Annals of Operations Research (2024) 343:639–661
https://doi.org/10.1007/s10479-024-06249-1

ORIGINAL - SURVEY OR EXPOSITION

Challenges and opportunities in crowdsourced delivery planning and operations—an update

Martin Savelsbergh[1] · Marlin W. Ulmer[2]

Received: 22 April 2024 / Accepted: 22 August 2024 / Published online: 10 September 2024

Abstract

How to best deliver goods to consumers has been a logistics question since time immemorial. However, almost all traditional delivery models involved a form of company employees, whether employees of the company manufacturing the goods or whether employees of the company transporting the goods. With the growth of the gig economy, however, a new model not involving company employees has emerged: relying on crowdsourced delivery. Crowdsourced delivery involves enlisting individuals to deliver goods and interacting with these individuals using the internet. In crowdsourced delivery, the interaction with the individuals typically occurs through a platform. Importantly, the crowdsourced couriers are not employed by the platform and this has fundamentally changed the planning and execution of the delivery of goods: the delivery capacity is no longer under (full) control of the company managing the delivery. We present the challenges this introduces, review how the research community has proposed to handle some of these challenges, and elaborate on the challenges that have not yet been addressed. In this update, we expand the literature review and discuss new challenges that have emerged in the past years. (This is an updated version of the paper "Challenges and Opportunities in Crowdsourced Delivery Planning and Operations" that appeared in 4OR, 20(1), 1-21 (2022)).

Keywords Gig economy · Crowdsourced delivery · Urban logistics · Optimization · Uncertainty · Behavior

1 Introduction

Some of the most visible and impactful societal changes of the last decade are the rapid evolution of the shared and gig economy. Companies at the forefront of these changes are AirBNB and Uber. Their business models have fundamentally changed our society and the longer-term implications are still clouded in uncertainty (the legal challenges to the business model of Uber and Lyft are a good example). We focus on one aspect of the evolving gig economy: crowdsourced delivery. How to best deliver goods to consumers has been a logistics question since time immemorial. However, almost all traditional delivery models involved a

✉ Marlin W. Ulmer
marlin.ulmer@ovgu.de

1 Georgia Institute of Technology, Atlanta, USA

2 Otto-von-Guericke Universität Magdeburg, Magdeburg, Germany

form of company employees, whether employees of the company manufacturing the goods or whether employees of the company transporting the goods. With the growth of the gig economy, however, a new model not involving company employees has emerged: relying on crowdsourced delivery. The Oxford dictionary defines crowdsourcing as "the practice of obtaining information or input into a task or project by enlisting the services of a large number of people, either paid or unpaid, typically via the internet". Crowdsourced delivery, therefore, involves enlisting individuals to deliver goods and interacting with these individuals using the internet. In crowdsourced delivery, the interaction with the individuals typically occurs through a so-called platform. A prototypical example of such a platform is the one provided by Grubhub, which links restaurants, diners, and individuals willing to deliver meals from a restaurant to a diner.

In crowdsourced meal delivery, the platform handles everything from facilitating the ordering of meals, to the scheduling of the delivery of the meal, to the associated payments (collecting payments for meals, distributing payments to restaurants, and distributing payments to crowdsourced drivers). Importantly, the crowdsourced drivers are not employed by the platform or by the restaurants. So why our focus on crowdsourced delivery? The answer is simple, it has fundamentally changed the planning and execution of the delivery of goods: the delivery capacity is no longer under (full) control of the company managing the delivery. This implies that certain aspects of goods delivery that were simple and straightforward in the traditional model are no longer so simple and straightforward. For example, what if a good is damaged while it is being transported by a crowdsourced driver? Who is responsible? The manufacturing company? The crowsourced driver? The customer? Stakeholders, including insurance companies, have had to grapple (and are still grappling) with these aspects of the new delivery model. Our interest, of course, is not the legal side of the new delivery model, but the planning and execution side. How do you plan when delivery capacity is uncertain? How do you execute when delivery capacity is uncertain? How can you ensure that you meet your service promises to your customers? Does it make sense to rely on (only) crowdsourced delivery capacity? When does it make sense and what does this depend on? Etc. This is a set of questions that the transportation science and logistics community never had to consider in the past. This is not to say that the efficient and effective delivery of goods was always easy; it was not. But the fact that the available delivery capacity was fully under the control of the planners (as drivers were company employees) provided enormous advantages.

In our previous review, Savelsbergh and Ulmer (2022), we focused on the issue that differentiates crowdsourced from conventional delivery systems: not only is demand uncertain, but delivery capacity is also uncertain. We have categorized the literature and identified promising research gaps. In our updated version, we will refresh the literature, analyzing what research gaps were closed, which ones remain unaddressed, and what new gaps emerged in the meantime.

In crowdsourced delivery operations, there are tactical as well as operational questions related to crowdsourced delivery capacity. At the tactical level, it is how to ensure that the required delivery capacity is available. At the operational level, it is how to adjust delivery capacity if either the expected delivery capacity does not materialize or if demand is higher than expected at a particular point in time, but also how to handle crowdsourced drivers not accepting offered delivery tasks or crowdsourced drivers executing accepted delivery tasks in unexpected ways. We address these, and related, issues in the following sections. However, before doing so, we need to look, briefly, at the reasons companies are so interested in this new delivery model even though it creates uncertainty and adds complexity. Not surprisingly, the first reason is cost. Because crowdsourced drivers are not employed by the company, the company does not have to include benefits as part of a crowdsourced driver's compensation. The second reason is flexibility. In many industry sectors, delivery time preferences of customers vary significantly during an operating period, and crowdsourced delivery capacity can complement existing delivery capacity when needed. Meal delivery is an extreme example of this phenomenon. Diners want meals delivered around lunch and dinner time. Thus the delivery capacity required has two huge peaks during the day. The flexibility offered by crowdsourced drivers, often willing to work for short periods of time and at specific times, is one reason for the tremendous growth in meal delivery. Retailers, such as Walmart and The Home Depot, may not have considered offering same-day delivery if they could not rely on the inherent flexibility of crowdsourced delivery capacity. For many small businesses, the use of crowdsourced delivery is the only way to participate in the booming e-commerce sector (Solomon, 2023). See Punel et al. (2019) for a discussion on why consumers might even prefer to use crowdsourced delivery services.

Not surprisingly, during the pandemic home delivery has seen enormous growth (especially in the grocery and meal delivery sectors) and that growth is expected to continue (Keane, 2020; Pasquini, 2021; Shveda, 2021; Sugar, 2021). Therefore, the use of crowdsourced delivery will likely continue to rise as well.

The remainder of this review is organized as follows. In Sect. 2, we define more precisely what we mean by crowdsourced delivery, introduce the terminology we will use throughout this review, and discuss the growing body of literature in the area of crowdsourced delivery. In Sect. 3, we delve deeper into a few of the aspects that characterize crowdsourced delivery and present research opportunities for the OR community. In Sect. 4, we briefly mention topics that are of interest, but were not discussed in detail and provide some final remarks.

2 Crowdsourced delivery

In this review, we characterize crowdsourced delivery environments as environments in which (at least some of the) deliveries are made by individuals that are not employed by the entity responsible for the deliveries, but who offer their service, i.e., their time and their vehicle, to the entity to make deliveries. We refer to these individuals as *couriers* and to the entity responsible for the deliveries as the *platform*. Because the couriers are not employed by the platform, the use of couriers introduces uncertainty. There is uncertainty regarding the availability of couriers, e.g., when and how long couriers will be available to make deliveries, and there is uncertainty regarding the behavior of couriers, e.g., whether or not they will accept an offered delivery task, how they will execute an accepted delivery task, and what they will do after completing an accepted delivery task. The uncertainty related to the delivery capacity is what distinguishes crowdsourced delivery environments from traditional delivery environments. Therefore, the focus of this review is on the planning and operational challenges introduced by this uncertainty, and the different ways to deal with these challenges.

A natural and pragmatic way to deal with the uncertainty related to the capacity available to make deliveries is to try and reduce that uncertainty. This can be done by asking (some of the) couriers for a commitment, e.g., to be available to make deliveries for a certain period of time and/or to accept at least a certain number of offered delivery tasks, and rewarding couriers for such a commitment, e.g., by guaranteeing a minimum compensation. Determining a set of *blocks*, or periods of time, to offer to couriers for commitment, prior to, or even during, an operating period, is an example of a novel planning problem that arises in the context of crowdsourced delivery. This planning problem not only needs to take into account predicted or forecast demand, but also predicted or forecast availability of other delivery capacity, i.e., of non-committed couriers. Rather than seeking commitments of couriers (and rewarding couriers for such a commitment), another option is to rely on dynamically adjusting courier compensation in response to observed demand so as to increase and decrease the number of available couriers. When and how to adjust courier compensation to ensure enough delivery capacity is available to handle observed demand is an example of a novel operational problem in the context of crowdsourced deliveries. (Dynamically adjusting courier compensation can be complemented by dynamically adjusting delivery charges in order to increase or decrease demand.) Of course, a platform can use a variety of planning and operational strategies to manage delivery capacity.

In this paper, we use the following setting as the basis for our discussion of crowdsourced delivery. We assume that consumers place orders through a platform and that the platform is responsible for the delivery of the orders. An order is characterized by a pickup location, an available time, a drop-off location, and a due time. In practice, other order characteristics may be relevant as well, for example order size, but we will ignore these. The platform uses couriers to make the deliveries. We will distinguish two types of couriers: *committed* couriers and *occasional* couriers. A committed courier agrees with the platform to be available to perform deliveries for a certain period of time, i.e., with an agreed upon start and end time, whereas the availability of an occasional courier is uncertain, i.e., starts and ends at times convenient for the individual. Even though the time that a committed courier is available to make deliveries is known, there is still uncertainty related to the courier's behavior, e.g., the courier may not accept all delivery tasks offered and the courier may decide where to relocate to after completing the last accepted delivery task. We use the term *fully committed* courier to refer to a courier whose availability and behavior are both controlled by the platform. An employed driver can be viewed as a fully committed courier and so our discussion covers situations in which a company (represented as the platform) uses both company drivers and crowdsourced capacity to make deliveries. We assume the platform assigns orders to couriers, i.e., assigns the delivery task associated with an order to a courier, and that couriers either accept or reject assigned orders.

Other mechanisms, such as posting orders, i.e., delivery tasks, and couriers selecting from posted orders are possible and will be discussed later. The chosen setting suffices to highlight and elaborate some of the novel issues encountered in crowdsourced delivery. In some settings, the entity responsible for the deliveries may also be the entity selling the goods, e.g., a retailer providing home delivery from its stores. In other settings, the entity responsible for the deliveries may be different from the one selling the goods, e.g., a meal delivery platform does not prepare and sell meals to diners, the restaurants the platform represents do.

We focus on the planning and operational decisions made by the platform. More specifically, we focus on the planning and operational decisions related to managing delivery capacity to ensure orders are delivered on time, i.e., before their due time. These decisions include the conventional decisions of assigning orders to couriers and of routing the couriers to serve their assigned orders, but adapted to handle the aforementioned uncertainties. However, these decisions also include decisions that are unique to the crowdsourced delivery environment and focus on ensuring the availability of the delivery capacity: the scheduling of (fully) committed couriers prior to the service period (offline scheduling), the scheduling (or adding) of committed couriers during the service period—in case demand is higher than expected or the turnout of occasional couriers is low (online scheduling), and the dynamic adjusting of courier compensation, e.g., to increase the likelihood that an assignment is accepted or to increase the likelihood that occasional couriers enter or stay in the system.

There are many other activities the platform engages in, such as demand forecasting and demand smoothing, but as these have been studied extensively in more traditional contexts, we choose to focus on the novel aspects arising due to the presence of crowdsourced delivery capacity.

Finally, as crowdsourced delivery (at this point in time) occurs mostly in metropolitan areas, often in densely populated areas, the "vehicles" used to deliver orders vary more than in traditional delivery settings and can include bicycles, tricycles, regular automobiles, and small vans, which introduces additional complexity in planning and operations.

2.1 Literature overview

As indicated above, the most challenging and intriguing aspects of crowdsourced delivery relate to ensuring the availability and the managing of the delivery capacity. Consequently, we focus our literature review on papers that incorporate or acknowledge these aspects. There are many more papers that focus on the courier-order assignment, or the matching of supply and demand. For an excellent discussion of the literature on these aspects, as well as an overview of companies/platforms in this space, see Alnaggar et al. (2021).

We start by providing a concise overview of the relevant literature in the form of a table. Table 1 is divided into three sections. The first section indicates what type of couriers are considered, i.e., fully committed, committed, and/or occasional. The second section indicates the types of uncertainty explicitly considered in the model, i.e., courier availability and/or courier behavior (accepting or rejecting of offered deliver tasks and following of route guidance provided), and whether this uncertainty is considered in the decision making. Even though the availability of occasional couriers is by definition uncertain, when research focuses on or only analyzes realizations of arrivals and departures of occasional couriers for the entire operating period, this uncertainty is not explicitly considered (neither in the model nor in the method). Similarly, the behavior of occasional and committed couriers is by definition uncertain, but by assuming that all offered orders are accepted and that route guidance directions are followed, this uncertainty is not explicitly considered. The third section indicates the decisions considered, i.e., offline and online scheduling of committed couriers, compensation, matching, and/or routing. As the availability of committed couriers is determined by the platform, this implies the need for scheduling. The scheduling may be offline, i.e., committed courier availability decisions for the upcoming operating period are made in advance, or online, i.e., committed courier availability decisions are made during the operating period (in response to observed demand). Couriers are not employed by the platform, but expect compensation. Committed couriers, especially, expect something in return for agreeing to be available for a specific period of time. Dynamically adjusting compensation in response to observed demand can influence the availability of couriers as well as their order acceptance rate. As decisions regarding the delivery capacity required depend on how couriers are assigned to orders and how couriers are routed, we include these decisions as well in our overview.

2.2 Literature discussion

The first thing that jumps out at you when looking at Table 1 is that the number of check marks in many of the columns is rather small. For example, even though by (our) definition the availability of occasional couriers is uncertain, many papers assumes full knowledge about when and how long occasional couriers are available. Such papers usually analyze the value that occasional couriers might bring to the platform and, to this end, assume perfect

Table 1 Literature

Paper	Couriers			Uncertainty			Decisions				
	Fully committed	Committed	Occasional	Availability	Matching	Routing	Offline scheduling	Online scheduling	Compensation	Matching	Routing
Archetti et al. (2016)	✓		✓							✓	✓
Wang et al. (2016)			✓							✓	
Cheng et al. (2017)			✓			$\checkmark^{+}$				✓	✓
Kafle et al. (2017)	✓		✓	✓	✓					✓	✓
Behrend and Meisel (2018)			✓							✓	
Gdowska et al. (2018)	✓		✓		$\checkmark^{+}$					✓	✓
Arslan et al. (2019)	✓		✓	✓						✓	
Yildiz and Savelsbergh (2019)			✓	$\checkmark^{+}$	$\checkmark^{+}$				✓		
Mofidi and Pazour (2019)			✓		$\checkmark^{+}$					✓	
Dahle et al. (2019)	✓		✓						✓	✓	✓
Behrend et al. (2019)			✓							✓	✓
Guo et al. (2019)	✓		✓	✓						✓	
Allahviranloo and Baghestani (2019)			✓	✓	✓					✓	
Al Hla et al. (2019)	✓		✓			✓				✓	✓
Dai and Liu (2020)	✓	✓	✓				✓		✓	✓	✓
Macrina et al. (2020)	✓		✓							✓	✓
Chen et al. (2020)			✓	$\checkmark^{+}$						✓	
Cao et al. (2020)	✓		✓	$\checkmark^{+}$	$\checkmark^{+}$				✓	✓	✓
Skålnes et al. (2020)	✓		✓	$\checkmark^{+}$						✓	✓
Dayarian and Savelsbergh (2020)	✓		✓	$\checkmark^{+}$			✓			✓	✓
Lei et al. (2020)	✓		✓	$\checkmark^{+}$		✓		✓		✓	
Ulmer and Savelsbergh (2020)	✓		✓	$\checkmark^{+}$			✓			✓	✓
Ahamed et al. (2021)	✓		✓							✓	✓
Archetti et al. (2021)	✓		✓							✓	✓

Table 1 continued

Paper	Couriers			Uncertainty			Decisions				
	Fully committed	Committed	Occasional	Availability	Matching	Routing	Offline scheduling	Online scheduling	Compensation	Matching	Routing
Boysen et al. (2021)	✓		✓							✓	✓
Horner et al. (2021)			✓		✓+					✓	
Le et al. (2021)			✓						✓	✓	✓
Tao et al. (2021)	✓	✓	✓	✓						✓	✓
Yıldız (2021a)			✓	✓+						✓	
Yıldız (2021b)	✓		✓							✓	
Zhang et al. (2021)	✓		✓	✓		✓+				✓	✓
Zhen et al. (2021)			✓							✓	✓
Ausseil et al. (2022)			✓	✓	✓+					✓	
Mancini and Gansterer (2022)	✓		✓			✓+				✓	✓
Nieto-Isaza et al. (2022)			✓	✓+							
Santini et al. (2022)	✓		✓		✓+					✓	✓
Torres et al. (2022)	✓		✓			✓+				✓	✓
Alnaggar et al. (2023)			✓	✓+					✓	✓	✓
Barbosa et al. (2023)	✓		✓	✓	✓+					✓	✓
Behrendt et al. (2023a)	✓		✓	✓+	✓		✓			✓	✓
Çınar et al. (2023)			✓		✓+				✓	✓	
Di Puglia Pugliese et al. (2023)	✓		✓							✓	✓
Mancini et al. (2023)	✓		✓	✓	✓+					✓	✓
Silva et al. (2023)	✓		✓	✓+			✓			✓	✓
Simoni and Winkenbach (2023)	✓		✓	✓						✓	✓
Auad et al. (2024)	✓		✓	✓+	✓			✓		✓	✓
Ausseil et al. (2024)			✓	✓	✓+					✓	
Behrendt et al. (2024)	✓		✓	✓+	✓		✓		✓	✓	✓

A "✓+" in the Uncertainty-column indicates that the corresponding method considers the uncertainty explicitly when making decisions information. We further observe that the second aspect of uncertainty, i.e., courier behavior—in terms of accepting offered delivery tasks and in terms of following any route guidance provided for the delivery tasks, has been considered less, but interest is growing. In Gdowska et al. (2018) and in Yildiz and Savelsbergh (2019), it is uncertain if an occasional courier accepts an offered delivery task. In Kafle et al. (2017), Allahviranloo and Baghestani (2019), and Mancini et al. (2023), which consider an environment in which couriers bid on delivery tasks, the bids are assumed to be uncertain. Finally, in Mofidi and Pazour (2019); Horner et al. (2021), and Ausseil et al. (2022), couriers are offered a set of delivery tasks (rather than a single one) and it is uncertain which of these delivery tasks the courier selects, if any. In Santini et al. (2022), the likelihood of delivery task acceptance is integrated in a probabilistic orienteering problem to determine the delivery tasks to crowdsource. In Çınar et al. (2023); Behrendt et al. (2023b) and Behrendt et al. (2024), the likelihood of acceptance is coupled to the compensation. In Ausseil et al. (2024), acceptance probabilities depend on travel distance, restaurant characteristics, and expected tipping amount.

The number of papers that not only model uncertainty, but also present methodology to handle the uncertainty, has also increased recently. To anticipate the availability of couriers, reported approaches calculate the probability of future courier availability either based on historical data (Chen et al., 2020), via sampling/simulation (Skålnes et al., 2020; Dayarian & Savelsbergh, 2020; Yıldız, 2021a), using reinforcement learning (Ulmer & Savelsbergh, 2020; Behrendt et al., 2023a; Silva et al., 2023), or analytically (Yildiz & Savelsbergh, 2019; Lei et al., 2020; Nieto-Isaza et al., 2022). To anticipate the acceptance of offered delivery tasks, reported methods rely on two-stage programming (Gdowska et al., 2018; Çınar et al., 2023), use expected values (Mofidi & Pazour, 2019), employ sampling (Ausseil et al., 2022), apply reinforcement learning (Santini et al., 2022) or, again, approach the problem analytically (Yildiz & Savelsbergh, 2019). Uncertainty in routing (or following route guidance provided) is considered either by analyzing historical trajectories (Cheng et al., 2017), based on expected values (Zhang et al., 2021), or via two-stage stochastic programming (Torres et al., 2022).

Finally, we observe that the majority of papers focus on courier-order assignment and routing decisions (i.e., the traditional decisions considered in the vehicle routing field). Very few papers consider offline or online scheduling or compensation decisions. For offline scheduling, Dai and Liu (2020) and Dayarian and Savelsbergh (2020) determine full-time shifts for fully committed couriers, either based on perfect information or via enumeration. Ulmer and Savelsbergh (2020) and Behrendt et al. (2023a) use reinforcement learning to learn the number of fully committed couriers and their shifts. Behrendt et al. (2024) determines the number of couriers analytically. For online scheduling, Lei et al. (2020) explore proactively asking couriers to commit for a certain period of time, based on anticipated future demand, and considering whether or not and when a courier accepts a commitment request. Auad et al. (2024) propose reinforcement learning methods to dynamically increase the number of couriers based on realized and expected demand. Compensation strategies to attract new couriers are evaluated by Yildiz and Savelsbergh (2019), to ensure acceptance of courier-order assignments by Dahle et al. (2019); Çınar et al. (2023), to retain active couriers (i.e., ensure they remain active longer) by Dai and Liu (2020), and to deal with delivery task urgency by Cao et al. (2020).

Basically, Table 1 reveals that even among the papers that incorporate or acknowledge the challenges related to ensuring the availability of delivery capacity and the management of this delivery capacity, the focus is heavily biased to the courier-order assignment and courier routing decisions. Few papers address the scheduling (offline or online) and compensation decisions related to delivery capacity. In our view, this is a major shortcoming and we hope that highlighting this deficiency encourages more researchers to focus on these aspects in the future.

2.3 Other literature

Even though the time-scale and the specifics are different, ensuring the availability of capacity at the right time and in the right place, which is a fundamental aspect of crowdsourced delivery, has been a ongoing challenge in the truckload transportation sector and exhibits certain similarities to crowdsourced delivery.

The need to ensure the availability of transportation capacity in a dynamic and uncertain environment, which are characteristics of the truckload transportation sector, has led to the creation of electronic market places (or transportation exchanges), which provide a market for the procurement of truckload transportation services (Caplice, 2007; Lafkihi et al., 2019). Auctions are the predominant mechanism used for strategic procurement of truckload services (Figliozzi et al., 2007; Miller et al., 2020). Carriers can bid on several loads at the same time (so called package bids) to exploit consolidation effects. Almost all shippers make use of electronic spot markets for operational procurement, i.e., to acquire (additional) short-term capacity. Even companies with a private or dedicated fleet rely on the use of an electronic spot market to handle variations in order volume, either anticipated or unanticipated. Strategic procurement of truckload services has similarities to balancing committed courier capacity and occasional courier capacity (Tsai et al., 2011). As most (long-term) contracts between shippers and carriers allow carriers to reject (some) offered loads, the load acceptance decisions of carriers (Powell, 1987; Kim et al., 2004) can be viewed (with some imagination) as related to delivery task acceptance behavior of couriers.

Another critical cost component of truckload transportation is repositioning (Powell, 1996; Regan et al., 1996; Ergun et al., 2007), i.e., traveling from a drop-off location to a pickup location, as no revenue is generated during repositioning. The impact of repositioning on truckload transportation costs has similarities to the impact of courier location (after completing a delivery task) on crowdsourced delivery system performance. However, in crowdsourced delivery systems the primary challenge may not be deciding the repositioning of couriers given uncertain future demand, but anticipating or managing the (uncertain) repositioning behavior of the couriers.

3 Discussion and research opportunities

As we have seen in our review of the pertinent literature, research on ensuring and managing capacity as well as on how to best compensate couriers in crowdsourced delivery environments is still very limited, therefore, in the following, we discuss open questions and potential future research directions.

3.1 Ensuring delivery capacity

To be able to deliver orders on time, the platform must ensure that sufficient delivery capacity (i.e., couriers) is available. The platform can schedule committed couriers to try and achieve this. However, this is challenging for two reasons. First, demand is uncertain and varies over time, space, and from day to day. Second, the number of occasional couriers is uncertain and varies over time and space during the day, and from day to day, but not necessarily in sync with demand. Furthermore, while both demand and available number of occasional couriers can have somewhat predictable patterns (e.g., lunch and dinner peaks in meal delivery), they are affected by a variety of factors, such as prevailing weather conditions. When scheduling delivery capacity (i.e., scheduling committed couriers), the platform has to consider both the predictable pattern as well as the spontaneous unpredictable variations that can occur within the operating period.

Even though we will not elaborate on it, we want to mention that predicting the number of available occasional couriers (over time and space) is an interesting research topic in and of itself, and is starting to attract attention, see for example Shen and Lin (2020).

Offline Scheduling For predictable demand patterns, a platform can schedule committed couriers offline, i.e., before the start of the operating period. Some platforms schedule couriers with maximum-length blocks (e.g., eight-hour shifts) (Dai & Liu, 2020). However, research has shown that in most environments scheduling couriers with maximum-length blocks causes unnecessary costs during off-peak hours and unnecessary service quality loss during demand peaks (Ulmer & Savelsbergh, 2020). Thus, a platform is typically better off scheduling couriers with shorter block lengths. When scheduling committed couriers offline, several research questions arise. How many committed couriers are required at any time during the operating period? When should committed couriers start and how long should their blocks be? Answering these questions is non-trivial. First, observe that the number of required committed couriers at a particular time not only depends on the number of active orders (orders that are placed, but not yet assigned to a courier) but also on the number of active occasional couriers. Second, depending on the flexibility provided by the service time promises, there can be consolidation opportunities. If there is a large number of active orders, the average distance between orders is small and there might be opportunities to bundle orders with the same pickup location (i.e., have a courier pick up more than one order at a pickup location and then visit multiple drop-off locations).

But it is not just about ensuring that a sufficient number of committed couriers is available at any time of the operating period, it is equally important to ensure that these committed couriers are available in the right locations within the service area. For example, a downtown area with many deliveries may attract a sufficient number of occasional couriers while a suburb with few deliveries may not, see, e.g., Ermagun and Stathopoulos (2018). Thus, a platform also needs to consider *where* a committed courier should make deliveries. This can be done, for example, by partitioning the service area into regions and designate (committed) couriers to one or more of these regions, i.e., only delivery tasks in their designated regions will be assigned to couriers. However, strict enforcement of regions may be too limiting and it may be necessary at times to allow a courier to leave its designated regions for a short period of time to assist neighboring regions where the number of active orders (far) exceeds the number of available couriers.

Ensuring that delivery capacity is available at the right time *and* in the right location leads to several interesting tactical and operational questions. How should the service area be partitioned into regions so as to ensure effective service within each region and avoid the need for couriers to leave their designated regions to temporarily assist other regions? Effective service can be achieved more easily by making the regions small (when sufficient delivery capacity is available), while avoiding the need to assist neighboring regions can be achieved by making the regions large. How should committed couriers be distributed over the regions? Should there be free floating committed couriers that can be deployed throughout the service area as well as dedicated couriers serving only designated regions? When and how should a courier be allowed to assist neighboring regions? etc. Recently, Auad et al. (2023) proposed dynamic adaptions of delivery regions to balance service flexibility with courier satisfaction. Partitioning the service area into regions and having a courier operate only in one or more designated regions may not only increase courier satisfaction (Rai et al., 2021). As a courier becomes more familiar with the designated regions (e.g., parking options), the courier will become more efficient and, as a result, earn more and provide better service. Courier satisfaction is becoming increasingly important as different platforms compete for the services of the couriers.

Online Scheduling Offline scheduling seeks to ensure the right amount of committed capacity at the right based regular patterns in order placements and occasional courier arrivals. Of course, daily variations occur in the order placements and occasional courier arrivals. For example, the number of meals ordered depends on the weather; earlier than expected rain- or snowfall tends to lead to an increase in order placements (Marshall, 2020). The effect is the opposite for bike couriers; earlier than expected rain- or snowfall tends to decrease the number of occasional couriers showing up. Importantly, spontaneous, unpredictable changes in order placements and occasional courier arrivals are a fact of life. As a result, even the best planned offline schedule of committed couriers may sometimes be insufficient to ensure the desired on-time performance. In response to or in anticipation of deviations of order placements and occasional courier arrivals from the regular patterns, platforms therefore also schedule committed couriers online, during the operating period.

That is platforms may call or message registered but inactive couriers and encourage them to commit to newly created blocks with start times in the (very) near future. This is challenging because there is uncertainty about the number of couriers that is available to start at short notice (Lei et al., 2020). Some couriers may be able to start immediately, others may only be able to start after some time, and some may not be available at all. A decision has to be made regarding compensation. Does the platform rely on loyalty and anticipation of higher than average earnings when asking to commit, or does the platform offer increased compensation when starting on short notice? Alternatively, the platform may ask active committed couriers to extend their block. Again, there is the question of whether extending a block should impact the compensation or not.

As with offline scheduling, the platform needs to carefully plan how many additional blocks to create and of what length (and which of these blocks to “convert” to extended blocks). The platform may also introduce the concept of *on-call* couriers, which commit to be available when needed. Students, for example, may be willing and able to be on-call for a small fee. In Auad et al. (2024), the value of such on-call couriers is investigated for the first time. As with offline scheduling, it is important to ensure that any additional couriers will become available in the parts of the service area where they are most needed.

As the research of Auad et al. (2024) shows, if a platform partitions the service area into regions and has couriers serving in designated regions, it can be worthwhile to consider adjusting the region definitions dynamically in response to observed demand, e.g., increasing the size of a region with fewer than expected active orders and decreasing the size of a region with more than expected active orders. Alternatively, committed couriers might be re-assigned to other regions than planned.

While occasional couriers are often incentivized using compensation, alternative, softer control mechanisms might be considered, e.g., providing couriers with information about (local) earning potential. In this context, the recently suggested demand *heatmaps* are relevant (Alnaggar, 2021; Haferkamp et al., 2024). Such heatmaps must be designed carefully to anticipate current and expected future demand as well as current and future courier movements. Consequently, Alnaggar (2021) and Haferkamp et al. (2024) propose data-driven learning procedures. While such information can improve online scheduling, the platform has to be aware of the strategic behavior of the couriers (i.e., the possibility of trying to "game" the system). For example, if couriers know or learn that in situations of insufficient delivery capacity, compensation increases, they may not disclose their availability until the platform raises the compensation. A platform may hedge against such behavior by offering bonuses for reliable couriers, i.e., couriers being regularly available (at certain times during the operating period).

Finally, an important trade-off worth investigating: the balance between offline and online scheduling, i.e., the reliance on planned delivery capacity and on-demand delivery capacity (Lechtape, 2017). Planned delivery capacity provides service reliability, but is costly in situations when demand is less than expected. Relying more on on-demand delivery capacity can reduce cost, but may also result in a drop in on-time performance and dissatisfied customers (and in a meal delivery environment, unhappy restaurants as well), see e.g., Boysen et al. (2020).

3.2 Managing capacity

How to ensure sufficient delivery capacity is only the first challenge a platform faces; how to manage available delivery capacity brings its own challenges. Because couriers are not employed by the platform, the platform may be unable to control the behavior of committed and occasional couriers. Couriers may, for example, reject offered delivery tasks or deviate from route guidance and/or repositioning suggestions.

courier-order assignments As the literature review revealed, the majority of the research carried out to date assumes that couriers' acceptance of offered delivery tasks is deterministic; even when couriers do not accept all offered delivery tasks, their behavior is generally assumed known. For example, it is assumed that occasional couriers deviate only a maximum distance from their planned route (Arslan et al., 2019). In reality, however, courier delivery task acceptance behavior is unknown, courier-dependent, and impacted by a variety of factors, such as the delivery location, the (expected) tip, the earnings so far, the weather, or, in the case of couriers on bicycles, even the slope of the roads to the delivery location.

Couriers rejecting an offered delivery task has many undesirable consequences. Rejected delivery tasks will remain in the system and the associated order experiences delay. In the worst case, if a delivery task is rejected more than once, the associated order is delivered late. Furthermore, because courier-order assignments are made holistically, i.e., considering all couriers and all orders simultaneously, a rejected delivery task may mean the other courier-order assignments may no longer be best possible. At the same time, a courier may be unhappy because, from the courier's point of view, the courier was offered an undesirable delivery task, which, in turn, may impact the courier's future delivery task acceptance behavior.

Figure 1 presents a simple courier-order—assignment instance, which we will use to illustrate some of the challenges encountered in crowdsourced delivery environments. There are two occasional couriers O_1 and O_2, a fully committed courier F, and two delivery tasks with pickup locations P_1 and P_2, respectively (see Fig. 1a). If all courier-order assignments are accepted, then a suitable, travel time minimizing courier-order assignment is shown in Fig. 1b. Courier O_1 is assigned to the delivery task with pickup location P_1 and courier F is assigned to the delivery task with pickup location P_2. However, if, for some reason, courier O_1 rejects the offered delivery task, we end up in an unfortunate, inflexible state; finding a courier for the delivery task with pickup location P_1 becomes a challenge, and, at the same time, courier O_2 is "stranded" and underutilized. Other, more robust, courier-order assignments are shown in Fig. 1c and d. These courier-order assignments hedge against delivery

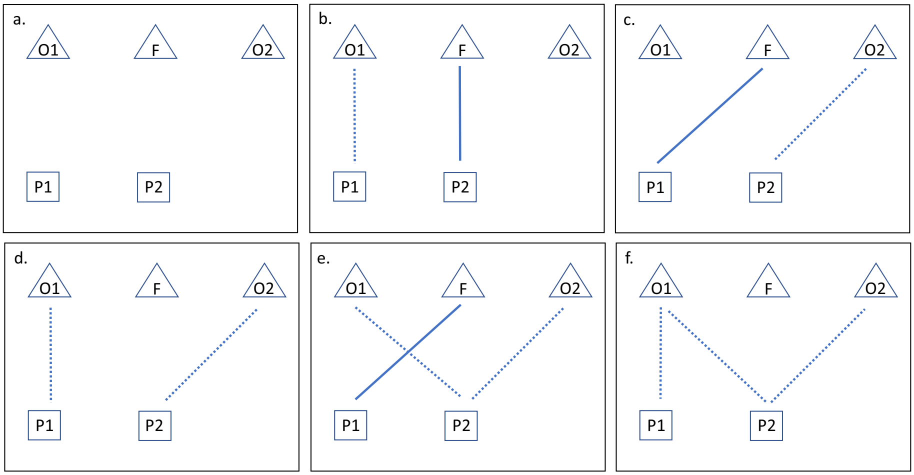

Fig. 1 Examples for courier-order assignment decisions/offers

task acceptance uncertainty as they result in situations that are more likely or even guaranteed to have successful courier-order assignments.

To incorporate acceptance behavior in courier-order assignment decisions, several challenges arise: (1) understanding the acceptance behavior, (2) modeling the acceptance behavior, and (3) embedding acceptance behavior models in courier-order assignment decision models. In the literature, courier acceptance behavior has so far been modeled as a random variable with a Bernoulli distribution, e.g., (Yildiz & Savelsbergh, 2019; Mofidi & Pazour, 2019; Le et al., 2019) – where in the latter two the probability depends on the deviation from the planned route. In practice, there can be many reasons for rejecting a delivery task offer and capturing them may require more detailed and involved models (possibly a learned behavior model). Relevant questions to be answered include: What are characteristics of delivery tasks that are rejected? Are delivery tasks with tight service promised more likely to be rejected? Are delivery tasks involving heavy items more likely to be rejected? Are delivery tasks with a drop-off location far away from a potential next pickup location more likely to be rejected? Are delivery tasks with a pickup location where it is difficult to park more likely to be rejected? Does it depend on the time of day? Does it depend on length of time a courier has already active? Does it depend on the (expected) tip? Etc. Recently, Barbosa et al. (2023) presented machine learning methods to predict acceptance probabilities for delivery tasks.

Research on modeling delivery task acceptance behavior can focus on general and individual aspects. It has been observed that meal delivery tasks with drop-off locations in the downtown area of a city are more likely to be accepted than others, because couriers expect that subsequent delivery tasks will require little repositioning (Ermagun et al., 2020b). The expected repositioning time after the completion of a delivery task is an example of a general aspect that may impact acceptance behavior. Individual aspects that may impact acceptance behavior include the familiarity with a particular area of the city or a preference for staying with their own neighborhood (Rai et al., 2021). Even the motivation for being a courier, e.g., to make money or to work out (bike courier), may affect the delivery task acceptance behavior. Consequently, it may be possible to learn a courier's delivery task acceptance behavior from past decisions. In a first approach to do so, Ausseil et al. (2024) shows that learning individually preferences can be quite valuable. Future work may explicitly explore the preferences of the couriers, e.g., by occasionally offering less desirable assignments to gain additional information of the courier's preferences.

When the delivery task acceptance behavior of couriers is known and captured in a courier acceptance behavior model, it should be embedded in the courier-order assignment technology. Initial attempts to do so include Yildiz and Savelsbergh (2019), in which the acceptance behavior is used to compute the expected revenue of an assignment, and Gdowska et al. (2018), in which potential acceptance decisions are sampled and assignment decision are based on the resulting scenarios. However, much more can and should be investigated. The optimal mix of committed and occasional couriers may change when their acceptance behavior is considered as they are likely different (especially if part of the commitment relates to the acceptance of offered delivery tasks). The optimal courier-order assignments may also change. For example, committed couriers might be preferred when assigning critical and/or less desirable delivery tasks or (some) committed couriers might be kept in reserve to assign to delivery tasks that are rejected by occasional couriers (as shown in Fig. 1d). The spatial distribution of committed and occasional couriers over the service area may be relevant. It may not be desirable to have only occasional couriers in one part of the service area and only committed couriers in another part of the service area. The courier-order assignment models developed so far recommend a particular courier for a given delivery task. It may be worth considering models that recommend more than one courier for a delivery task and offer the delivery task to all of them simultaneously to increase the chance that it will be accepted (as shown in Fig. 1e). Of course, such an approach also requires processes to handle situations where more than one courier accepts the delivery task.

In our basic setting, inspired by meal delivery environments, we assume that the platform offers a delivery task to each courier, i.e., a push model. Alternatively, the available delivery tasks can be posted, bulletin board style, and the couriers can select (or bid for) their preferred delivery task, i.e., a pull model. Even a mix of the two is possible, see Allahviranloo and Baghestani (2019). Another variation is to offer each courier a courier-specific menu of delivery tasks to choose from (Mofidi & Pazour, 2019; Ausseil et al., 2022) (as shown in Fig. 1f). Offering multiple delivery tasks to couriers increases the likelihood a courier will accept a delivery task. However, offering multiple delivery tasks to choose from may lead to assignments that are less desirable than a well-planned pushed courier-order assignment. Couriers may, for example, all select delivery tasks with a drop-off location in the city center, but none in less desirable suburban areas. Adjusting compensation, to be discussed later in this section, can also be used to influence delivery task acceptance behavior. Finally, a platform may decide to offer a bundle of delivery tasks to couriers, e.g., delivery tasks with the same pickup location and ready times and drop-off locations that are near each other (Mancini & Gansterer, 2022; Mancini et al., 2023). A bundle of delivery tasks may be attractive to a courier as it likely provides higher earnings per unit time. The platform may consider bundling desirable and less desirable delivery tasks in order to implicitly increase courier delivery task acceptance. However, delivery task bundles are no panacea for dealing with courier delivery task acceptance behavior. Creating the right bundles at the right time and offering them to the right couriers is extremely challenging. Even though a delivery task differs substantially from a truckload transportation service, the workings of electronic spot markets (Miller et al., 2020) and auction-based systems (Figliozzi et al., 2007), in which the success of package bids is also uncertain, may provide useful ideas and insights.

In practice, there are other factors that complicate the courier-order assignment process. Couriers may not respond immediately to offered delivery tasks, e.g., because communications have been lost, because they are driving, because they are taking a short break, or simply because they are evaluating the offer. Thus, the status of some delivery tasks may be uncertain when the next set of courier-order assignments are made. There will be deviations from the time a delivery task is expected to take, for example due to unfamiliarity with the drop-off location or the delivery process itself in case the courier is new (Ermagun & Stathopoulos, 2020). It has been observed that the importance of on-time performance and trust issues with crowdsourced delivery depend on the value of the order (Punel & Stathopoulos, 2017). Thus, the value of an order may be another consideration when making courier-order assignments and, possibly, to prefer (fully) committed couriers for the delivery tasks of more valuable orders. The situation gets even more complicated when customers do not want to entrust crowdsourced couriers with their order (Punel et al., 2018). Finally, having a less sophisticated, but transparent and easy to understand courier – order assignment mechanism can increase couriers' willingness to participate and, in the long run, system performance (Möhlmann & Henfridsson, 2019).

Routing and Repositioning The routing and repositioning behavior of couriers is also uncertain, i.e., route guidance and repositioning recommendations may be ignored. Especially bike couriers may use routes that are different from what is expected and may travel at speeds that are different from what is expected. In some cases, bike couriers may even sequence stops differently, e.g., to consolidate orders or to avoid biking through high-traffic areas. This leads to uncertainty about the time it takes to perform a delivery task and can impact service quality and operational decision making (as it is uncertain when a courier will be available for a next assignment).

Uncertainty about the time it takes to perform a delivery task can be problematic when delivery times are communicated to the customers, or when delivery time promises are very tight. Uncertainty about when and where couriers will become available for their next assignment may lead to ineffective courier-order assignments and may lead to an unbalanced distribution of couriers (i.e., couriers be in the wrong location at the wrong time).

A first step towards addressing routing and repositioning uncertainty is obtaining a better understanding of courier behavior (Cheng et al., 2017; Zhang et al., 2021). Not surprisingly, it has been observed that couriers have a tendency to reposition towards areas that are perceived to have higher earning potential, i.e., areas with a higher density of pickup locations (Ermagun & Stathopoulos, 2018). On the other hand, couriers also prefer to be in familiar areas, e.g., their own neighborhood (Rai et al., 2021).

The above suggests that it may be of interest to explore courier-order assignment technology that is aware of a courier's observed/learned routing behavior. Furthermore, even though we mentioned repositioning recommendations at the start of this section, we are not aware of research that has investigated the benefits of repositioning recommendations or how to best expand courier-order assignment models to incorporate repositioning recommendations. As with delivery task acceptance behavior, adjusting compensation may be used to influence routing and repositioning behavior.

As mentioned earlier, crowdsourced delivery (at this point in time) occurs mostly in metropolitan areas, often densely populated areas. This implies that courier familiarity with an area can have substantial efficiency benefits (e.g., knowledge of where to park, or what streets to avoid at certain times of the day). Area familiarity not only benefits the platform, as it can increase on-time performance and the customer experience, but also benefits the courier, as it can increase earnings. Incorporating hard-to-quantify aspects such as familiarity into courier-order assignment is another research avenue with high-impact potential.

Finally, there is an increasing tendency of couriers to indicate their availability to multiple platforms simultaneously (Soper, 2020), goods delivery as well as passenger transportation platforms (Cleophas et al., 2019). How to best recognize and accommodate this behavior in courier-order assignment decisions is yet another possible research direction.

3.3 Compensation

Next, we supplement and complement the above discussion with an exploration of the (potential) role of market mechanisms in the crowdsourced delivery environment. For convenience, we use compensation to refer to what couriers receive from the platform and we use pricing to refer to what customers have to pay to the platform. The importance of market mechanisms, e.g., compensation schemes, is highlighted in Ermagun et al. (2020a) and Archetti and Bertazzi (2021); the former finding that "pricing [compensation] is the variable with the highest potential to increase delivery probability followed by the timing of the request".

The typical compensation for an occasional courier has two components: (1) a payment for performing a delivery task, a per-task payment, and (2) a payment that is a function of the distance between the pickup location and the delivery location, a per-mile payment. Observe that the per-mile payment does not cover the cost of traveling to the pickup location. Although this is a simple and easy to understand compensation scheme, it may have unintended consequences in terms of courier behavior. As a courier has to pay for any travel between consecutive delivery tasks, a courier may decide to reject delivery tasks with a pickup location far away from the courier's current location or with a delivery location far away from potential future pickup locations. Even though expressed in terms of distances, a courier may base its delivery task accept or reject decision on time considerations rather than distance considerations. In meal-delivery settings, where the pickup locations are restaurants and the delivery locations are home addresses, couriers may therefore prefer to provide their service in densely populated areas with many restaurants rather than sparsely populated areas with few restaurants. Meal delivery platforms using this compensation scheme have indeed observed what is sometimes referred to as "courier drainage", i.e., sparsely populated areas with few restaurants loosing couriers to densely populated areas with many restaurants.

A third compensation component is the tip, i.e., money paid by the customer to the courier for performing the delivery task. Often a tip amount is specified when a customer places an order. The platform does not directly benefit from the tip, as they simply includes the tip in the compensation of the courier, but it may use it to their advantage in their decision making. Couriers are more likely to accept an offered delivery task (or select an available delivery task in case a bulletin board system is used) when the tip amount in the compensation is large (regression analysis on historic delivery task offer response data from a large meal delivery platform shows that the tip amount is an important predictor) and this knowledge may guide/influence courier-order assignment decisions.

To convince couriers to commit to be available for a certain period of time to perform deliveries, i.e., sign up for a block, the platform has to offer something beyond the standard compensation, see, e.g., Moss (2020). As occasional couriers are not compensated for the time between performing consecutive delivery tasks, one option is to guarantee a minimum per-hour payment. The design of an effective compensation scheme for committed couriers is non-trivial. The design needs to take into account, among others, offerings of potential competitors for the services of the couriers, the average per-hour compensation of occasional couriers (based on the average number of delivery tasks performed per hour), and the average delivery task acceptance rate of occasional couriers. Other aspects that need to be given thought to are whether the compensation should be different for different blocks (i.e., in terms of block start time and/or block length), e.g., whether the minimum per-hour payment guarantee for longer blocks should be higher than for shorter blocks. Due to the similarities, a closer look at contract design for freight delivery (Tsai et al., 2011) might be informative. Further, although the primary commitment the platform seeks from the courier is being available for a specific period of time, the platform may also seek commitment in terms of courier behavior, e.g., at most one offered delivery task can be rejected per hour or accepting repositioning suggestions (after completing a delivery task).

Recently, Alnaggar et al. (2023) analyzed different compensation schemes that includes a minimum per-hour payment guarantee. This introduces novel and interesting challenges in the (operational) courier-order assignment problem as it may be preferable to assign an order to a committed courier, so as to avoid paying the minimum required payment, rather than an occasional courier in a better position to perform an order. Ideally, from the platform's perspective, the compensation of a committed courier should be the same as that of an occasional courier (i.e., the number of delivery tasks performed should determine the actual compensation and not the minimum pay guarantee). Another aspect of compensation, especially pertinent to settings in which couriers select delivery tasks from a bulletin board, is whether or not to increase the compensation for a delivery task as a function of the time remaining to the due time of the associated order, and, if so, how to do this. Would it sometimes be worth to increase the compensation even beyond the price a customer pays for the delivery (to capture intangibles such as the value of repeat business)? However, also in settings with committed couriers questions regarding dynamically adjusting compensation, even possibly the minimum per-hour payment guarantee, are relevant. Whenever observed demand is higher than predicted/forecast and the available delivery capacity is likely to be insufficient to maintain the desired service level, the platform has to try and increase the delivery capacity. Increasing compensation is one option. However, this has to be done with care to avoid "gaming" by couriers. If couriers observe or even sense that they might be better off as an occasional courier in times of uncertain/high demand, they may no longer sign up for blocks.

We, knowingly and purposely, will not discuss dynamically adjusting prices for deliveries. Even though consumers have accepted dynamic pricing of personal transportation (e.g., the surge pricing employed by Uber and Lyft), consumers have proven to be reluctant to accept dynamic pricing for the delivery of goods (in part, because Amazon has stayed away from dynamic pricing of their delivery offerings). Furthermore, in a crowdsourced delivery environment, we are typically dealing with a 3-sided market (retailers, customers, couriers) as opposed to the 2-sided market (customers, drivers) seen in the personal transportation space. Whereas in the 2-sided market the price the customer pays is for the transportation, in the 3-sided market the price the customer pays is for the goods (the primary reason for the transaction) as well as for the delivery (a service providing convenience).

3.4 What is new?

While much of the early research focused on delivery by crowdsourced couriers from stores to customers, in recent years, the focus has expanded. How is the order assembled? How is service quality ensured? What happens if the customers are not at home to receive their goods? Dayarian and Pazour (2022) proposes crowdsourced order picking by in-store customers who may or may not perform the actual delivery. Further, with potentially several stores relying on the same delivery platform, individual pickup of parcels in stores might be inefficient (Ackva

& Ulmer, 2023). Micro-hubs where deliveries can be temporarily stored and where couriers can pick up bundles of orders for delivery (Voigt & Kuhn, 2022; Mousavi et al., 2022; Wang et al., 2023a) may provide a better option. But even when picking and bundling are done efficiently, a successful delivery requires finding the customer's address and the customer being there to receive. These aspects are critical, but little research has considered them. A novel way to avoid incomplete or missed deliveries is "crowdkeeping" where individuals, for a small compensation, act as an always-available delivery point (Wang et al., 2024).

4 Final remarks

In this review, we have focused on what we believe is the main feature that distinguishes crowdsourced delivery from traditional delivery: uncertain delivery capacity, in terms of both availability and behavior. As such crowdsourced delivery may provide a fantastic opportunity to progress research on how to best integrate behavioral aspects into optimization-based decision making (e.g., using a discrete choice model or a machine learning model). This is a research area that is still in its infancy, but with a huge potential for practical impact.

Another area of research that we believe still offers many opportunities and challenges is service area sizing. There is a trade-off between the additional demand a larger service area may generate and the additional cost incurred by serving that demand. The use of crowdsourced delivery and tight service time promises substantially complicates the trade-off analysis (as does time-varying demand as seen in meal delivery environments).

We mentioned earlier that dynamically adjusting delivery prices may not (yet) be a realistic option for a platform to manage a mismatch between order volume and delivery capacity. However, in the data-rich environments we are considering, a platform has other options. Specifically, the platform can employ information on the location of its couriers. In the meal delivery environment, for example, the platform can influence delivery efficiency (and, thus, average order processing time) by adjusting the order in which restaurants are displayed in their app. Many of the diners ordering a pizza do not mind ordering it from a pizzeria with many nearby couriers (as opposed to a pizzeria with no nearby couriers). Thus, the platform can favor pizzerias with many nearby couriers when it orders the pizzerias to be displayed in their app. This has advantages for diners and couriers. Couriers have to reposition only a short distance, and diners will receive their order quickly. If changing the order in which restaurants are displayed in the app cannot be altered, then it may be possible to suggest a more favorable alternative when a diner selects a restaurant. An alternative that is more favorable for the platform, in most cases, is likely more favorable for the diner as well as it likely means a faster delivery. However, it may also lead to unequal service opportunities for participating restaurants. While optimal use of screen space for product display (or display of advertisements) is a well-known topic in marketing, optimal use of screen space to facilitate efficient delivery of goods has not been studied by the transportation and logistics community.

Because couriers are not employed by the platform, couriers can offer (and in practice are offering) their service to multiple platforms simultaneously. This is another reason why platforms offer rewards for committing to be available to make deliveries for the platform for a period of time. Other techniques the platform can use to create "loyalty" is introduce benefits that rely on completing a certain number of deliveries for the platform during a longer period, e.g., a bonus when a certain number of deliveries are performed in a month. Again, how to design and implement effective loyalty schemes in the crowdsourced delivery environment is an area that has received little or no attention so far.

The original version of our review of crowdsourced delivery planning and operations highlighted many of its challenges and opportunities as well as research needs in this area. Some of the identified research gaps have significantly shrunk, others remain, e.g., the need for an end-to-end view of the fulfillment process from order picking, to the handover to couriers, to the actual delivery. Without such an end-to-end view of the fulfillment process, quality and effectiveness will suffer and customers may look for alternatives. Crowdsourced delivery platforms must also be aware (as do all online platforms) of the risk of "enshittification" (Zimmer & Sutton, 2024), a stepwise decline of service quality and customer trust, e.g, due to poor handling of the deliveries or due to false courier identities (Lee & Bitter, 2023). As recent research has shown, issues of trust and privacy have become increasingly important (Wang et al., 2023b) and an impeccable service quality is essential for customer loyalty (Yuen et al., 2023).

Funding Open Access funding enabled and organized by Projekt DEAL. Marlin Ulmer's work is funded by the DFG Emmy Noether Programme, project 444657906. We gratefully acknowledge their support.

Declarations

Conflict of interest Martin Savelsbergh declares that he has no Conflict of interest. Marlin Ulmer declares that he has no Conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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