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Crowd-shipping delivery performance from bidding to delivering

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ABSTRACT

Crowd-shipping is an innovative delivery model using digital platforms to match the demand for shipments with supply using excess transport capacity and drivers from the crowd. This sharing economy delivery concept has attracted growing attention to address the pressing challenges of urban goods deliveries. Little is known about the actual performance of crowd-shipping platforms due to limited data-availability and operational transparency. A particular challenge is that part of the delivery outcome is determined in the platform's digital space related to bidding and matching of supply and demand, followed by a real-world delivery operation, typically carried out by non-expert couriers. This paper provides the first comprehensive analysis of the entire crowd-shipping process from the bidding stage, through shipment acceptance, pickup, and final delivery. Using parametric hazard modeling applied to a unique U.S. national database of 16,850 crowd-shipping delivery instances, we examine which factors play a role in each phase of the delivery process. The findings illustrate that shipping requests and packages, built environment, and socioeconomic characteristics have a variable impact on each delivery stage. In particular, posting in the morning or evening hours and for business-to-consumer shipments significantly accelerates the digital phase, but has no effects on the final delivery phase. Moreover, the results reveal that performance loss occurs non-uniformly in the platform process, with a more significant loss in delivery rates related to the digital posting and bidding. A more substantial loss of delivery speed performance occurs in converting from digital to real delivery in negotiating the pickup arrangement. Crowd-shipping companies will benefit from the research to improve the management of their peer-to-peer-based mechanism.

1. Introduction

In recent years, urban goods distribution is increasingly under pressure from the expanding volume of online purchases and growing customer expectations on delivery performance (Macharis & Kin, 2017; Savelsbergh & Van Woensel, 2016). In this highly competitive setting, the ubiquity of communication technologies, accessibility of information, the flexibility of resources in time and space, and the open-source revolution has facilitated the evolution of crowd-shipping initiatives (Macharis & Kin, 2017). Crowd-shipping is an asset-light business model wherein the infrastructure of warehouses, vehicle fleets, and employed drivers are substituted for communication technologies and the use of on-demand resources from the crowd (Carbone, Rouquet, & Roussat, 2015; Mladenow, Bauer, & Strauss, 2016). In a typical arrangement, the crowd-shipping platforms operate in five steps: (1) Publication: the service requester publishes a delivery order on the crowd-shipping platform, (2) Bidding: registered crowd couriers make offers to deliver the package, (3) Accepting: the service requester selects one of the couriers, providing bids are received, (4) Picking-up: the requester and selected courier arranges a time to pick up the package, and (5) Delivering: the selected courier delivers the package.

Crowd-shipping offers potential advantages for different stakeholders. The pool of potential drivers, which represents the crowd resources, can benefit from flexible earning opportunities (Rougès & Montreuil, 2014) along with opportunities to connect and empower communities with new employment and delivery solutions (Carbone et al., 2015). Customers benefit from faster or more affordable delivery (Arslan, Agatz, Kroon, & Zuidwijk, 2016; Chen, Mes, & Schutten, 2017; Mladenow et al., 2016), personalization, and access to new products (Rougès & Montreuil, 2014). For businesses, the benefits include a reduction in delivery costs, operating costs, and a need to balance inventory in stock among retail stores, which is linked to an asset-light and flexible business model with an ability to reach a large service area (Carbone et al., 2015). The potential gains for society include minimizing the environmental footprint, minimizingtraffic congestion, and helping communities harness otherwise idle logistical resources (Chen,

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Pan, Wang, & Zhong, 2017; McKinnon, Browne, Whiteing, & Piecyk, 2015; Mladenow et al., 2016; Paloheimo, Lettenmeier, & Waris, 2016).

As crowd-shipping business models increasingly penetrate the market, researchers have tackled the analysis of crowd-sourced platforms from the three perspectives of *supply* (Dablanc et al., 2017; Fatnassi, Chaouachi, & Klibi, 2015), *demand* (Devari, Nikolaev, & He, 2017; Ermagun, Shamshiripour, & Stathopoulos, 2019; Ermagun & Stathopoulos, 2018; Le & Ukkusuri, 2019a; Punel, Ermagun, & Stathopoulos, 2018), and *operations* (Archetti, Savelsbergh, & Speranza, 2016; Chen, Pan, et al., 2017; Kafle, Zou, & Lin, 2017; Wang, Zhang, Liu, Shen, & Lee, 2016). Le, Stathopoulos, Van Woensel, and Ukkusuri (2019) conducted a comprehensive literature review on current practice, research, and empirical crowd-shipping case studies in areas of demand, supply, and operations. The knowledge of the fundamental functioning and levers for improving crowd-shipping is still rudimentary. One notable gap is the connection between operational and supply-demand analysis in managerial insights. While Rougès and Montreuil (2014) and Carbone, Rouquet, and Roussat (2017) have used case-studies to identify business models, there is a significant variation in the customer base (P2P to C2C), operational scope (last mile to international), and models of matching, pricing, and operations. Across the crowd-sourced models, several areas of tension can be highlighted. First, the role of the crowd-shipping *customer* is increasingly active (Carbone et al., 2017), and research suggests that crowd-shipping operators need to emphasize platform usability, system performance, as well as building trust in the system (Frehe, Mehmann, & Teuteberg, 2017; Buldeo Rai, Verlinde, Merckx, & Macharis, 2018; Ermagun, Punel, & Stathopoulos, 2020). Yet, crowd-shipping operators have limited guidance on the significant value, or loss, related to the platform functionality and performance to build a customer base. Second, each crowd-shipping system has a mechanism for spatio-temporal matching between the sender's location requests and courier's location and routes (Buldeo Rai et al., 2018). Despite the initial analysis of driver (Le & Ukkusuri, 2019b; Miller, Nie, & Stathopoulos, 2017) and sender behavior (Punel, Ermagun, & Stathopoulos, 2018), general matching performance, especially the differences between virtual matching on the platform, and the challenges of real-world delivery coordination for pickup and delivery is poorly understood. Third, a common theme across this new breed of shipping platforms is the reliance on the crowd. There is still limited understanding of the role of peer-to-peer operations in crowd-shipping, for example, successful deliveries rely on pickup and shipping operations being carried out by non-expert couriers.

In brief, business management to improve operations and delivery performance in this new breed of shipping companies faces unique challenges. Specifically, the crowd-shipping business models need to manage peer-to-peer interactions, and carry out matching of compatible supply and demand trajectories for goods that range from the digital space of the platform into real-world operations. Unlike traditional logistics, the success requires companies to master both management of the online platforms and the physical delivery all carried out by ad-hoc resources and often coordinated by peer-to-peer interactions. In this research we therefore study the entire shipping process and break down the logistical operations into four stages, namely bidding, accepting, picking-up, and delivering. In addition, rather than focusing merely on the rate of successful outcomes at each stage, we examine the time intervals between delivery stages, which provides a more apt measure of the performance of a peer-to-peer shipping platform. The critical focus on *durations* is motivated by the evolving consumer expectations of expedited logistics processes that are more challenging to meet when using crowd resources.

The goal is to model and evaluate the performance of the crowd-shipping delivery mechanism. We contribute to the newly emerging literature on crowd-shipping in three ways. First, we empirically assess the delivery performance by employing a national data set consisting of 16,850 delivery requests across the United States throughout the two-year period between January 2015 and December 2016. Second, we develop a number of parametric duration models to examine the time-to-event performance for each delivery stage (bidding, accepting, pickup, and delivery time intervals) and analyze a range of factors that impact the performance of the crowd-shipping system, grouped as (1) shipping request and package, (2) built environment, and (3) socioeconomic characteristics. Third, we identify the main factors and related interventions to improve the performance of future crowd-shipping systems. Our analysis is complementary to the performance assessments established in previous research using the same dataset. Three earlier studies examine, respectively, shipping requests and packages, built environment, and socioeconomic factors that impact the probability of successful bidding, accepting, and delivery outcomes. None of these works examine the time-to-event performance, nor emphasize the specific performance or determinants for each delivery stage.

The remainder of the paper is organized as follows. First, we discuss the data used for the analysis along with the complementary data sources used to augment the crowd-shipping data. Second, we present descriptive statistics and a functional description of the crowd-shipping delivery mechanism from bidding to delivery. Third, we discuss the methodology used to analyze the delivery mechanism and the modeling approach. Fourth, we represent the results of the parametric duration models along with reporting the acceleration factors and odds ratios. Fifth, we analyze and discuss the results and elaborate on the influential factors of the delivery time performance. Sixth, we provide managerial insights related to three critical aspects of performance loss, phase interdependence, and service tailoring. Finally, we conclude by summarizing the key findings and making a number of recommendations for strategic planning.

2. Crowd-shipping data: a real-world example

We obtained the data of the package delivery process on 16,850 requests for the period of January 2015 through December 2016, from one of the leading crowd-shipping companies in the United States. The entire crowd-shipping package delivery process consists of five consecutive steps:

- **Step 1:** The client (either a private customer or a retailer representative) posts a delivery request on the crowd-shipping platform, which details the shipping and package characteristics and requirements.
- **Step 2:** The posted delivery request becomes visible on the platform system and all registered couriers within a specified geographic range can begin communicating with the customer and bidding. The bidding is related to pick up arrangements such as flexibility or timing, and does not include shipment pricing which is determined by the platform using a size and distance-based formula. This makes up the bidding phase in our modeling, namely from posting to receiving a first bid from a driver.
- **Step 3:** The client can then decide to "accept" or "decline" the courier offers, representing the accepting phase (i.e. from the first bid to acceptance of a driver). If no courier is selected, the request is cancelled by the system.
- **Step 4:** The accepted delivery order enters into its picking up phase (from acceptance to pick up) where the timing and location specifics are negotiated.
- **Step 5**: The last is delivering phase by the courier (from pickup to delivery), while the service requester is able to track the shipment.

The company provides an app-based platform to connect service requesters with couriers in all 50 states and the District of Columbia. By the end of 2016, the platform had 203,419 registered users in 2070 American cities. Most crowd-shipping operators focus on specific areas of operation such as last mile deliveries of specific goods categories (Rougès & Montreuil, 2014). The company studied here has a relatively broad operational repertory, targeting both the consumer-to-consumer

(C2C) market, and business-to-consumer (B2C) shipments, including a large gamut of goods categories from perishable to electronics in various sizes. In addition, the company has a broad geographical scope of the entire United States, covering all shipment distances from urban last-mile to national shipments. This broad operational focus allows us to explore the shipping performance for both long-distance and last-mile shipments, as well as for C2C compared to B2C markets.[1] A limitation of our data, however, is the lack of representativeness of data from a single company, dating from 2015–2016, at a relatively early stage of market penetration which is likely not fully representative of mature system performance. We argue that the ambitious operational scope of the functions, the size and duration of the database, taken together with extreme scarcity of any comparative databases, supports the relevance and value of this data-source to understand fundamental principles of crowd-shipping performance analysis for different operational conditions.

We conducted rigorous delivery time validations for each of the 16,850 shipping requests. By means of expert judgment and consultation with our industrial partner a number of records were removed, including those with a short total delivery time window (less than 5 min) and a long delivery time window (more than 28 days), company test requests, company incentivized/promotional shipments, and records with missing time-stamps or other critical information, which resulted in excluding 1992 shipping requests. The final dataset included 14,858 valid observations (88.2% of data).

Fig. 1 portrays the percentage-distribution of the set of requested vs. the effectively delivered shipments as a function of four factors. The "requested" bar shows the publishing stage including 14,858 requests and the "delivered" bar shows the delivery stage calculated using the 6992 delivered packages. The difference between two bars represent the drop between publishing and delivery that includes any drop in the bidding, acceptance, pickup, and delivery stage.

Fig. 1a shows that medium and oversized packages are the most in demand, while the large and long size packages are the least requested shipments. It is also shown that 67.9% (15.6/23 × 100) of small packages and 54.1% (17.4/32.2 × 100) of medium packages are delivered, while only 36.2% (9.2/25.4 × 100) of oversized packages are delivered to their destinations. This means the probability that an oversized package moves from the platform digital posting stage to the delivery stage is relatively low. Looking at the requested bar in Fig. 1b, we note that most of the shipping requests are published either in fall or summer. Comparing the requested bar with the delivered bar, however, it is inferred that 60.7% (10.1/16.6 × 100) of the delivery requests posted during winter had a successful outcome, while this percentage equals 47.1%, 49.3%, and 54.4%, in fall, summer, and spring, respectively. Fig. 1c portrays the age distribution of service requesters for both published and delivered packages. This figure illustrates that people between 25 and 44 years old are the most frequent users, while people younger than 18 years and older than 65 years barely use this delivery service. However, 68.2% of packages requested by people younger than 18 years are delivered to their destinations. Fig. 1d, interestingly, shows that 74.3% of shipping requests have a deadline, among which 99.6% have a one-day deadline. This means most crowd-shipping users require a quick turn-around window for packages to be delivered.

To analyze a range of factors that impact the performance of the crowd-shipping system, we augmented the data with external information describing the built-environment and socioeconomic characteristics of the trip origin and the trip destination at the census block group level. The crowd-shipping data records the latitude and longitude coordinates of both the trip origin and the trip destination for each delivery request. Using reverse geocoding, we converted the latitude and longitude coordinates to their corresponding census block group. We extracted the built-environment characteristics from the 2014 Smart Location Database prepared by the U.S. Environmental Protection Agency (Ramsey & Bell, 2014). The database consists of more than 90 land use and urban form variables summarizing conditions for every census block group at the national level.

The land use and urban form variables fall into five major categories, the so-called 5D's of built-environment: (1) density, (2) diversity, (3) design, (4) distance to transit, and (5) destination accessibility. The socioeconomic characteristics were extracted from the 2015 American Community Survey (ACS) (US Census Bureau, 2015). The ACS is conducted among 3.5 million citizens per year on a rotating basis. The database encompasses demographic and socioeconomic information, including ethnicity, education, age, and gender. The data augmentation process expanded our explanatory variables into three categories: (1) Shipping request and package characteristics, (2) Built-environment characteristics, and (3) Socioeconomic characteristics. Table 1 gives a description of the variables used in this research along with their basic statistics including the average and the standard deviation. For dummy and categorical variables, the average represents the share of each category. Looking at the distribution of the size of the packages, we observe that 26.5%, 9.8%, 32.6%, and 10% of packages are oversized, large, medium, and long, respectively.

It is important to note that demographic and socioeconomic variables represent the characteristics of the trip origin and the trip destination, and not the people carrying out the transactions. O_BLACK, for example, is the percentage of the African-American population at the block group level of the trip origin, and not the registered users of the crowd-shipping platform. The reader should therefore be cautious when interpreting the impact of ethnicity, level of income, and age variables.

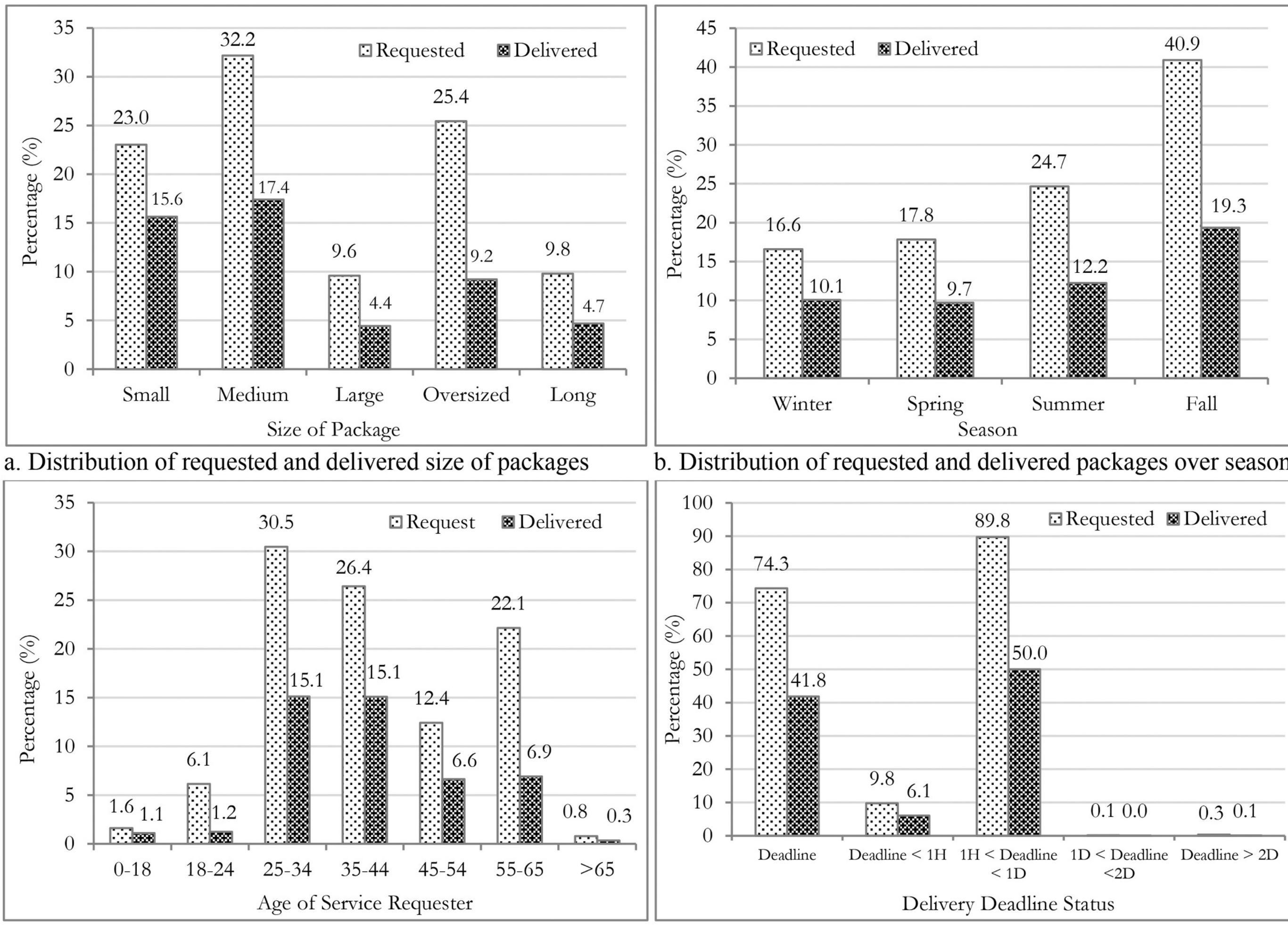
3. Crowd-shipping delivery mechanism

This section aims to shed light on the crowd-shipping delivery mechanism. Rather than simply focusing on the time from pickup to delivery, the entire process of delivery is disentangled and examined. This allows a thorough analysis of obstacles and barriers also in the digital pre-pickup stages characterized by peer-to-peer interactions to match shipments.

A schematic of the crowd-shipping delivery mechanism is shown in Fig. 2. The figure illustrates two critical perspectives of delivery phases to access system performance: the discrete outcome of each shipment stage and the time interval between each of the phases. As far as the status of the shipment is concerned, out of 14,858 shipment requests, 11,567 received a bid (77.85% of posted cases). The shipment requests were published by 7028 service users, which indicates an average of 2.1 requests per user over the study period. Within the bidding and accepting phases, 160 offered cases were withdrawn. The remaining 11,407 cases that received at least one bid continued to the accepting phase, in which 70.96% of them are finally accepted by the service requesters. Within the accepting and picking up phases, 18 cases were withdrawn from the analysis. This resulted in 8077 accepted cases. Of these, 86.87% were picked up. Finally, 6992 cases, representing 99.55% of picked-up cases and 47.05% of originally published cases, are delivered by the courier. The 6992 delivered packages were shipped by 1407 drivers, which yields 4.9 deliveries per driver on average over the study period.

Fig. 2 shows the evolution of the delivery probability performance in the traced slopes. It can be observed that the largest performance losses in terms of the rate of a shipment moving to the next phase are experienced in the first two digital phases, before a physical pickup. Moving on to explore the time-threshold performance, Fig. 2 shows that the largest portion of time is consumed following the physical pickup of the shipment. In preparation for the modeling it is important to note that there are three distinct kinds of shipment observations:

[1] Unfortunately goods categories are not recorded for specific shipments, only discrete shipment sizes.



a. Distribution of requested and delivered size of packages

b. Distribution of requested and delivered packages over seasons

c. Distribution of age of service requesters

d. Delivery deadline status of packages

Fig. 1. Descriptive characteristics of requested (n = 14,858) and delivered (n = 6992 [47%]) packages.

(1) **Survivor:** the shipment complete its current phase and meets one of the bidding, accepting, picking-up, or delivering events of interest. In Fig. 2, shipments A, B, C, and D satisfy this condition.
(2) **End-of-monitoring censoring:** the shipment meets a fate other than fulfillment, such as deletion, cancellation, withdrawal, or staying in the system after the phase interval. In Fig. 2, shipments E, F, and G exemplify this situation, in which they start a phase during the observation period but remain in the platform after the phase interval while never meeting the event of interest.
(3) **Loss-to-follow-up censoring:** the shipment meets an event other than the event of interest, such as deletion due to time-limits, cancellation, or withdrawal, during the observation period. In Fig. 2, shipments I, J, and K meet this condition.

Not only does the time to the event performance vary in each phase for different shipments, but it also varies within each phase. To illustrate this, Fig. 3 splits the overall delivery process into quantiles to show how the various crowd-shipping phases evolve, revealing the specificity of each phase. As shown in Fig. 3, the total bidding process ranges from 1 min to 28,772.3 min (about 20 days). However, excluding some strongly delayed bids this phase still performs well, with 75% of the requests receiving at least one bid within 372.5 min (about 6 h). For the acceptance phase, the overall time interval is longer, lasting up to 40,278.5 min (about 28 days) reflecting the challenges of negotiation in a subset of cases. However, in most instances the performance is high, with 75% of acceptances completed within 200.6 min (3 h) from selecting a bid. Interestingly, the pickup time interval lasts from 9.5 min to 36,094.7 min (about 25 days), while 75% of the accepted cases are picked up within 21 h. On the whole, the pickup phase is the most time consuming in the entire delivery process. The delivery phase can last up to 35,726.2 min (about 25 days). We speculate that long delivery transactions happen due to the time gap between the convenient pickup and delivery phases. A service requester, for example, might be flexible on the delivery timing, but not the pickup time resulting in a large gap between the pickup and delivery phases.

The short minimum delivery durations (5% of cases <12 min) are likely due to some users employing crowd-shipping for short-distance moving (e.g. moving furniture) rather than an actual shipment. Considering the relatively long maximum delivery times, we speculate that couriers do not always pick up and deliver the shipment in a single, dedicated journey. Rather, they might include the delivery in a planned trip or make a detour to pick up a shipment. As a result, the environmental footprint of crowd-shipping systems is difficult to determine without additional insights on how it ties to planned travel or added detours.

4. Model formulation

To determine model time-to-event outcomes, we employ survival analysis (Miller Jr, 2011). In any survival analysis, two quantitative terms describe the time-to-event outcome: (1) the survival function and (2) the hazard function. The former gives the probability that the

Table 1
Description of variables used in the analysis.

Variables	Description	Average	Std. Dev.
Shipping request and package characteristics			
OVERSIZED	1: If the package size is oversized/ 0: Otherwise	0.265	0.441
LARGE	1: If the package size is large/0: Otherwise	0.098	0.298
MEDIUM	1: If the package size is medium/0: Otherwise	0.326	0.469
LONG	1: If the package size is long/0: Otherwise	0.100	0.300
WINTER	1: If demand request is posted in winter/0: Otherwise	0.158	0.365
SPRING	1: If demand request is posted in spring/0: Otherwise	0.171	0.376
FALL	1: If demand request is posted in fall/0: Otherwise	0.420	0.493
SATURDAY	1: If demand request is posted on Saturday/0: Otherwise	0.095	0.293
SUNDAY	1: If demand request is posted on Sunday/0: Otherwise	0.087	0.282
MONDAY	1: If demand request is posted on Monday/0: Otherwise	0.140	0.347
FRIDAY	1: If demand request is posted on Friday/0: Otherwise	0.172	0.377
MORNING	1: If demand request is posted between 6:00 AM and 3:00 PM/0: Otherwise	0.643	0.479
EVENING	1: If demand request is posted between 3:01 PM and midnight/0: Otherwise	0.329	0.469
DEADLINE	1: If the delivery has a deadline/ 0: Otherwise	0.735	0.441
DEADLINE <1H	1: If the deadline of the delivery is less than an hour/0: Otherwise	0.063	0.244
DEADLINE >2D	1: If the deadline of the delivery is more than two days/0: Otherwise	0.002	0.050
SAGE 35–44	1: If the age of sender is between 35 and 44 years/0: Otherwise	0.084	0.277
SAGE 45–54	1: If the age of sender is between 45 and 54 years/0: Otherwise	0.040	0.197
SAGE 55–65	1: If the age of sender is between 55 and 65 years/0: Otherwise	0.075	0.263
RAGE 35–44	1: If the age of courier is between 35 and 44 years/0: Otherwise	0.174	0.379
RAGE 45–54	1: If the age of courier is between 45 and 54 years/0: Otherwise	0.121	0.327
RAGE 55–65	1: If the age of courier is between 55 and 65 years/0: Otherwise	0.019	0.139
OUTSTATE	1: If the delivery request is for out-of-state/0: Otherwise	0.293	0.455
DISTANCE	Distance between pickup and drop-off points (Mile)	268.65	514.53
B2C	1: Business-to-customer market/0: Otherwise	0.248	0.432
NO. BIDS	Number of bids	2.149	2.931
BIDDINGTIME	Time-to-bid for each delivery request (minutes)	1178.88	3442.69
ACCEPTINGTIME	Time-to-accept for each delivery request (minutes)	842.09	3064.12
PICKINGUPTIME	Time-to-pick up for each delivery request (minutes)	1747.31	4104.17
Built environment characteristics			
O_POPDENS	Residential density of the trip origin (Household unit per Acre)	5.674	16.065
D_POPDENS	Residential density of the trip destination (Household unit per Acre)	5.809	18.253
O_NDENS	Total road network density of the trip origin	16.044	9.024
D_NDENS	Total road network density of the trip destination	16.184	9.254
O_PDENS	Pedestrian-oriented intersection density of the trip origin	14.454	26.745
D_PDENS	Pedestrian-oriented intersection density of the trip destination	16.342	29.548
O_ACCESS	Number of jobs within 45 min auto travel time at the trip origin	214,775.6	186,491.0
D_ACCESS	Number of jobs within 45 min auto travel time at the trip destination	210,843.5	188,256.2
Socioeconomic characteristics			
O_BLACK	Percentage of African-Americans at the block group level of the origin	0.173	0.198
D_BLACK	Percentage of African-Americans at the block group level of the destination	0.198	0.241
O_HAWAIIAN	Percentage of Hawaiian at the block group level of the origin	0.001	0.002
D_HAWAIIAN	Percentage of Hawaiian at the block group level of the destination	0.001	0.003
O_LOWWAGE	Percentage of low wage workers at the block group level of the origin	0.219	0.065
D_LOWWAGE	Percentage of low wage workers at the block group level of the destination	0.225	0.069
O_AGE 35–44	Percentage of population aged between 35 and 44 in the trip origin	0.151	0.042
D_AGE 35–44	Percentage of population aged between 35 and 44 in the trip destination	0.137	0.043
O_NOVEHICLE	Percentage of families without any vehicles	0.108	0.151
O_COURIERS	Number of couriers in the origin of the trip	11.472	15.533
D_COURIERS	Number of couriers in the destination of the trip	9.601	14.228

random variable T exceeds the specified time t. The latter gives the instantaneous rate of experiencing an event, given that the observation is event-free at time t. Eq. (1) formulates the survivor function. The hazard function is given by Eq. (2).

$$S(t) = P(T > t) \tag{1}$$

$$h(t) = \lim_{\Delta t \to 0} \frac{P(t \le T < t + \Delta t \mid T \ge t)}{\Delta t} \tag{2}$$

Survival analyses fall into three major categories: (1) non-parametric, (2) semi-parametric, and (3) parametric (Klein & Moeschberger, 2005). Although the first two categories are extensively used to measure the hazard ratio, the parametric models provide a complete description of the hazard function without a need for the proportional hazards assumption. Duration modeling has a long history in passenger transportation analysis (e.g. Hensher & Mannering, 1994) while applications in the logistics sector are much less prevalent. Exceptions include truck trip chaining (Holguín-Veras & Patil, 2005), truck stop durations (Sharman & Roorda, 2013; Sharman, Roorda, & Habib, 2012), and freight delivery break-taking patterns (Tian et al., 2017). To the best of our knowledge, there are no previous applications of a phase-specific duration model analysis as presented in this paper, nor any application of this family of models to crowd-shipping analysis.

4.1. Model specification

For each phase of bidding, accepting, picking up, and delivery, we develop a separate parametric survival model to examine the variations in the factors that impact the performance of each phase. The parametric survival model requires the specification of a distributional assumption for the survival curve, such as Exponential, Weibull, Gompertz, Lognormal, Loglogistic, and Generalized Gamma. In practice, the appropriate parametric distribution is selected comparing the fit of models, along with theoretical or empirical assumptions, for a variety of distinct distributions. We use the Akaike Information Criteria (AIC)

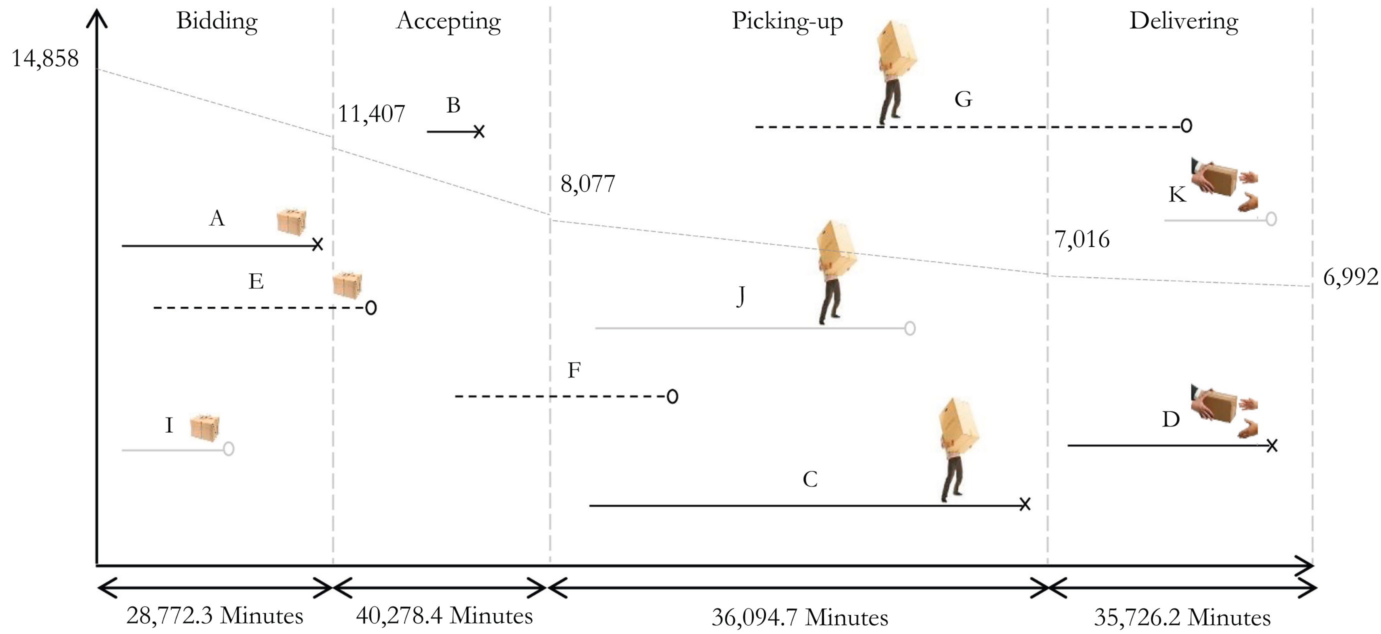
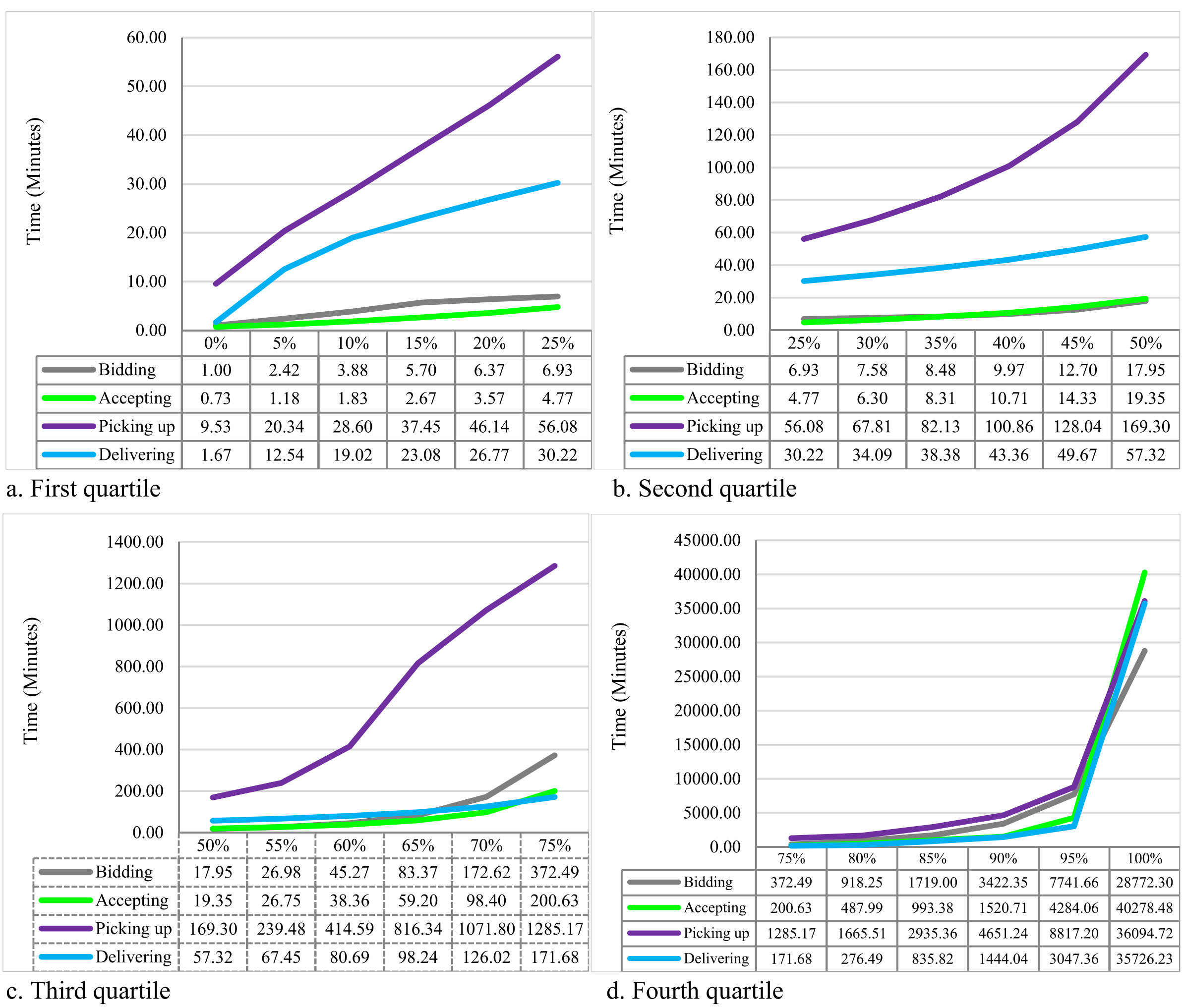


Fig. 2. A schematic illustration of a crowd-shipping delivery mechanism and performance.



a. First quartile

	0%	5%	10%	15%	20%	25%
Bidding	1.00	2.42	3.88	5.70	6.37	6.93
Accepting	0.73	1.18	1.83	2.67	3.57	4.77
Picking up	9.53	20.34	28.60	37.45	46.14	56.08
Delivering	1.67	12.54	19.02	23.08	26.77	30.22

b. Second quartile

	25%	30%	35%	40%	45%	50%
Bidding	6.93	7.58	8.48	9.97	12.70	17.95
Accepting	4.77	6.30	8.31	10.71	14.33	19.35
Picking up	56.08	67.81	82.13	100.86	128.04	169.30
Delivering	30.22	34.09	38.38	43.36	49.67	57.32

c. Third quartile

	50%	55%	60%	65%	70%	75%
Bidding	17.95	26.98	45.27	83.37	172.62	372.49
Accepting	19.35	26.75	38.36	59.20	98.40	200.63
Picking up	169.30	239.48	414.59	816.34	1071.80	1285.17
Delivering	57.32	67.45	80.69	98.24	126.02	171.68

d. Fourth quartile

	75%	80%	85%	90%	95%	100%
Bidding	372.49	918.25	1719.00	3422.35	7741.66	28772.30
Accepting	200.63	487.99	993.38	1520.71	4284.06	40278.48
Picking up	1285.17	1665.51	2935.36	4651.24	8817.20	36094.72
Delivering	171.68	276.49	835.82	1444.04	3047.36	35726.23

Fig. 3. Crowd-shipping delivery time-performance variation in each quartile of shipments.

goodness-of-fit measure (Akaike, 1981) to select an appropriate distribution for the outcome variables as depicted in Table 2. As shown, the loglogistic distribution is preferred for each delivery step. The log-logistic distribution has an important practical advantage as it allows for high flexibility in the shape of the hazard function.

The log-logistic survival and failure functions are expressed by Eq. (3) and Eq. (4). The log-logistic distributions have two parameters λ and p, which is called the shape parameter. If the shape parameter is ≤ 1, the hazard function decreases over time. If the shape parameter is >1, the hazard rate increases to a maximum point and then decreases over time. The parameter λ is typically reparameterized in terms of predictor variables while the shape parameter is held fixed.

$$S(t) = \frac{1}{1 + \lambda t^p} \tag{3}$$

$$1 - S(t) = \frac{\lambda t^p}{1 + \lambda t^p} \tag{4}$$

For model development, variables with a significance at the 90% confidence interval are included, controlling for adherence to conceptually expected signs. To select among models with highly correlated variables, we judge the inclusion or exclusion using the AIC goodness-of-fit measure.

4.2. Acceleration factor and odds ratio

An intriguing aspect of crowd-shipping delivery analysis is to examine the importance of factors affecting the time threshold of each delivery phase. In exploring this topic, it is essential to differentiate between the factor identification and the magnitude of their impacts for the purpose of drawing useful conclusions from the models. Here, we calculate the acceleration factor along with the odds ratio of each variable.

The *acceleration factor* measures the effect of independent variables at the time of an event. In the log-logistic regression accelerated failure-time model, the acceleration factor is derived from Eq. (5), where β is the coefficient of the variable of interest. If the acceleration factor is less than 1, it indicates the deceleration at the time of an event. If the acceleration factor is greater than 1, it indicates the acceleration at the time of an event. For example, if the coefficient of OVERSIZED variable in the bidding phase equals 0.416, the acceleration factor becomes exp $(-0.416) = 0.65$. This means the time for bidding is decelerated for clients with OVERSIZED packages compared to other size of packages by an estimated factor of 0.65.

$$AF = exp(-\beta) \tag{5}$$

The *odds ratio* represents the probability of occurrence of an event as a function of a given independent variable. The failure odds ratio is defined as the ratio of failure odds for two groups of subjects as shown in Eq. (6).

$$\frac{1 - S(t)}{S(t)} = \frac{\frac{\lambda t^p}{1+\lambda t^p}}{\frac{1}{1+\lambda t^p}} = \lambda t^p \tag{6}$$

In the log-logistic regression accelerated failure-time model, the odds ratio is derived from Eq. (7). For example, if the coefficient of OVERSIZED variable in the bidding phase equals 0.416 and the shape parameter equals 0.72, the odds ratio becomes $\exp(-0.416 \times 0.72) = 0.74$. This means the odds of bidding is 0.74 relative to a reference situation.

$$OR = exp(-\beta \times p) \tag{7}$$

Both calculations are unit dependent, which makes the comparison between variables with different units of measurements uninformative. However, it gives us a fair comparison between dummy variables or other variables with identical units of measurements. It also allows us to compare the effect of variables in different delivery phases for the purpose of managerial performance analysis.

Table 2
Summary of AIC for different survival distributions.

Models	Akaike Information Criteria (AIC)				
	Exponential	Weibull	Gompertz	Lognormal	Loglogistic
Bidding	86323.12	62316.68	73304.52	59388.78	**59162.52**
Accepting	70336.91	47889.34	58744.85	46437.44	**46330.16**
Picking-up	37558.02	31942.10	33523.36	30315.16	**30256.94**
Delivering	27692.70	24984.18	25435.14	22323.74	**21295.86**

5. Model results

Table 3 presents the model results. The models are developed by STATA 13 using the maximum likelihood estimation (StataCorp, 2014). The R^2 suggested by Royston and Sauerbrei (2004) show the improvement of the fitted model over the null model and falls between 0 and 1, with values closer to 1 representing better fit. Looking at Table 3, it is found that the picking up model has the lowest fit. The models described are between 36% and 48% of the variability of the delivery mechanism.

The shape parameter is less than one for the bidding, accepting, and picking-up phases, illustrating the decreasing nature of the hazard distribution over time. Instead, the shape parameter in the delivery phase indicates the hazard increases to a maximum point and then decreases monotonically. As shown, time for bidding, accepting, picking-up, and delivering is a function of the shipping request and package, built-environment, and socioeconomic characteristics. Notably, each delivery phase is affected to a different magnitude by the covariates.

The acceleration factor and odds ratio values are depicted in Table 4 and Table 5 for dummy and continuous variables, respectively. We cluster the continuous variables with identical units in Table 5. This enables the reader to compare the magnitude of effects across these variables.

6. Discussion

This section discusses the results of the acceleration factor and odds ratio and elaborates on factors accelerating or decelerating the time an event (i.e. bidding, accepting, picking up, and delivering).

6.1. Factors that accelerate crowd-shipping deliveries?

Considering the categorical variables, shown in Table 4, we find that B2C status, shipment posting time-of-day, and delivery deadlines are the factors causing the most acceleration. The offering and accepting time in the B2C market is, respectively, 2.27 and 2.56 times faster than in the C2C case, while the odds ratio is about 1.8. The acceleration is reduced to 1.29 times in the picking-up phase, while there is no difference between the B2C and C2C markets in the delivery phase. This reflects the higher efficiency of businesses than peer-discussion in the negotiation of shipments on the platform. For shipment requests posted between 6 AM and 3 PM, the offering time is 2.32 times, the accepting time is 4.76 times, and the picking up time is 1.96 times faster than publishing the shipping request at other times of the day. The offering, accepting, and picking-up are also more likely to happen with the odds of 1.85, 2.45, and 1.92, respectively. A similar trend is observed for the shipment requests posted between 3 PM and midnight, while it only affects the offering and accepting times. In this situation, the odds increase by 1.52 for bidding, and 1.61 times for accepting. Having a delivery deadline accelerates the delivery phase, while it has a mixed effect on the accepting and picking-up phases. Both the accepting and picking up durations for shipping requests with a deadline are less than half of the shipping requests without any deadline. It is also more likely that a shipment is offered, accepted, picked-up, and delivered if it has a deadline. For a hard deadline of less than an hour, the odds of picking up

Table 3
Results of the parametric survival models.

Variables	Bidding		Accepting		Picking-up		Delivering	
	Coefficient	z-test	Coefficient	z-test	Coefficient	z-test	Coefficient	z-test
Constant	5.868	26.52	5.280	15.54	6.241	42.65	4.547	72.51
Shipping request and package characteristics								
OVERSIZED	0.416	8.10	0.663	8.53	1.404	20.47	0.159	3.95
LARGE	–	–	–	–	0.582	6.99	0.151	3.01
MEDIUM	–	–	–	–	0.449	8.27	0.075	2.33
LONG	–	–	–	–	0.920	11.13	0.236	4.73
WINTER	−0.266	−4.73	–	–	–	–	–	–
SPRING	0.119	2.17	0.158	1.93	−0.143	−2.59	–	–
FALL			0.216	3.27	0.096	2.10	0.122	4.73
SATURDAY	0.468	6.55	0.429	4.04	−0.199	−2.71	–	–
SUNDAY	0.304	4.06	0.0196	1.79	–	–	–	–
MONDAY			−0.231	−2.73	–	–	–	–
FRIDAY	0.187	3.46			–	–	–	–
MORNING	−0.855	−6.58	−1.539	−7.24	−0.667	−14.49	–	–
EVENING	−0.583	−4.42	−0.816	−3.79	–	–	–	–
DEADLINE	−0.184	−3.30	−0.786	−9.15	−0.751	−12.31	−0.205	−5.32
DEADLINE <1H	–	–	–	–	−0.298	−3.77	−0.144	−3.04
DEADLINE >2D	1.250	2.89	–	–	2.054	4.16	–	–
SAGE 35–44	–	–	–	–	–	–	−0.101	−2.40
SAGE 45–54	0.166	1.62	−0.516	−3.56	−0.352	−3.66	−0.172	−2.94
SAGE 55–65	0.283	2.97	2.726	18.69	–	–	−0.399	−6.06
RAGE 35–44	–	–	–	–	–	–	−0.047	−1.83
RAGE 45–54	–	–	–	–	−0.155	−3.23	–	–
RAGE 55–65	–	–	–	–	−0.488	−4.59	−0.254	−4.02
OUTSTATE	2.049	28.48	1.406	12.46	0.822	9.80	1.394	24.37
DISTANCE	0.001	18.91	0.001	11.49	5.03×10^{-4}	5.35	0.002	27.58
B2C	−0.824	−15.60	−0.952	−13.29	−0.266	−5.49	–	–
NO. BIDS	–	–	0.494	41.05	–	–	–	–
BIDDINGTIME	–	–	1.94×10^{-4}	14.97	2.72×10^{-5}	2.64	–	–
ACCEPTINGTIME	–	–	–	–	4.36×10^{-5}	5.28	–	–
BID+ACCEPTTIME	–	–	–	–	–	–	6.18×10^{-6}	1.71
PICKINGUPTIME	–	–	–	–	–	–	1.82×10^{-5}	4.89
Built environment characteristics								
O_POPDENS	0.014	7.26	0.019	6.05	0.012	5.64	–	–
D_POPDENS	0.009	5.92	0.019	3.15	0.007	3.93	–	–
O_NDENS	–	–	–	–	–	–	−0.005	−2.73
D_NDENS	–	–	–	–	–	–	−0.006	−3.10
O_PDENS	0.003	4.32	0.010	7.57	0.009	9.04	–	–
D_PDENS	0.0042	5.35	–	–	0.002	2.64	0.001	2.37
O_ACCESS	-2.46×10^{-6}	−13.51	-1.42×10^{-6}	−5.24	-1.61×10^{-6}	−8.47	-1.84×10^{-7}	−1.62
D_ACCESS	-6.64×10^{-7}	−4.36	–	–	–	–	-4.77×10^{-7}	−4.25
Socioeconomic characteristics								
O_BLACK	−1.328	−10.90	−0.368	−2.02	−0.940	−7.43	−0.311	−4.81
D_BLACK	−0.723	−7.42	−0.626	−4.43	−0.450	−4.51	–	–
O_ HAWAIIAN	23.569	2.87	47.144	3.18	–	–	–	–
D_ HAWAIIAN	46.602	6.13	–	–	–	–	–	–
O_LOWWAGE	3.141	7.91	2.894	4.85	2.825	6.55	–	–
D_LOWWAGE	1.925	5.26	3.395	6.15	0.897	2.27	–	–
O_AGE 35–44	−3.628	−6.57	−3.382	−4.25	–	–	–	–
D_AGE 35–44	−3.315	−6.58	−2.472	−3.48	–	–	–	–
O_NOVEHICLE	1.559	7.58	−0.796	−2.57	–	–	–	–
O_COURIERS	−0.021	−13.28	−0.020	−9.03	−0.007	−4.98	−0.004	−4.57
D_COURIERS	−0.019	−12.34	−0.018	−8.51	−0.007	−5.10	−0.004	−5.40
Shape Parameter	0.72		0.58		0.97		1.68	
No. of Subjects	14,858		11,407		8077		7023	
No. of Failures	11,567		8095		7027		6992	
Adjusted R-Squared	0.47		0.48		0.36		0.45	

equals 1.34 and the odds of delivering equal 1.27. Finally, considering personal characteristics, the picking up phase is more likely to occur and occur faster for the couriers between 45 and 65 years of age.

As for the continuous variables depicted in Table 5, there are a handful of variables that accelerate each delivery phase. The percentage of the African-American population, population aged between 35 and 44 years, and a higher number of registered couriers accelerate the delivery process, particularly in offering and accepting times. For example, a 10% increase in the African-American population in the trip origin accelerates the offering and picking up phases by 1.14 and 1.09 times, respectively. A 10% increase in the African-American population in the trip destination, however, accelerates the first three delivery phases by a small margin of 1.06 times. The offering and accepting phases are accelerated by an increase in the population aged between 35 and 44 years. The results show that a 10% increase in this population segment in the trip origin, accelerates the first two phases by almost 1.4 times. This effect is attenuated in the trip destination. This implies that the supply of occasional crowd-shipping drivers is unevenly distributed over different geographical areas, with denser pockets in areas with a higher percentage of the African-American population and the population aged between 35 and 44 years. If the trip origin or the trip destination is in geographical areas with a higher percentage of the African-American population and the population aged between 35 and 44 years, it is expected to have a higher and faster probability of successful outcomes for

Table 4
Results of the acceleration factors and odds ratios for dummy variables.

Variable	Acceleration factor				Odds ratio			
	Bid	Accept	Pick	Deliver	Bid	Accept	Pick	Deliver
OVERSIZED	0.65	0.51	0.24	0.85	0.74	0.68	0.25	0.77
LARGE	–	–	0.55	0.86	–	–	0.57	0.78
MEDIUM	–	–	0.63	0.92	–	–	0.64	0.88
LONG	–	–	0.39	0.78	–	–	0.41	0.67
WINTER	1.29	–	–	–	1.21	–	–	–
SPRING	0.88	0.85	1.14	–	0.92	0.91	1.15	–
FALL	–	0.80	0.90	0.88	–	0.88	0.91	0.81
SATURDAY	0.62	0.64	1.21	–	0.71	0.78	1.21	–
SUNDAY	0.73	0.98	–	–	0.80	0.99	–	–
MONDAY	–	1.26	–	–	–	1.14	–	–
FRIDAY	0.82	–	–	–	0.87	–	–	–
MORNING	2.32	4.76	1.96	–	1.85	2.45	1.92	–
EVENING	1.78	2.27	–	–	1.52	1.61	–	–
DEADLINE	1.20	2.17	2.12	1.23	1.14	1.58	2.08	1.41
DEADLINE <1H	–	–	1.35	1.14	–	–	1.34	1.27
DEADLINE >2D	0.28	–	0.12	–	0.41	–	0.13	–
SAGE 35–44	–	–	–	1.11	–	–	–	1.19
SAGE 45–54	0.84	1.66	1.42	1.19	0.89	1.35	1.41	1.34
SAGE 55–65	0.75	0.06	–	1.49	0.82	0.21	–	1.96
RAGE 35–44	–	–	–	1.05	–	–	–	1.08
RAGE 45–54	–	–	1.16	–	–	–	1.16	–
RAGE 55–65	–	–	1.63	1.28	–	–	1.61	1.53
OUTSTATE	0.12	0.24	0.43	0.24	0.23	0.44	0.45	0.10
B2C	2.27	2.56	1.29	–	1.81	1.74	1.30	–

Table 5
Results of the acceleration factors and odds ratios for continuous variables.

Unit	Variable	Acceleration Factor				Odds Ratio			
		Bid	Accept	Pick	Deliver	Bid	Accept	Pick	Deliver
Normal	DISTANCE	0.990	0.990	0.995	0.980	0.999	0.999	1.000	0.997
	NO. BIDS	–	0.610	–	–	–	0.750	–	–
	O_POPDENS	0.870	0.827	0.887	–	0.990	0.989	0.988	–
	D_POPDENS	0.914	0.827	0.932	–	0.994	0.989	0.993	–
	O_NDENS	–	–	–	1.052	–	–	–	1.008
	D_NDENS	–	–	–	1.062	–	–	–	1.010
	O_PDENS	0.971	0.905	0.914	–	0.998	0.994	0.991	–
	D_PDENS	0.959	–	0.980	0.990	0.997	–	0.998	0.998
	O_ACCESS	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
	D_ACCESS	1.000	–	–	1.000	1.000	–	–	1.000
	O_COURIERS	1.021	1.020	1.007	1.004	1.015	1.012	1.007	1.007
	D_COURIERS	1.019	1.018	1.007	1.004	1.014	1.011	1.007	1.007
	BIDDINGTIME	–	0.998	0.999	–	–	1.001	1.001	–
	ACCEPTINGTIME	–	–	0.999	–	–	–	1.001	–
	(BID+ACCEPT)TIME	–	–	–	0.999	–	–	–	1.001
	PICKINGUPTIME	–	–	–	0.999	–	–	–	1.001
Percentage	O_BLACK	1.142	1.037	1.099	1.032	1.010	1.002	1.009	1.005
	D_BLACK	1.075	1.065	1.046	–	1.005	1.004	1.004	–
	O_ HAWAIIAN	0.095	0.009	–	–	0.844	0.760	–	–
	D_ HAWAIIAN	0.009	–	–	–	0.715	–	–	–
	O_LOWWAGE	0.730	0.749	0.754	–	0.978	0.983	0.973	–
	D_LOWWAGE	0.825	0.712	0.914	–	0.986	0.980	0.991	–
	O_AGE 35–44	1.437	1.403	–	–	1.027	1.020	–	–
	D_AGE 35–44	1.393	1.280	–	–	1.024	1.014	–	–
	O_NOVEHICLE	0.855	1.083	–	–	0.989	1.005	–	–

offering, accepting, and picking-up.

6.2. Factors that decelerate crowd-shipping deliveries?

As for the dummy variables, looking at the heat map portrayed in Table 4, we observe that out-of-state shipping requests, size of packages, soft deadlines for delivery, and the age of the service requester are the factors causing the most deceleration. All four phases of the delivery process decelerate when a delivery is requested out-of-state. The offering and accepting times for out-of-state deliveries are 8.33 (1/0.12) and 4.16 (1/0.24) times longer than in-state deliveries, respectively. A similar effect is observed in the pickup and delivery phases. The time to pick up and to deliver out-of-state deliveries is around 2.32 and 4.16 times longer than in-state deliveries, respectively. If a shipment request has a deadline of more than 2 days, the offering and picking-up phases are decelerated by 3.57 and 8.33 times, respectively. The offering and picking up are also less likely to occur with the odds of 0.41 and 0.13, respectively. Interestingly, service requesters aged between 55 and 65 years are acting slowly in responding to a received offer, but they perform better than peers in package delivery. The accepting time for this group of crowd-shipping users is 16.6 times longer than other age groups. We further noticed that the size of the package is among the most sensitive factors for the delivery duration, particularly in the picking up and delivering phases. The oversized package is the only size that decelerates all delivery process phases. The magnitude of the effect, however, is greatest in the picking up phase where it quadruples. The odds of picking up are also low with a value of 0.25.

As for the continuous variables outlined in Table 5, a significant number of variables decelerate the delivery process. Among the variables with identical percentage units, the percentage of Hawaiian and low-wage populations cause the largest performance reduction. A 10% increase in the low-wage salary population in the trip destination decelerates all delivery process phases, except the delivery phase. There is no significant difference between the trip origin and the trip destination.

7. Managerial insights

The crowd-shipping business model managerial insights from this work are related to three critical aspects of performance loss, phase interdependence, and service tailoring.

7.1. Managing platform performance from digital to real

The first managerial insight is the definition of performance criteria not just from the perspective of delivery rates, but more broadly by examining the delivery timeliness for each stage of the process. An important finding from the analysis is that performance loss occurs non-uniformly in the platform process, with a greater loss in the delivery rate related to the digital posting and bidding, and a greater loss of delivery speed performance occuring in the conversion from digital to real delivery in negotiating the picking up arrangement. There are several implications from these findings, ranging from the need for a careful selection of performance criteria that is responsive to the specific challenges and goals of the operator, as well as tailored system incentives for different stages of the shipment. For example, many shipments experience a significant slowing at the courier pickup stage, specifically related to larger sized packages and longer distance deliveries. This suggests a need for improved strategies and guidance to help crowd-couriers better match a specific shipment size to their vehicle, provide intermediate drop-off or storage points to facilitate complex negotiations of pickup, or assist in the sender-courier negotiation of pickups. Specifically, for the out-of-state shipments, which represent 30% of requests, there is a need to create incentives or assist couriers dealing with the challenges related to crossing state boundaries such as insurance and legal differences (Le et al., 2019). Considering that extending the shipping services to long-distance or even an international level is a goal of many crowd-shipping companies, this area thus requires more attention.

Future work should focus on identifying the experiences of the customer, such as frustration or sense of control, for the different stages of the delivery and how this relates to repeat usage. This analysis gives rise to important operational decisions of how companies should balance service level performance between rates of delivery failure and time-performance.

7.2. Interdependence across stages

In this work we controlled for correlation between time intervals across stages, and find that bidding, accepting, picking-up, and delivering time-intervals are positively correlated. More precisely, we found the bidding time impacts the accepting time, the accepting time impacts the pickup time, and the pickup time impacts the delivery time. This means time-to-event at one phase of the delivery process can impact later phases. In terms of managerial guidance, this implies that any performance improvement efforts need to be balanced across the entire set of stages to avoid negative cascading effects. For example, if a manager were to focus solely on reducing the delivery time phase, which is a visible performance factor, it could have a limited impact on the overall delivery time. Our results instead suggest that an improvement in the earlier phases might improve the delivery performance of the overall crowd-shipping system.

Specific guidance can further be given based on the duration model covariate analysis. For example, platform managers ought to promote postings in the morning or evening hours (owing to higher visibility or scheduling compatibility with drivers), and setting stricter deadlines (presumable signaling delivery urgency) to promote a positive performance spill-over across stages.

7.3. Tailored strategies for recruitment and matching

The model reveals systematic patterns in the delivery performance related to the shipment context or participant characteristics. While there is limited information on the personal characteristics of customers and couriers, we observe a significant impact across age groups. Specifically, the performance of couriers aged between 35 and 65, more so between 55 and 65 years, is higher than younger couriers. Their pickups and deliveries are 1.6 times faster compared to other age groups. This suggests managerial insights on the side of recruitment strategies focusing on encouraging older drivers to join the crowd-shipping platform system to boost the delivery performance of the system. Moreover, our modeling suggests that customers spend significant time in the acceptance phase, seeking to select an appropriate courier, even with a relatively small number of courier bids. This suggests a likely need to add more information or improve the platform communication to facilitate effective matching.

A future area of performance analysis relates to the optimal degree to which platform clients should be informed about the potential delivery performance of couriers, specifically with regard to the variation across stages. This implies that crowd-shipping companies need to develop a system to evaluate the expected performance of their registered couriers, and offer guidance and training to improve communication in the critical early platform exchanges. Detailed modeling of the delivery performance among different courier groups as proposed here can be used to calculate delivery odds and durations to communicate more transparently and effectively to service requesters.

8. Concluding remarks

Crowd logistic services provide an opportunity for retailers and logistics providers to improve delivery service, reduce costs, and increase customer satisfaction. As different crowd-logistics models built on cooperation and collaboration between service requesters and couriers from the crowd are growing rapidly, assessing the performance of this relationship to reliably deliver shipping requests is a central concern among the service providers. To develop better customer service and expand the crowd-shipping market, the area with the most urgent need for analysis is to assess the delivery performance of the system, especially in its start-up phase.

This research was the first to bridge this gap by introducing analysis that disentangles the factors that affect each phase in the entire crowd-shipping delivery process. We developed four parametric hazard duration models not only to examine the time-to-event for each phase of delivery, but also to investigate factors characterizing the entire delivery mechanism. We tested three categories of variables, including shipping requests and packages, built-environment, and socioeconomic characteristics. Thereby our analysis contributes to a comprehensive start-to-end framework for monitoring and analyzing the performance of crowd-shipping deliveries. Results showed that each phase of this delivery mechanism is affected by either a different group of variables or a different magnitude of effects, which emphasizes the need to examine the delivery process as phases that make up a comprehensive process. The first "virtual" phase of posting and bidding were characterized by the peer-negotiations of delivery conditions via the online platform. This virtual phase of the shipment was mainly impacted by the timing of the posting, the characteristics of senders, and the delivery distance. Instead, the performance in latter phases, related to coordinating the actual delivery, was more strongly influenced by the practical barriers such as the package size, delivery deadlines, and the age of users. The findings from this analytical framework provide more detailed, accurate, and relevant information to crowd-shipping companies for strategic planning and both short- and long-term decision making.

From a managerial point of view, the delivery performance analysis helps crowd-shipping companies calibrate their logistical capabilities and implement evidence-based initiatives. Crowd-shipping companies might put the findings of the current research into practice in several ways to improve the management of the delivery platform. A well-managed delivery process aligns the logistical strategies of crowd-shipping companies with competitive requirements of senders. Notably, an improvement in the delivery performance of the crowd-shipping that meet user requirements not only enhances the loyalty of existing users, but also increases the odds of attracting new customers. Crowd-shipping companies can also use the delivery process performance analysis developed in this study to detect service quality weaknesses and strengths. This leads them to allocate corporate resources to the important delivery phases and regions which suffer from low service quality.

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Author contribution statement

Alireza Ermagun contributed to conceptualization, data curation, formal analysis, investigation, methodology, visualization, and writing - original draft. Amanda Stathopoulos contributed to methodology, project administration, resources, supervision, and writing - original draft. All authors discussed the results and contributed to the final manuscript.

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