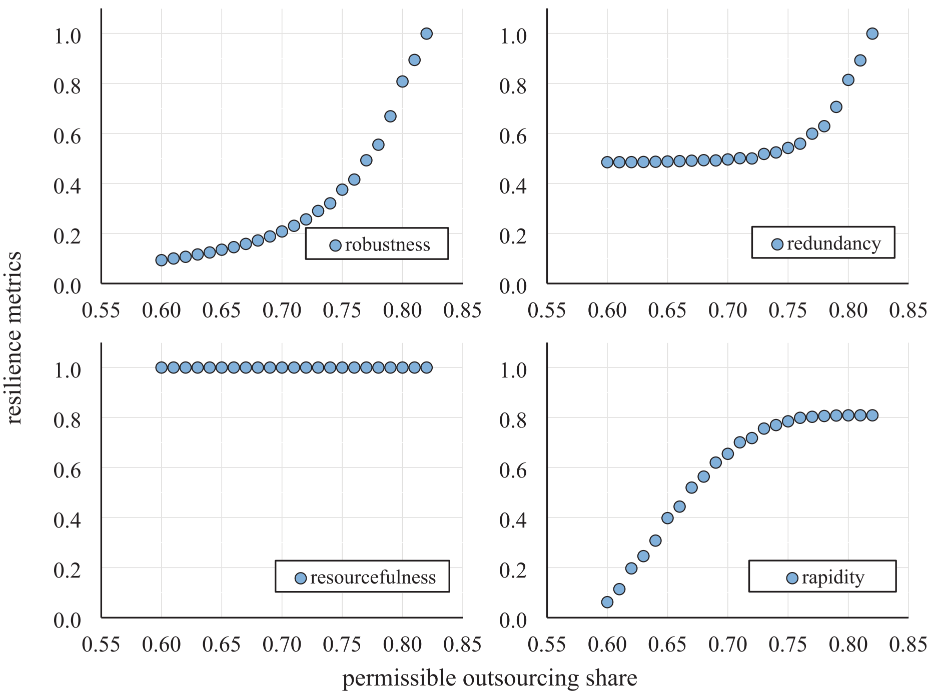

Fig. 9. Resilience dynamics of last-mile distribution (outsourcing delivery with logistics service provider).

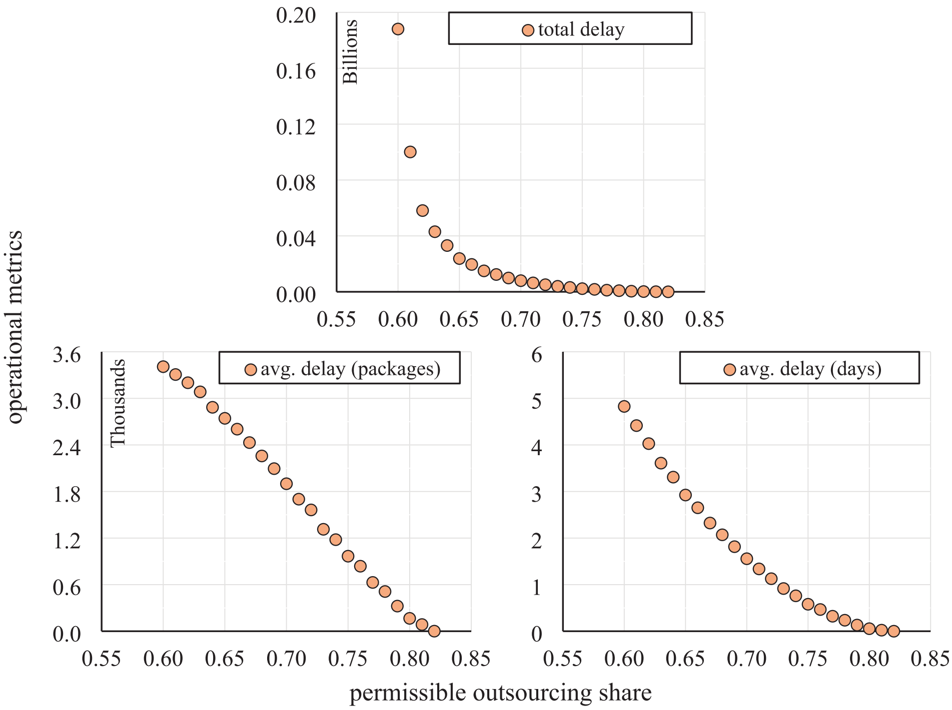

Fig. 10. Operational dynamics of last-mile distribution (outsourcing delivery with logistics service provider).

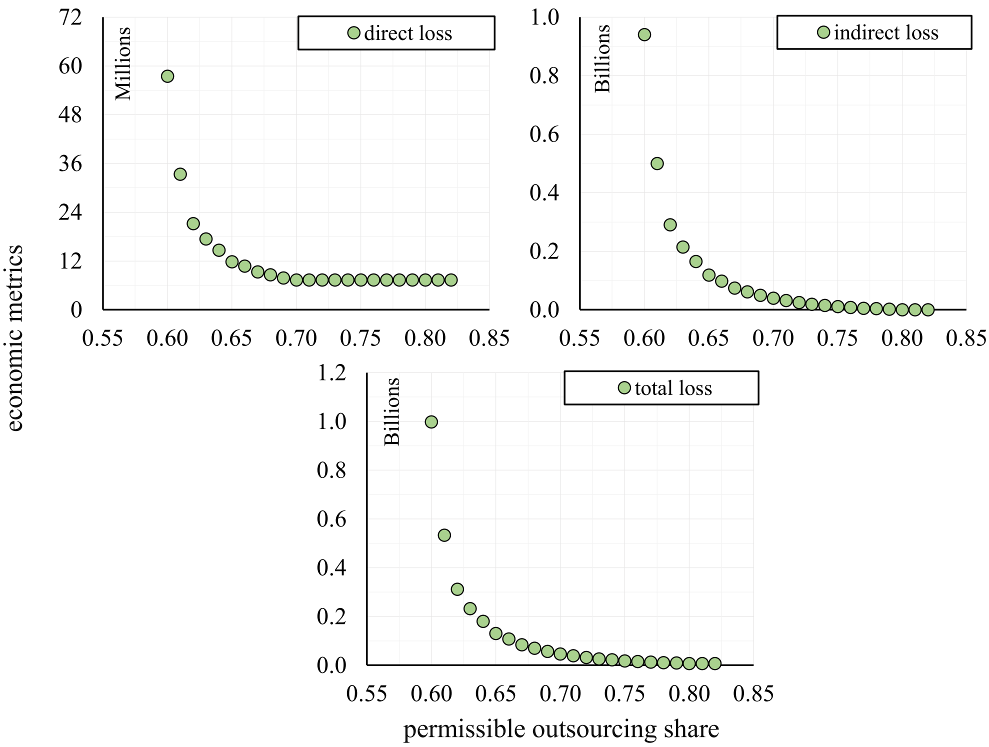

Fig. 11. Economic dynamics of last-mile distribution (outsourcing delivery with logistics service provider).

Table 3
Resilience metric elasticity with respect to permissible outsourcing share.

Outsourcing	Robustness	Redundancy	Resourcefulness	Rapidity
w/ crowdsourced fleet	3.592	1.700	0.000	3.207
w/ collection-points	7.374	2.877	0.000	9.487
w/ logistics service provider	7.626	3.218	0.000	8.475

Table 4
Operational metric sensitivity with respect to permissible outsourcing share.

Outsourcing	Total delay (bill. package-days)	Average delay (thousand packages)	Average delay (days)
w/ crowdsourced fleet	−0.132	−6.014	−7.849
w/ collection-points	−0.628	−11.79	−15.76
w/ logistics service provider	−0.322	−11.71	−15.61

Table 5
Economic metric sensitivity with respect to permissible outsourcing share.

Outsourcing	Direct loss (m$)	Indirect loss (b$)	Total loss (b$)
w/ crowdsourced fleet	−17.37	−0.660	−0.677
w/ collection-points	−46.83	−3.138	−3.185
w/ logistics service provider	−81.36	−1.611	−1.692

5.2. Sensitivity analysis - market disruptions (in general) with varying characteristics

Having assessed the e-retailer's response to the market disruption that ensued with the COVID-19 pandemic, the authors assess the e-retailer's response to disruptions in general in this subsection. This market disruption triggers a generalized increase in e-commerce demand and a generalized reduction in traffic congestion, as modeled in *equation (42) and (43)*, respectively. The analysis here performs sensitivity analysis by varying disruption characteristics - growth/decay factor (% increase to/from peak disruption), growth/decay half-life (days to half the increase/decrease to/from peak disruption), and inverse growth/decay rate (inverse of the rate of increase/decrease to/from peak disruption), and in turn assesses the e-retailer's reponse gauging the resilience, operational, and economic metrics of its last-mile distribution. Again, much like in the previous subsection, the sensitivity analysis here varies the disruption characteristics such that the e-retailer has enough distribution capacity to serve the post-disruption demand but not enough to serve the peak peri-disruption demand. This allows for an analysis of the e-retailer's operations at a reduced level of service, albeit with the e-retailer having enough resources to restore and recover to full level of service. Table 6 lists the range of values of the distribution characteristics employed in this sensitivity analysis, with Table 7, 8 and 9 presenting the resilience elasticity, operational sensitivity, and economic sensitivity, respectively, in this range.

$$N_t = N_o\left(1+\frac{\alpha_1}{\left(1+\exp\left(\frac{-(t-\mu_1)}{\theta_1}\right)\right)}-\frac{\alpha_2}{\left(1+\exp\left(\frac{-(t-\mu_2)}{\theta_2}\right)\right)}\right) \tag{42}$$

$$\phi_t = \phi_o\left(1+\frac{\alpha}{\left(1+\exp\left(\frac{-(t-\mu_1)}{\theta_1}\right)\right)}-\frac{\alpha}{\left(1+\exp\left(\frac{-(t-\mu_2)}{\theta_2}\right)\right)}\right) \tag{43}$$

$$\forall t \geq t_s; N_o = 30,000, \phi_o = 0.887$$

To begin, an increase in the value of two of the six disruption characteristics, growth factor and decay half-life, and a decrease in the value of the other four disruption characteristics, results in an effective increase in the severity of the disruption. This then results in a reduction in the robustness and redundancy of last-mile distributions, but also increases rapidity, highlighting the elastic nature of the last-mile response to disruption (Table 7). The elasticity of resourcefulness with respect to the disruption characteristics is zero, since any amount of slack capacity enables the e-retailer to service delayed demand and thereby to restore the level of service, as discussed before. Concomitantly, this increase in disruption severity renders an increase in direct loss and also an increase in indirect loss owing to the increased amount of package delays (Table 8), thereby increasing the total loss from disruption for the e-retailer (Table 9). For instance, for an e-retailer outsourcing last-mile to the customers for pickup at collection-points, a % increase in growth factor increases disruption severity rendering an additional ∼ 4.1 k (24.0 %) packages delayed on average every day which results in a 4.5 % reduction in robustness, a 3.0 % reduction in redundancy, and $48.3 m (10.4 %) more in total loss from the disruption. On the other hand, for this e-retailer, a % decrease in decay rate (or a % increase in inverse decay rate) reduces disruption severity, resulting in 120 (1.19 %) fewer

Table 6
Range of values of distribution characteristics for sensitivity analysis.

Distribution characteristics	Lower threshold	Upper threshold
Growth factor -α_1		
w/ crowdsourced fleet	0.685	1.000
w/ collection-points	0.710	0.840
w/ LSP's micro-hubs	0.700	0.900
Growth half-life -μ_1		
w/ crowdsourced fleet	37	48
w/ collection-points	37	42
w/ LSP's micro-hubs	37	48
Inverse growth rate -θ_1		
w/ crowdsourced fleet	0.5	8.0
w/ collection-points	0.4	6.0
w/ LSP's micro-hubs	0.5	8.0
Decay factor -α_2		
w/ crowdsourced fleet	0.100	0.425
w/ collection-points	0.180	0.270
w/ LSP's micro-hubs	0.260	0.400
Decay half-life -μ_2		
w/ crowdsourced fleet	95	150
w/ collection-points	95	150
w/ LSP's micro-hubs	95	150
Inverse growth rate -θ_2		
w/ crowdsourced fleet	0.5	7.5
w/ collection-points	0.3	5.1
w/ LSP's micro-hubs	0.5	7.5

package delays on average per day, which renders a 0.15 % increase in robustness, a 0.11 % increase in redundancy, a 0.57 % reduction in rapidity, and $1.07 m (0.19 %) fewer losses from disruption.

These results can help inform the e-retailer's decision making against similar future disruptions. In particular, the elasticity of robustness with respect to disruption severity (Table 7) shows last-mile distribution with packages outsourced for customer pickup from collection-points to be the least sensitive channel to the severity of the disruption, rendering resilient operations despite its dependence on the e-retailer for fulfillment, followed by distribution with a LSP, while crowdsourced delivery is most sensitive to disruption severity. Noting the magnitude of operational sensitivity across the three outsourcing channels (Table 8), again, the results conclude that last-mile distribution with crowdsourced deliveries to be most sensitive to the severity of disruption, followed by distribution with a LSP, while customer pickup at collection-points is least sensitive to disruption severity. These trends in turn reflect the indirect loss sensitivity for the three outsourcing channels. A % increase in growth factor renders a $46.2 m (34.0 %) increase in indirect monetary losses to the e-retailer for last-mile distribution with packages outsourced for collection-point pickup, in contrast to a $154.7 (27.1 %) increase with packages outsourced for distribution via a LSP, and as much as a $229.7 m (22.3 %) increase with

Table 7
Resilience elasticity to disruption characteristics.

Resilience elasticity		Robustness	Redundancy	Resourcefulness	Rapidity
w/ crowdsourced fleet					
Growth factor	α_1	−5.088	−2.054	0.000	0.000
Decay factor	α_2	0.273	0.122	0.000	0.000
Growth half-life	μ_1	0.978	0.649	0.000	−1.572
Decay half-life	μ_2	−2.616	−0.914	0.000	1.527
Inv. growth rate	θ_1	0.306	0.228	0.000	−0.325
Inv. decay rate	θ_2	0.246	0.155	0.000	−0.397
w/ collection-points					
Growth factor	α_1	−4.475	−3.022	0.000	7.383
Decay factor	α_2	0.168	0.089	0.000	0.000
Growth half-life	μ_1	0.465	0.253	0.000	−1.429
Decay half-life	μ_2	−1.830	−0.855	0.000	2.082
Inv. growth rate	θ_1	0.201	0.172	0.000	−0.513
Inv. decay rate	θ_2	0.150	0.105	0.000	−0.569
w/ logistics service provider					
Growth factor	α_1	−5.053	−2.612	0.000	0.000
Decay factor	α_2	0.113	0.000	0.000	0.000
Growth half-life	μ_1	0.829	0.595	0.000	−1.825
Decay half-life	μ_2	−2.460	−0.924	0.000	1.774
Inv. growth rate	θ_1	0.283	0.223	0.000	−0.383
Inv. decay rate	θ_2	0.224	0.150	0.000	−0.445

All results here are statistically significant with 95% confidence.

Table 8
Operational sensitivity to disruption characteristics.

Operational sensitivity		Total delay (mill. package-days)	Average delay (thousand packages)	Average delay (days)
w/ crowdsourced fleet				
Growth factor	α_1	45.93	7.132	5.741
Decay factor	α_2	0.000	−0.245	−0.242
Growth half-life	μ_1	−6.904	−1.108	−0.828
Decay half-life	μ_2	9.796	2.204	2.036
Inv. growth rate	θ_1	0.000	−0.340	−0.219
Inv. decay rate	θ_2	0.000	−0.236	−0.126
w/ collection-points				
Growth factor	α_1	9.244	4.163	2.222
Decay factor	α_2	−0.466	−0.135	−0.094
Growth half-life	μ_1	−1.448	−0.423	−0.289
Decay half-life	μ_2	5.593	1.258	0.986
Inv. growth rate	θ_1	−0.383	−0.188	−0.101
Inv. decay rate	θ_2	−0.241	−0.120	−0.053
w/ logistics service provider				
Growth factor	α_1	30.94	5.947	3.763
Decay factor	α_2	0.000	−0.146	−0.152
Growth half-life	μ_1	−6.428	−0.849	−0.524
Decay half-life	μ_2	8.150	1.955	1.722
Inv. growth rate	θ_1	0.000	−0.295	−0.171
Inv. decay rate	θ_2	0.000	−0.199	−0.088

All results here are statistically significant with 95% confidence.

Table 9
Economic sensitivity to disruption characteristics.

Economic sensitivity		Direct loss (m$)	Indirect loss (m$)	Total loss (m$)
w/ crowdsourced fleet				
Growth factor	α_1	9.946	229.7	238.3
Decay factor	α_2	−2.300	0.000	0.000
Growth half-life	μ_1	−4.192	−34.52	−37.08
Decay half-life	μ_2	4.507	48.98	52.41
Inv. growth rate	θ_1	0.000	0.000	0.000
Inv. decay rate	θ_2	0.000	0.000	0.000
w/ collection-points				
Growth factor	α_1	2.927	46.22	48.34
Decay factor	α_2	−0.326	−2.331	−2.566
Growth half-life	μ_1	−2.587	−7.238	−8.591
Decay half-life	μ_2	2.776	27.97	30.94
Inv. growth rate	θ_1	−0.055	−1.913	−1.911
Inv. decay rate	θ_2	0.081	−1.207	−1.074
w/ logistics service provider				
Growth factor	α_1	30.47	154.7	182.9
Decay factor	α_2	−3.850	0.000	0.000
Growth half-life	μ_1	−10.19	−32.14	−40.25
Decay half-life	μ_2	12.24	40.75	51.71
Inv. growth rate	θ_1	0.000	0.000	0.000
Inv. decay rate	θ_2	0.000	0.000	0.000

All results here are statistically significant with 95% confidence.

packages outsourced for crowdsourced deliveries. However, outsourcing last-mile distribution operations to a LSP results in a substantial direct loss to the e-retailer, owing to the high operational costs of distribution, with as much as a $30.5 m (2.44 %) increase in direct loss for a % increase in growth factor, in contrast to a $9.95 m (2.69 %) increase with packages outsourced for crowdsourced delivery, and only a $2.93 m (1.10 %) increase with packages outsourced for collection-point pickup. Recall that at peak disruption, the e-retailer could operate at a full level of service for a total cost of $2.89 per package with distribution outsourced to a LSP, in contrast to $1.74 with crowdsourced delivery, and $1.53 with packages outsourced for collection-point pickup. Nonetheless, operations with a crowdsourced fleet or with collection-points are susceptible to the willingness of stakeholders, drivers, and customers, to engage in the distribution process, while distribution via a LSP is not constrained by such uncertainties. Considering these opportunities and challenges associated with the different outsourcing channels, the e-retailer must carry out appropriate pre-disruption planning to ensure sufficiently robust, redundant, resourceful and rapid last-mile distribution at reasonable costs (direct and indirect loss) by A) creating a suitable platform and providing adequate incentives to establish reliable crowdsourced deliveries, B) negotiating contracts with several LSPs to deploy backup distribution, especially, and C) establishing a sufficient number of lockers and enough collection-points near customers' residential and workplace areas to ensure customer willingness to self-collect packages, customer safety and compliance with social-distancing guidelines (in epidemic/pandemic events). The e-retailer must also gauge the disruption as it evolves in different phases and appropriately re-evaluate the incentives offered for crowdsourced service, the use of collection-points and lockers for customer pickup, and the need for backup last-mile distribution.

6. Discussion

In the years prior to the pandemic, consumer shopping trends had seen a steady and significant shift towards online retail. Despite the prevalence of e-commerce platforms with lucrative shopping offers for consumers, traditional in-store shopping still dominated daily consumer purchases. Nonetheless, more and more consumers had been engaging in omnichannel behavior, with product search, trial, and final purchase occurring in different channels. However, the COVID-19 pandemic significantly inhibited public movement, and an unprecedented number of consumers, including many first-time users, took to e-commerce platforms for the purchase of critical goods, daily essentials, groceries, medications, and health-care products. Beyond the typical B2C services, some e-retailers also delivered personal protective equipment, including gowns, masks, and gloves to frontline healthcare services. Typically, these e-retailers account for only minor day-to-day and seasonal disruptions and thereby design their distribution structures for low-cost just-in-time deliveries, leaving the supply-chain vulnerable to such severe and unforeseen disruptions. Given the role of e-retailers in supply of essential goods not only to the typical customer but also to frontline services, in this study, the authors assessed last-mile distribution resilience in terms of an e-retailer's ability to maintain and efficiently restore level of service in the event of such a low-probability high-severity disruption. To cope with such low-probability high-severity disruptions, this work assumes that the e-retailer outsources part of its operations via one of the many outsourcing channels available, namely, with crowdsourced fleet of light-duty trucks, or collection-points for customer pickup (lockers), or via a logistics service provider (LSP) operating from micro-hubs using a fleet of electric cargo-bikes.

Research on low-probability high-severity disruptions in the context of transportation is limited to disaster management, humanitarian logistics, and relief operations for earthquakes, tsunamis, hurricanes, terrorist attacks, etc. (Renne et al., 2020). However, the total breakdown of global supply-chains and the consequent surge in e-commerce demand witnessed for months after the initial SARSCoV2 outbreak was unlike any other low-probability high-severity disruption, and therefore warrants dedicated research. To this end, the authors integrated the R4 resilience framework (Bruneau et al., 2003) and the resilience triangle concept (Tierney and Bruneau, 2007), thus developing the R4 Resilience Triangle Framework to assess the resilience of an e-retailer's last mile distribution operations developed using Continuous Approximation (CA) techniques. This novel resilience framework quantifies the qualitative properties of resilience, i.e., robustness, redundancy, resourcefulness, and rapidity using the resilience triangle thereby characterizing the drop in performance of the system due to the disruption. Considering the simple yet comprehensive use of triangles to quantify resilience, this framework is well capable of assessing the impact on the performance of a system for varying types of disruption with varying degrees of severity including multi-peak and multi-surge disruptions. Moreover, the domain-agnostic nature of this resilience framework enables assessment of a system's response to disruption not only in the context of transportation systems, but across varying domains. Thus, given the flexible nature of this framework, the authors believe that the R4 Last Mile Distribution Resilience Triangle Framework can significantly contribute towards operations management, humanitarian logistics, and relief operations studies.

In addition to the resilience metrics, this work developed operational and economic metrics quantifying package delay and monetary loss to the e-retailer due to the disruption, respectively. With these metrics, the e-retailer can identify the most appropriate strategy for the different potential disruptions and performance objectives. In particular, this study finds distribution structure slack capacity to be the driving force affecting resilience and operational metrics, while economic metrics are additionally contingent to the underlying distribution structure. Thus, an e-retailer offering rush delivery may value rapidity and hence could employ a fleet of crowdsourced drivers considering the flexible and on-demand nature of crowdshipping. On the other hand, another e-retailer may want to mitigate the monetary loss from the disruption and could therefore plan for the deployment of collection-points for customer pickup. Yet, a more traditional retailer may want to ensure robustness and could consequently outsource part of its last-mile distribution via a (or multiple) logistics service provider(s). Nonetheless, considering the overall opportunities and challenges explored with the different outsourcing channels (Table 10), it could be useful to establish crowdsourced deliveries to cope with low severity disruptions, deploy backup distribution for moderately severe disruptions, and encourage customers to self-collect packages to cope with high severity disruptions (Table 11).

However, the e-retailer must carry out appropriate pre-disruption planning to create suitable platforms and incentives to ensure reliable crowdsourced deliveries, position sufficient number of lockers near residential areas to ensure customer willingness to self-

Table 10
Opportunities and Challenges with the different outsourcing channels.

Outsourcing with	Opportunities	Challenges
crowdsourced fleet	relatively low distribution cost unconstrained by e-retailer's distribution channel	susceptible to driver (un)availability
collection-points	relatively moderate distribution cost constrained by e-retailer's distribution channel	susceptible to customer willingness to collect package
logistics service provider	reliable distribution operations	relatively high distribution cost constrained by e-retailer's distribution channel

Table 11
Sustainability and Resilience of the different outsourcing channels.

Outsourcing with	Sustainability	Resilience
crowdsourced fleet	economically viable environmentally inefficient socially equitable	low slack capacity low resilience
collection-points	economically viable environmentally efficient socially inequitable	high slack capacity high resilience
logistics service provider	economically viable environmentally efficient socially equitable	moderate slack capacity moderate resilience

collect packages, and negotiate contracts with several LSPs to ensure backup last-mile distribution. Moreover, as the disruption evolves, the e-retailer must gauge the availability of crowdsourced drivers, the willingness of customers to self-collect packages, and the capability of the LSPs to ensure functionality of its distribution channel, so that the e-retailer can deploy the appropriate outsourcing channel(s) during the different phases of the disruption. And finally, as the disruption recedes, the e-retailer must re-engage strategic and tactical decision-making process not only to restore the level of service efficiently and in a timely manner, but also to plan ahead for a changed post-disruption landscape. Moreover, consistent with other studies in the resilience literature (Hosseini et al., 2016; Paul and Chowdhury, 2020; Pujawan and Bah, 2022), this study highlights the need for organizational, social, economic, and engineering units of last-mile distribution to consistently perform pre-disruption mitigation, appropriately respond during the disruption, and efficiently carry out post-disruption analysis and recovery for last-mile distribution to be resilient to disruption.

7. Conclusions

In this study, the authors developed a holistic understanding concerning the capability of e-retailers' last-mile distribution operations to maintain and efficiently restore service levels under disruption. To this end, this work developed last-mile distribution resilience metrics (robustness, redundancy, resourcefulness, and rapidity), operational metrics (total delay, average packages delayed, and average days delayed), and economic metrics (direct loss, indirect loss, and total loss) and subsequently assimilated these metrics qualitatively to understand the opportunities and challenges associated with the different distribution channels. With this, the e-retailer can identify the most appropriate strategy for the different potential disruptions and performance objectives. In addition, the e-retailer must also consider equity implications for its staff, workers, and drivers in order to ensure safe working environment and prevent any job hazard not only under business-as-usual conditions, but with special protocols for each phase of the disruption. Equally, the e-retailer and the regulatory bodies must consider general equity implications of last-mile distribution in terms of exposure to freight related externalities, home-based accessibility to last-mile delivery services, etc. (Figliozzi and Unnikrishnan, 2021).

The authors also acknowledge the key limitations of this study, in particular in terms of concerns pertaining to A) the availability of drivers for crowdsourced operations - this study does not explicitly account for the impact of incentives to ensure the consistent availability of drivers willing to crowdsource; B) the analysis accounts for unobserved costs from delayed service, yet, other unobserved costs such as the customer's value of time traveling to collect packages from the collection-points and the impact of those costs on customers' willingness to self-collect packages are outside the scope of this work; C) the analysis accounts for some second-order impacts of disruption, such as reduction in traffic congestion leading to increased vehicle speeds and increase in distribution capacity, however, it does not consider other second- order disruption effects that could inhibit distribution capacity, such as the unavailability of human resources both for the e-retailer and for the logistics service providers; and D) the study solely focuses on disruption impacts on the outbound logistics for the e-retailer assuming undisrupted/resilient inbound logistics. Nonetheless, the analyses performed in this study present robust results that can guide e-retailers' decision-making in the event of future disruptions to maintain and efficiently restore level of service. Additionally, the results can support the development of plans to mitigate the risks associated to the e-retailers' distribution operations, as well as those from the outsourced channels.

Importantly, this work highlights the importance of holistic outlook for system design to develop a (sustainable) economically viable, environmentally efficient, and socially equitable system adept in coping with high-probability low-severity fluctuations, but also a (resilient) robust, redundant, and resourceful system that can rapidly recover from low-probability high-severity disruptions. Consistent with the suggestions from Esmalian et al. (2022) and Kurth et al. (2020), future work must analyze last-mile distribution structures with such a holistic outlook of system design to ensure sustainable and resilient operations.

CRediT authorship contribution statement

Anmol Pahwa: Conceptualization, Methodology, Software, Formal analysis, Validation, Writing – original draft. **Miguel Jaller:** Supervision, Funding acquisition, Conceptualization, Formal analysis, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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