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Crowd Logistics Platform's Informative Support to Logistics Performance: Scale Development and Empirical Examination

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Abstract: Using the organization information processing theory, we explored the process through which the informative support of crowd logistics platforms affects logistics performance. After collecting data from 321 respondents from two crowd logistics companies in China, we proposed and tested the theoretical framework empirically using SEM. To conduct the empirical study, we developed scales for platform's informative support and the degree of logistics resources-demand match, respectively. The results indicate that a platform's informative support improves logistics performance via two mediators, i.e., logistics resources-demand match and logistics agility. Moreover, a platform's ease of use moderates the indirect process through which its informative support promotes logistics performance via logistics resources-demand match. However, a platform's ease of use has no significant effect on the indirect process of its informative support affecting logistics performance via logistics agility. This paper extends our understanding on how the informative support of crowd logistics platforms predicts logistics performance.

Keywords: crowd logistics platforms; informative support; logistics performance; scale development

1. Introduction

Crowd logistics is an innovative business model in sharing economy. In crowd logistics, drivers use their own vehicles to provide logistics services as independent contractors, and shippers outsource logistics tasks to a large number of drivers through technology platforms [1]. The crowd logistics platforms integrate enormous logistics tasks, contributing to optimal allocation of logistics resources by providing drivers with informative support. In practice, the positive impacts of crowd logistics on logistics performance have emerged. Taking China as an example, compared with traditional logistics enterprises, the utilization rate of vehicles increased by 50% in some crowd logistics initiatives and logistics costs fell by about 6–8% [2]. Thus, we think that informative support of crowd logistics platforms may predict logistics performance, which is yet to be explored.

Previous studies proposed that crowd logistics platforms; by collecting, processing and sharing much necessary information with drivers about logistics service requests, routing solutions, traffic conditions and so on [3–5]; promote the match between demand and supply for logistics resources and empower drivers to undertake logistics tasks [6]. Although substantial studies on the function of crowd logistics platforms have been conducted, some theoretical gaps remain unsolved, as follows.

Firstly, previous studies cannot construct a theoretical underpinning on why and how a platform's informative support improves logistics performance. In particular, the mechanisms through which a platform's informative support affects logistics performance are yet to be explored and it remains

unclear how the boundary conditions affect the logistics performance. Secondly, rare empirical research has explored the impact of a platform's informative support on logistics performance. Thirdly, valid and reliable instruments are insufficient for a platform's informative support. To explore further, this paper proposes a research question:

How does a platform's informative support influence drivers' logistics performance?

In response, our study aims to investigate the mechanism through which a platform's informative support impacts logistics performance. We generate a theoretical framework, which shows that a platform's informative support influences logistics resource-demand match and logistics agility, further contributing to logistics performance. Moreover, we also contribute to the organization information processing theory literature by outlining a moderator of the process. Specifically, we argue that a platform's ease of use probably moderates the process. The conceptual framework we have proposed is depicted in Figure 1. To conduct an empirical test on this explanatory theoretical framework, we develop scales for a platform's informative support and logistics resources-demand match by following the standard procedures suggested by Churchill [7].

Our study contributes to the literature in several ways. To our knowledge, it is the first time that a theoretical framework has been constructed to explain the process through which a platform's informative support casts influence on logistics performance. Based on the organization information processing theory, we improved the understanding of the mechanisms of crowd logistics platforms predicting logistics performance. Secondly, this paper expands the crowd logistics platform literature by figuring out how a platform's informative support and platform's ease of use interact to influence logistics performance. This study tests a moderated-mediation model and gives a better understanding of the relationship between a platform's informative support and logistics performance. Thirdly, we developed scales for a platform's informative support and logistics resources-demand match before conducting an empirical test. Such a scale development research allows other scholars in this field to use the tested instrument for further studies [8].

This paper is organized as follows. Section 2 introduces the theoretical background. In Section 3, a research framework is developed, along with hypotheses based on organization information processing theory. Thereafter, we present a detailed research methodology section consisting of scale development, data collection, hypotheses testing, and results. Finally, we report and discuss our findings and conclude with theoretical and managerial implications, and directions for future research.

2. Theoretical Backgrounds

2.1. Platform's Informative Support

Prior to examining the relationship between a platform's informative support and logistics performance, it is important to provide a unified definition of a platform's informative support. Extant literature identifies two categories of platform's informative support.

The first category refers to the information processing mechanism that allows for information collection, data processing and information sharing to coordinate demand and supply for logistics resources [6,9]. In general, with the support of this first category, "a shipper can place a request for a delivery service on the platform and all users located near the task can be notified automatically" [6]. Moreover, a platform helps to assign customers' service requests to available drivers according to the characteristics of the requests (time, destination, capacity) and the characteristics of drivers (location and capability) [5].

The second category refers to the information processing mechanism that empowers the crowd drivers and helps them to make logistics decisions collectively [3]. Specifically, a platform provides drivers with real-time scheduling and routing by using a GPS system to help drivers "undertake logistics tasks as efficiently as possible" [4]. It can also collect and give quite useful information about the current driving conditions based on a GPS system. For example, drivers can share traffic and other road data through the platform, which uses such information to help drivers change routes and avoid

the jam [6]. In all, the second category of platform's informative support allows for the communication and processing of information to make and adjust logistics solutions [10,11].

Above all, a platform's informative support can be defined as a type of information processing mechanism, which ensures the objective of matching demand and supply for logistics resources and providing timely logistics solutions. It helps in sharing information about logistics service requests, logistics resources, and delivery schedules [12].

2.2. Organization Information Processing Theory

Organization information processing theory (OIPT) posits that organizations require a lot of information to take decisions [13]. However, there is usually information disconnection between the necessary information and the information available to the organization for decision-making [14]. Such information disconnection leads to uncertainty. To cope with uncertainty, organizations need to organize and use information effectively when executing tasks [15,16]. To do so, organizations must deploy an information processing mechanism that facilitates the collection and processing of information [17]. The concept of fit is another core construct in organization information processing theory [14]. The OIPT posits that organizations will be more effective when there is a match between their information processing requirements and information processing mechanism [15,17,18].

By applying OIPT to the context of crowd logistics, the crowd drivers can be considered as independent organizations that require a lot of information to tackle uncertain tasks. Specifically, as an independent individual, a crowd driver requires necessary information to find suitable logistics service requests and undertake logistics tasks effectively. Thus, the crowd drivers need effective information processing mechanisms to deal with uncertainty. Information processing mechanism can be conceptualized as a mechanism that utilizes information to support decision-making. According to Tushman and Nadler [17], information systems are able to facilitate the process of information processing. Based upon this assumption, other researchers have suggested that information technology is a key aspect of an organization's information processing mechanism [19]. In this study, we continue this tradition by considering a platform's informative support as an information processing mechanism provided for the crowd drivers, because it can help them acquire and process information.

3. Hypotheses

3.1. A Platform's Informative Support and Drivers' Logistics Performance

Logistics performance means that drivers are capable of delivering goods and services in the quantities and at the precise times required by customers [20]. According to previous supply chain studies, IT contributes to reducing operational costs and improving customer service by promoting information sharing [21–23]. A platform's informative support can be considered as a type of information technology. We assume that it also facilitates logistics performance.

On one hand, by using matching algorithms, a platform's informative support ensures the match between customers' service requests and drivers' logistics resources. Furthermore, it provides drivers with abundant information about logistics requests, leading to a decrease in uncertainty when looking through orders. It decreases drivers' searching costs, contributing to good logistics performance. In addition, when drivers' logistics orders are matched with their own logistics capabilities, they are able to provide the required service; this, in turn, predicts logistics quality.

On the other hand, a platform's informative support helps drivers collect and process information from external environment and customers. Without this support, it is difficult for drivers to understand customers' needs and respond effectively, thus inhibiting speedy delivery [24]. Platforms can also design logistics operation processes for drivers, helping strengthen the control of logistics activities and lead to a higher delivery reliability [25]. Besides, real-time communication with customers supported by platforms also makes sure that the drivers' services respond to customers effectively, leading to

higher satisfaction [24]. Therefore, a platform's informative support can help enhance drivers' logistics performance. We thus posit that:

H1: A platform's informative support is positively related to drivers' logistics performance.

3.2. *The Mediating Effect of Logistics Resource-Demand Match*

Logistics resources-demand match examines the extent to which drivers' logistics resources meet the demands of shippers [26]. The match between demand and supply for logistics resources has been considered to be the main request from drivers and shippers in the context of crowd logistics. Specifically, drivers need to find logistics requests, while customers need to find logistics services. However, there is no effective communication mechanism between them. The process of drivers searching for service requests online and undertaking logistics tasks offline is full of uncertainty. Thus, there are information requirements from drivers in order to find suitable service requests. Drivers need effective information-processing mechanisms to match with information requirements.

Based on the OIPT view, a platform's informative support can be treated as a type of information processing mechanism. Particularly, platforms offer customers informative service that helps them issue their logistics service requests to drivers [27]. Platforms then categorize such information according to the characteristics of service requests and construct a multidimensional database. Moreover, platforms provide drivers with fit tasks supported by the technology of machine learning [28]. A match is achieved based on drivers' availability and customers' requests [5]. In this way, a platform's informative support provides drivers with matched logistics service requests, which contributes to an increase in the accuracy and effectiveness of logistics resources-demand match. Thus, we posit that:

H2a: A platform's informative support is positively related to logistics resources-demand match.

Logistics resources-demand match means that crowd drivers can, in a short period of time, find logistics service requests that are matched with their preferences. For example, if an order requiring cold chain delivery is assigned to a driver whose vehicle is not set with refrigerated equipment, the loss of perishable products will be high, resulting in loss to the customer. In addition, if a platform provides a driver with an order beyond his delivery scope, it will increase the driver's bypass distance, leading to unnecessary logistics costs. Therefore, logistics resources-demand match empowers drivers to meet customers' needs, thus improving customer satisfaction and logistics reliability. In addition, logistics resources-demand match is achieved through a platform's informative support. It can be seen that a platform's informative support contributes to the improvement of drivers' logistics performance by matching the supply and demand for logistics resources. Thus, we posit that:

H2b: Logistics resources-demand match is positively related to logistics performance.

H2c: Logistics resources-demand match mediates the relationship between a platform's informative support and logistics performance.

3.3. *The Mediating Effect of Logistics Agility*

Logistics agility, in this study, refers to drivers' ability to rapidly respond to changes in market and customer demand [12]. It is considered to be critical to tackle unanticipated changes deriving from environments and customer needs [29]. Extant studies in supply chain text point out that information-management capabilities lead to agility [30,31], because information integration supported by information-management capabilities enables an organization to achieve rich and real-time information across the supply chain [32]. Such information integration allows an organization to adjust plans rapidly, with minimal resource costs [33].

In the context of crowd logistics, a platform's informative support can also be considered a type of information management capability. Thus, we think that it leads to logistics agility. Platforms usually

equip drivers with GPS systems and help them schedule [4,28]. When customers put forth personalized requirements, platforms can provide drivers with responsive logistics solutions. On the other hand, platforms can also adjust logistics plans by collecting information from external environments. For example, platforms provide drivers with channels to share traffic data, which can be used to adjust delivery solutions, thus increasing response speed to accidents [6]. That is to say, a platform's informative support provides necessary information to the drivers to deal with non-routine incidents such as traffic accidents, and changes in delivery timelines and destinations [34].

In view of the above research, a platform's informative support, as part of the information-processing mechanism, will have a positive impact on the improvement of logistics agility. From this, we can draw the following hypothesis:

H3a: A platform's informative support is positively related to logistics agility.

In supply chain research, scholars think that supply chain agility is able to contribute to performance by a more effective response to external supply disruptions [35]. In particular, supply chain agility can help affirm master marketplace changes [36,37], thereby reducing the cost of demand uncertainty [38]. Besides, agility also helps to react effectively to a customer's individual specifications by providing mass customization [39], achieving high customer responsiveness. Following this view, since logistics agility can aid drivers' efforts to "identify changes from the environment and customers' needs quickly or neutralize threats from turbulent environments" [40], we can see that logistics agility empowers drivers to adapt to changing environments and ultimately lead to logistics performance [41]. In addition, logistics agility is predicted by real-time information sharing and logistics solutions with the help of a platform's informative support. It can be seen that a platform's informative support can improve drivers' logistics performance by improving logistics agility. Thus, we make the following assumptions:

H3b: Logistics agility is positively related to logistics performance.

H3c: Logistics agility mediates the relationship between a platform's informative support and logistics performance.

3.4. The Moderating Effects of Platform's Ease of Use

Platform's ease of use means that using a platform is effortless for users [42]. According to organization information processing theory, we think that the easier a platform is to use, the better the platform's informative support will be. In particular, if a platform is too difficult to use, a driver may be limited to using only certain functions of the platform, thus missing out on more useful information. The easier a platform is to use, the richer is the information drivers receive, and the stronger drivers' information processing capabilities will be in dealing with task-related uncertainties. Therefore, we believe that a platform's ease of use plays a positive role in the relationship between its informative support, and logistics resources-demand match and logistics agility. Thus, we draw the following hypotheses:

H4a: A platform's ease of use strengthens the positive relationship between its informative support and logistics resources-demand match, such that the relationship is stronger when the platform is easier to use.

H4b: A platform's ease of use strengthens the positive relationship between platform's informative support and logistics agility such that the relationship is stronger when the platform is easier to use.

We have developed theoretical arguments for the mediating effects of logistics resources-demand match and logistics agility. In addition, we also underpinned the moderating effects of a platform's ease of use on the relationship between its informative support and logistics resources-demand match as well as its informative support-logistics agility relationship. In particular, the high level of logistics resources-demand match predicts a high level of logistics performance. With informative support

provided by a platform that is easier to use, drivers can effortlessly get richer information about logistics service requests and logistics solutions, further predicting a high level of logistics performance. Hence, this suggests a moderated mediation relationship to further posit that:

H5a: A platform's ease of use strengthens the indirect effect of its informative support on logistics performance via logistics resources-demand match, such that the indirect effect is stronger when a platform is easier to use.

H5b: A platform's ease of use strengthens the indirect effect of its informative support on logistics performance via logistics agility, such that the indirect effect is stronger when a platform is easier to use.

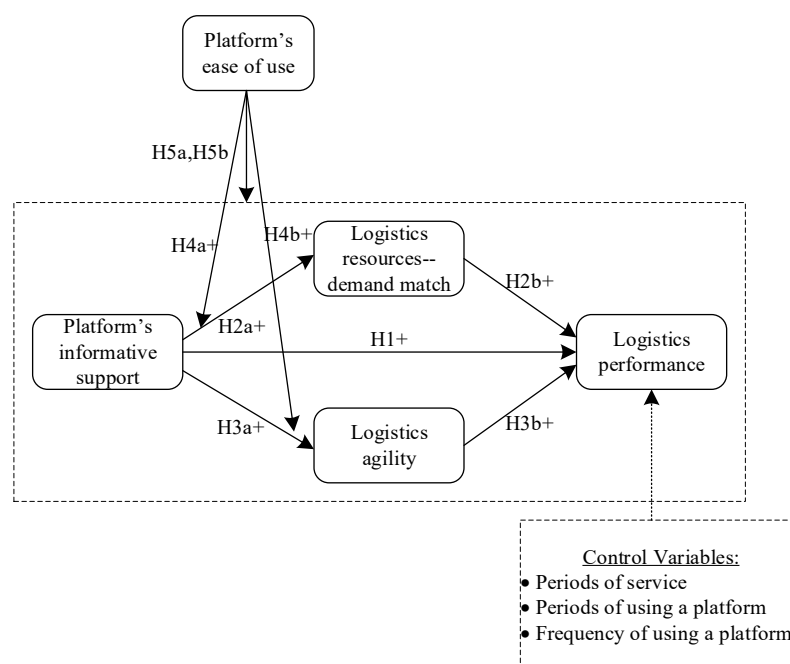


Figure 1. Theoretical framework.

4. Methodology

In this section, we developed scales for platform's informative support and logistics resources-demand match for further empirical study. Based on the scale development, we conducted a survey using new measures for informative support and logistics resources-demand match and pre-established measures for logistics performance, logistics agility, and the platform's ease of use.

4.1. Pretest Procedure for PIS And LRDM Scale Development

To develop scales for platform's informative support (PIS) and logistics resources-demand match (LRDM), we employed several steps to build and test scales [7]. In the first step, we analyzed related literature to specify the concepts of the two constructs and collected existing items to measure similar variables. We mainly refer to several aspects examined by Daugherty, Myers, and Richey [43], Daugherty et al. [44] and Jeffers [45] in measuring information technology and the items proposed by Astakhova, Beal, and Camp [46] and Cable & DeRue [26] in measuring demand-capabilities match. We then conducted in-depth interviews with managers of several crowd logistics companies to further collect information. Before conducting interviews, we randomly chose 25 crowd logistics companies, which were selected by the Chinese government to pilot crowd logistics. These samples have achieved great performance in the development of crowd logistics and could represent the basic characteristics of the objects under study. After we e-mailed an introduction of our study to their managers, respectively, six companies responded and agreed to participate in the interviews. We then e-mailed the managers

of these companies a specific study plan and an interview protocol to inform them of the specific interview steps. The interviews were conducted in August 2018. We summarized the information obtained and developed new items that were not mentioned in previous literature. We generated 11 items for PIS and 5 items for LRDM from a thorough investigation of the literature. The items for PIS describes the support provided by the platform that promotes the match of logistics resources with drivers, and provides drivers with delivery schedules. The items for LRDM describes the congruence between logistics service requests and drivers' capabilities and preferences.

After generation of the initial items, we conducted more interviews. This procedure is recommended when a construct is relatively new in the field and has seen limited to no operationalization [47]. We consulted, in August 2018, academic experts and practitioners (the managers who were interviewed in the first step) who were familiar with crowd logistics platforms to assess the appropriateness of items. We also asked drivers who used logistics platforms to evaluate the initial questionnaire; taking their feedback into consideration, we revised the questionnaire and improved its readability and practicality. According to the feedback, we merged some items and were finally left with 6 items for PIS and 4 for LRDM.

In the final step, we conducted a pretest in a crowd logistics company in China in September 2018 to assess our initial scale with 7 Likert-type scale items by collecting data from drivers who used the crowd logistics platform. After generating initial items, we contacted the managers who were interviewed before and e-mailed them the initial questionnaires to show the specific contents of our survey. One of these companies agreed to support us with data collection. At the start of our survey, we conducted a brief interview with the respondents (i.e., the drivers) to confirm that they had a good knowledge of the platform's informative support and logistics resources-demand match. We collected a total of 300 questionnaires and deleted questionnaires wherein respondents had selected the same number for all questions. A total of 265 valid questionnaires were obtained.

We conducted reliability and validity analysis in the pretest. First, we tested the reliability of the scale we developed. Generally, Cronbach's alpha coefficient is used to show the reliability of the scale [48]. Related studies considered 0.7 as the cut-off value of reliability. As shown in Table 1, the Cronbach's alpha values of the two variables are greater than 0.7. These results suggest that the scales exhibit good reliability.

Table 1. Scale development-EFA results.

Factors	Number of Items	Mean	S.D.	Cronbach's Alpha	Range of Factor Loadings
PIS	6	5.552	1.05	0.884	0.763–0.829
LRDM	4	5.598	1.10	0.883	0.818–0.900

Second, we conducted exploratory factor analysis (EFA) on the two variables in SPSS using principal component analysis and extracted the factors whose eigenvalues are greater than 1.00 [49]. The results showed that the Keyser-Meyer-Olkin (KMO) measure of sampling adequacy of PIS was 0.887 and the χ^2 was 765.662 (d.f. = 15, p = 0.000), while that of LRDM was 0.824 and the χ^2 was 575.464 (d.f. = 6, p = 0.000). As the KMO measures of the two variables are greater than the benchmark value of 0.6, it suggests that factor analysis can provide reliable factors [50]. By conducting EFA, we also attained the factor loading of each item in the scale. The factor loadings of all items are all greater than the recommended value of 0.50, which suggests convergent validity. These values are provided in Table 1.

Third, we assessed discriminant validity of the constructs. Discriminant validity between two constructs can be measured by constraining the estimated correlation parameter between them to 1.0 and then conducting a chi-square difference test on the results of the two competing models—the constrained and unconstrained ones [51]. A significant chi-square difference shows that discriminant

validity between the two constructs is established [52]. The results in Table 2 indicates the discriminant validity between the two constructs.

Table 2. Test for measurement of discriminant validity.

Construct Pairs		Unconstrained Model	Constrained Model	χ^2 Difference	P
PIS	LRDM	$\chi^2 = 71.657$ d.f. = 34	$\chi^2 = 89.628$ d.f. = 35	17.972	0.000

4.2. Sample and Data Collection

Our sample is from two large crowd logistics companies in China. To conduct a large-scale survey, we contacted the previous interviewed managers who were familiar with our study. We e-mailed them both the final questionnaires and the survey plan to inform them of the specific data collection process, and also promised to offer a study report that would highlight drivers' perception of platform support, analyze the pros and cons of their own business model, and offer advice based on that data. Two of these companies agreed to help us with the survey. After obtaining the CEOs' consent, the staff of the information service and logistics business departments helped us conduct the survey. In order to ensure accuracy of data and response rates, we selected drivers who used crowd logistics platforms. It is reasonable to expect that the drivers had good knowledge of platform informative support because they use such platforms frequently.

We sent printed questionnaires to the respondents. Accompanied by staff of the logistics business departments, we visited the logistics distribution centers of the two companies in October 2018 with printed questionnaires for the drivers. At the beginning of the survey, the researchers introduced our research purpose to the respondents and emphasized on the anonymity of this survey. To motivate the drivers to participate in our survey, we gave every driver who completed the questionnaire a reward of 10 RMB. The drivers were asked to complete the questionnaire and return it to the investigator at the earliest. A total of 343 questionnaires were collected in this data survey. We deleted invalid questionnaires and were left with 321 questionnaires. A profile outline of the respondents is given in Table 3.

Table 3. Profile of respondents.

Profile (n = 321)	%
Gender	
Male	85.7%
Female	14.3%
Age	
<20	4.4%
20–30	42.1%
30–40	38.6%
40–50	14.0%
>50	0.9%
Industry	
Inter-city Full Truck Load Logistics	32.7%
Inter-city Less-Than Truck Load Logistics	23.7%
Local Full Truck Load Logistics	20.6%
Local Less-Than Truck Load Logistics	23.1%

We tested non-response bias by comparing the answers of early (top 30) and late respondents (last 30). At the 5% significance level, there are no significant differences between the answers of early and late respondents. According to Armstrong & Overton (1977), we believe that there is no non-response bias in our data collection [53].

Given that a single data source (i.e., drivers) responds to the items of our study, we need to check for a possible common method bias. To do so, we used the Harman's one-factor test [54].

The results showed that there were five factors with eigenvalues greater than 1.0 emerging from the factor analysis, accounting for 80.957% of the variance. The first factor accounted for 32.983% of the variance, lower than the cut-off value of 40%, which indicated that the common method bias was not a serious problem [55].

4.3. Measures

All scales used in this essay are based on scales that are already published, in addition to PIS and LRMD scales. In order to guarantee equivalence in meaning of the scales used in this research, we applied a standard double-back-translation method. We invited two Ph.D. candidates to complete the translation work. One helped us translate the English scale into Chinese, the other translated the Chinese questionnaire back into English to ensure that there were not semantic differences between the two versions. In addition, we consulted several scholars and asked employees in crowd logistics companies to verify the items in the Chinese edition. According to feedback from the people mentioned above, we slightly modified some items in the scale. Unless otherwise stated below, all participants completed a 7-point Likert-type scale (1 = Strongly Disagree, 4 = Neutral, and 7 = Strongly Agree) for all the items. Appendix A shows the items in the questionnaire.

Logistics performance (LP): Logistics performance was measured by 6 items adapted from Zacharia, Nix and Lusch [56]. The respondents were asked to self-evaluate their performance on a Likert scale, ranging from strongly disagree (1) to strongly agree (7). A sample item includes: “Quicker delivery results” and “Improved quality”. The Cronbach’s alpha of the scale in our study was 0.935.

Logistics agility (LA): Logistics agility was measured by the 4 items that increase customization and improve delivery performance, adapted from Swafford, Ghosh and Murthy [46]. This scale has been widely used in measuring logistics agility and was validated in the empirical study [31,57]. The respondents were asked to self-evaluate their performance on a Likert scale ranging from strongly disagree (1) to strongly agree (7). A sample item includes: “Speed in adjusting delivery solutions” and “Speed in improving customer service”. The Cronbach’s alpha of the scale in our study was 0.923.

Platform’s ease of use (PEU): Ease of use was measured by 4 items adapted from Pavlou [42]. This scale has been widely used in measuring ease of use and it was validated in the empirical study [58,59]. Respondents were asked to self-evaluate their performance on a Likert scale ranging from strongly disagree (1) to strongly agree (7). A sample item includes: “I find this platform easy to use” and “I find it easy to locate the information that I need in this platform”. The Cronbach’s alpha of the scale in our study was 0.969.

Control variables: This study considered three control variables, namely, periods of service (PS), periods of using a platform (PUP), and frequency of using a platform (FUP). The longer drivers participate in the logistics industry, the more experienced they are; and the more reliable their logistics services will be, the better the logistics performance will be. According to the OIPT, the longer a driver uses a platform and the more frequently a driver uses a platform; and the more information the platform will get from the driver, the more precise the match between demand and supply will be. From this perspective, these three control variables will have an impact on logistics performance. The periods of service were assessed by the item: “How long have you been engaged in logistics?” on a Likert scale. The periods of using a platform was measured by the item: “How long have you been using the platform” on a Likert scale. The frequency of using a platform was assessed by the item: “How often do you use the platform”.

4.4. The Measurement Model

We employed CFA by using Mplus 7 to assess the reliability and validity of the scales. In CFA, comparative fit index (CFI), Tucker-Lewis index (TLI) and root mean square error of approximation index (RMSEA) are used to assess the measurement model [60]. A model is considered to be satisfactory if $\chi^2/df < 3$, CFI > 0.90, RMSEA < 0.08, and TLI > 0.90 [61]. The CFA results indicated that a good fit of

the measurement model ($\chi^2/\text{d.f.} = 1.685$, RMSEA = 0.046, SRMR=0.039, CFI = 0.977, TLI=0.973). The CFA results are shown in Table 4.

Table 4. The fit indexes of the measurement model.

Fit Index	Benchmark Value	Results
$\chi^2/\text{d.f.}$	$1 < \chi^2/\text{d.f.} < 3$	1.685
CFI	>0.9	0.977
TLI	>0.9	0.973
RMSEA	<0.08	0.046
SRMR	<0.08	0.039

We used factor loadings, composite reliability (CR) of constructs, and average variance extracted (AVE) to test convergent validity. The factor loadings of all items were higher than the suggested value of 0.50, as shown in Table 5 and they are all significant at the level of 0.01, which showed high convergence. As Table 5 shows, the CR values are from 0.925 to 0.970 and the AVE scores range from 0.691 to 0.889. If the CR coefficients are greater than the benchmark of 0.7 and the AVE values are above the suggested value of 0.5, the convergent validity is considered to be supported [62]. We then conducted a chi-square difference test to assess discriminant validity. We employed the chi-square difference test for every two latent variables, as shown in Table 6. The results indicate a significant chi-square difference for each pair of latent variables, which support the discriminant validity for every two constructs.

Table 5. Summary statistics (convergent validity).

Construct	Range of Factor Loadings	CR	AVE
Platform's informative support	0.789–0.886	0.931	0.691
Logistics resources-demand match	0.865–0.931	0.943	0.806
Logistics performance	0.789–0.875	0.935	0.707
Logistics agility	0.794–0.912	0.925	0.757
Platform's ease of use	0.935–0.949	0.970	0.889

Table 6. Test for measurement of discriminant validity.

MODEL	χ^2	d.f.	$\Delta\text{d.f.}$	$\Delta\chi^2$	P
Default model	406.578	242			
PIS-PEU	439.006	243	1	32.428 **	0.000
PIS-LRDM	416.334	243	1	9.756 **	0.002
PIS-LA	411.565	243	1	4.987 *	0.026
PIS-LP	412.815	243	1	6.237 *	0.013
PEU-LRDM	411.998	243	1	5.420 *	0.020
PEU-LA	418.325	243	1	11.747 **	0.001
PEU-LP	416.759	243	1	10.181 **	0.001
LRDM-LA	417.177	243	1	10.599 **	0.001
LRDM-LP	411.014	243	1	4.436 *	0.035
LA-LP	413.575	243	1	6.997 **	0.008

* $p < 0.05$, ** $p < 0.01$.

4.5. Descriptive Analysis

Table 7 shows the means, standard deviations of variables in our study. In addition, the square roots of the AVEs for all constructs were greater than the correlations coefficients between constructs, which confirmed the discriminant validity of the measurement model [63].

Table 7. Means, standard deviation, and correlations.

Variables	1	2	3	4	5	6	7	8
1 PS	1							
2 PUP	0.481 **	1						
3 FUP	0.217 **	0.291 **	1					
4 PIS	0.093	0.009	−0.008	0.831				
5 LRDM	−0.062	−0.101	−0.010	0.221 **	0.898			
6 LP	0.056	0.029	0.003	0.297 **	0.351 **	0.841		
7 LA	0.056	−0.133 *	−0.052	0.337 **	0.289 **	0.363 **	0.870	
8 PEU	−0.110 *	−0.085	−0.023	−0.017	0.215 **	0.191 **	0.176 **	0.943 ²
Mean	2.620	2.726	4.125	4.731	4.685	4.840	4.696	4.680
Std.	1.334	1.620	1.556	1.398	1.436	1.348	1.456	1.746 ¹

¹ * $p < 0.05$, ** $p < 0.01$. ² Numbers in bold, on the diagonal indicate square root of AVE; numbers below the diagonal are the inter-construct correlations.

5. Analysis and Results

5.1. Structural Relationship Model

We used Mplus 7 to calculate the results of the structural equation model (SEM) and present the standardized coefficients (Figure 2). In this study, we included PS, PUP, and FUP as control variables. The results showed a good fit between the structural model and the data ($\chi^2/\text{d.f.} = 1.782$, RMSEA = 0.049, CFI = 0.968, TLI = 0.964).

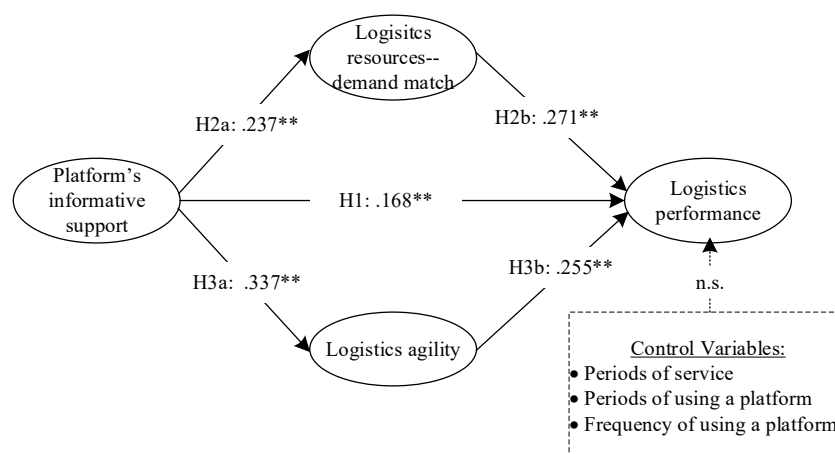


Figure 2. Results of Structural Relationship Analysis. Note: * $p < 0.05$, ** $p < 0.01$, $\chi^2 = 395.624$, $df = 222$, CFI = 0.968, TLI = 0.964, RMSEA = 0.049.

The results shown in Table 8 demonstrated that the hypotheses H1, H2a, H2b, H3a, H3b were supported. The results indicated that PIS had a positive effect on LP ($\beta = 0.168$, $p < 0.01$), as anticipated in H1. PIS was also positively related to LRDM ($\beta = 0.237$, $p < 0.01$) and LA ($\beta = 0.337$, $p < 0.01$), thus supporting H2a and H3a, respectively. Consistent with H2b and H3b, both LRDM ($\beta = 0.271$, $p < 0.01$) and LA ($\beta = 0.255$, $p < 0.01$) were positively related to LP. However, the control variables had no significant effects on the dependent variable, LP.

Table 8. Results with path coefficients for direct hypotheses testing.

Hypothesis	IV	DV	Estimate	S.E.	Z	P-Value	R2	Results
H1	PIS	LP	0.168 **	0.057	2.944	0.003	Support	H1
H2a	PIS	LRDM	0.237 **	0.056	4.211	0.000	Support	H2a
H2b	LRDM	LP	0.271 **	0.055	4.953	0.000	Support	H2b
H3a	PIS	LA	0.337 **	0.054	6.260	0.000	Support	H3a
H3b	LA	LP	0.255 **	0.058	4.416	0.000	Support	H3b

* $p < 0.05$, ** $p < 0.01$.

5.2. Mediating Effect Testing

We aimed to explore whether LRDM and LA mediate the relationship between PIS and LP with the method of bootstrapping approach (with $n = 5000$ bootstrap resamples) proposed by Preacher and Hayes [64]. We employed the bootstrap method instead of the method proposed by Baron and Kenny [65] and Sobel Test [66] because the bootstrap method showed more statistical power and made the test robust [67]. It can be used to examine multiple mediation effects simultaneously and test the overall indirect effects [64]. If zero is not contained in the 95 percent confidence interval, the point estimates of indirect effects are considered significant [68].

The bootstrapping analysis results attained by Mplus 7 are presented in Table 9. The results showed the significant mediating effect of LRDM ($\beta = 0.064$) in the relationship between PIS and LP at $p < 0.05$ with 95% CI = [0.033–0.108], as anticipated in H2c. Moreover, consistent with H3c, the mediating effect of LA ($\beta = 0.086$) in the relationship between PIS and LP was also significant at $p < 0.05$ with 95% CI = [0.044–0.141]. In addition, PIS still showed a significant direct impact on LP ($\beta = 0.168$, $p < 0.01$), which indicated the partial mediating effects of the two mediators [68].

Table 9. Bootstrapping results for mediation relationship tests.

IV	MV	DV	IV-MV	MV-DV	Indirect Effects	Direct Effects	Total Effects	95% CI		Results
								Lower Bounds	Upper Bounds	
PIS	LRDM	LP	0.237 **	0.271 **	0.064 **	0.168 **	0.318 **	0.033	0.108	Support
PIS	LA	LP	0.337 **	0.255 **	0.086 **	0.168 **	0.318 **	0.044	0.141	Support

* $p < 0.05$, ** $p < 0.01$.

5.3. Moderating Effect Testing

We performed hierarchical multiple regression analysis using SPSS to test whether PEU moderated the effect of PIS on LRDM and LA. After controlling for the effects of the control variables, we introduced the independent variable PIS, the moderator PEU and the interaction of PIS with PEU into the model, one by one. It was found that the interaction of PIS with PEU had a significant positive effect on LRDM ($\beta = 0.141$, $p < 0.01$), thus supporting H4a. That is to say, the positive relationship between PIS and LRDM is stronger at a high level of PEU, as compared to a lower level. Figure 3 illustrates the interaction effects by using Stone and Hollenbeck's [69] procedure. In addition, the interaction of PIS with PEU was not significantly related to LA ($\beta = 0.051$, $p = 0.325$). Thus, H4b was rejected. The specific results are shown in Table 10.

Furthermore, results in Table 11 provide empirical tests for our moderated mediation hypotheses H5a and H5b. Table 12 demonstrates that PEU significantly moderates the indirect relationship between PIS and LP via LRDM ($\beta = 0.022$, 95% CI = [0.008, 0.041]), supporting H5a. However, PEU does not significantly moderate the indirect relationship between PIS and LP via LA (95% CI = [−0.007, 0.025]); thus, H5b was rejected. Specifically, LRDM has a significant mediation effect on the relationship between PIS and LP when PEU is at a high level (i.e., conditional mediation effect = 0.116, 95% CI = [0.065, 0.186]) as compared to a lower level (i.e., conditional mediation effect = 0.005, n.s.).

In addition, the conditional mediation effects of PIS on LP via LA have no significant differences at a high level ($\beta = 0.115$) as opposed to a lower level ($\beta = 0.075$).

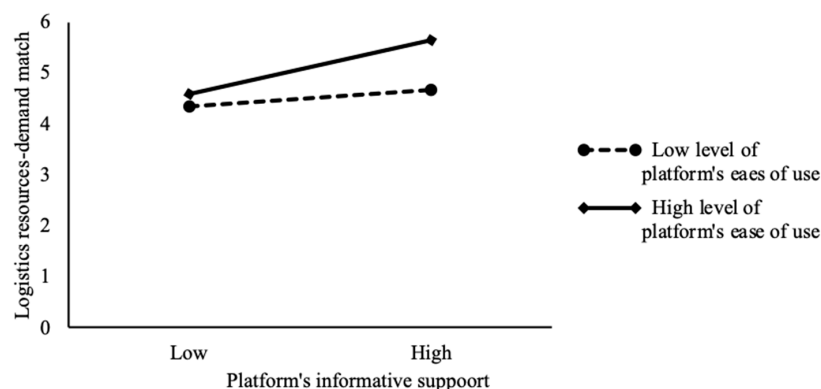


Figure 3. Moderating Effect of A Platform's Ease of Use on the Relationship Between PIS and LRDM.

Table 10. The Moderating Effect of PEU on the Relationship between PIS and LRDM.

	Dependent Variable: LRDM				Dependent Variable: LA			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Control variables								
PS	−0.019	−0.045	−0.027	−0.020	0.159 *	0.121 *	0.137 *	0.139 *
PUP	−0.099	−0.089	−0.080	−0.074	−0.201 **	−0.188 **	−0.180 **	−0.177 **
FUP	0.023	0.027	0.025	0.030	−0.028	−0.021	−0.023	−0.021
Independent variables: PIS		0.226 **	0.228 **	0.236 **		0.327 **	0.328 **	0.331 **
Moderator: PEU			0.210 **	0.211 **			0.181 **	0.182 **
Interaction: PIS × PEU				0.141 **				0.051
R2	0.011	0.062 **	0.105 **	0.125 **	0.037 **	0.143 **	0.175 **	0.178
ΔR2	0.011	0.051 **	0.043 **	0.020 **	0.037 **	0.106 **	0.032 **	0.003
F	1.171	5.193 **	7.394 **	7.449 **	4.081 **	13.164 **	13.375 **	11.307 **

* $p < 0.05$, ** $p < 0.01$, all coefficients are standardized coefficients.

Table 11. Index of Moderated Mediation.

Mediator	Effect	BootLL95% CI	BootUL95% CI
LRDM	0.022	0.008	0.041
LA	0.008	−0.007	0.025

Table 12. Conditional Indirect Effects at Values of the Moderators.

Logistics Performance				
Mediator	PEU	Effect	BootLL95% CI	BootUL95% CI
LRDM	1.750	0.005	−0.041	0.053
LRDM	3.500	0.044	0.015	0.082
LRDM	5.000	0.077	0.044	0.124
LRDM	6.000	0.099	0.057	0.158
LRDM	6.750	0.116	0.065	0.186
LA	1.750	0.075	0.025	0.148
LA	3.500	0.089	0.049	0.145
LA	5.000	0.101	0.060	0.155
LA	6.000	0.109	0.064	0.171
LA	6.750	0.115	0.064	0.185 ¹

Values for quantitative moderators are 10th, 25th, 50th, 75th, and 90th percentiles.

6. Discussion

Our study provides novel and important insights into the process through which a platform's informative support influences logistics performance as well as under what conditions such a process

is affected. We find that logistics resources-demand match and logistics agility mediate the platform informative support-logistics performance relationship. Furthermore, a platform's ease of use shows moderating effects. Our results provide empirical support for a theoretical model based on scale development for platform's informative support and logistics resources-demand match.

6.1. Theoretical Implications

First, a contribution of our study is that we construct a theoretical framework for the platform's informative support-logistics performance relationship based on organization information processing theory. By conducting case studies, scholars pointed out that crowd logistics platforms assist drivers in providing customers with faster and more flexible logistics services and help save costs [27,28]. However, few studies could explain how crowd logistics platforms contribute to logistics performance. Our study investigated the process through which a crowd logistics platform's informative support affects logistics performance and conducted an empirical study. The empirical results show that logistics resources-demand match ($\beta = 0.064$, 95% CI = [0.033–0.108]) and logistics agility ($\beta = 0.086$, 95% CI = [0.044–0.141]) partially mediate the relationship between a platform's informative support and drivers' logistics performance. These novel results expand the crowd logistics platforms literature by specifying why and how informative support by platforms influences logistics performance.

Second, a further contribution of our study to the crowd logistics platform literature is that we found a moderator of this process by which a platform's informative support affects logistics performance. Extant literature only suggested that crowd logistics platforms contributed to logistics performance through case studies [4], but did not specify the boundary conditions that affect the relationship between platform's informative support and logistics performance. In contrast, this study posits that a platform's ease of use is the boundary condition, and strengthens the relationship between platform's informative support and logistics resources-demand match ($\beta = 0.141$, $p < 0.01$). Furthermore, a platform's ease of use also strengthens the indirect relationship between a platform's informative support and logistics performance via logistics resources-demand match ($\beta = 0.022$, 95% CI = [0.008, 0.041]). In particular, platform's informative support has a greater influence on logistics resources-demand match at a high level of ease of use as opposed to a lower level. Moreover, platform's informative support also indirectly predicts more logistics performance at a high level of the platform's ease of use.

Third, this paper developed scales for the two constructs: platform's informative support and logistics resources-demand match. Because of the nascent nature of crowd logistics, scholars normally conduct qualitative, instead of quantitative studies. The literature explores the business model of crowd logistics [5,6,70], the basic functions of crowd logistics platforms [28], and the value outcomes of crowd logistics [27]. However, a few of them have conducted empirical studies to explore the relationship between crowd logistics and logistics performance because of a lack of measures. We developed initial items through extant literature and interviews and purified the scales by consulting academic experts and managers of crowd logistics companies. We then received 265 valid responses by conducting surveys, and tested the structure, reliability and validity by performing EFA and CFA. The results showed that we developed 6 items for platform's informative support and 4 items for logistics resources-demand match. The scale development research contributes to theoretical literature by providing a tested instrument, which allows for in-depth empirical studies on related topics.

6.2. Managerial Implication

The findings of this study provide insights into the design of effective strategies for informative support in order to enhance logistics performance.

Firstly, according to empirical research results, a platform's informative support can reduce logistics costs and improve logistics efficiency. We have illustrated that the crowd logistics supported by information technology can help drivers reduce costs and contribute to urban transport sustainability. This finding provides insights for practitioners that crowd logistics is a sustainable business model, which provides efficient logistics service for customers.

Secondly, it emphasizes the important role of a platform's informative support in promoting drivers' logistics performance. Based on this finding, the development of crowd logistics companies needs to focus on the informative functions. Machine learning algorithm, GPS system, decision support systems, database, and other information support systems are required for platforms to provide drivers with matching orders, effective routing solutions, and information sharing channels.

Thirdly, a platform's ease of use moderates the relationship between a platform's informative support and logistics resources-demand match. Based on this finding, the simplification of a platform's design is another direction that needs to be focused. Crowd logistics companies should take into account users' experience and perceived utility to make platforms easier to use.

6.3. Limitations and Future Research

First, this article only studies the impact of a platform's informative support on logistics performance. However, crowd logistics platforms not only provide informative support but also provide feedback systems, secure online payment system, and insurance [70]. These supports control risks and ensure the security of transaction and operational processes [4]. Thus, they play important roles in improving the reliability of logistics services, contributing to logistics performance. Therefore, future research can conduct in-depth research on the mechanisms through which risk control support provided by crowd logistics platforms impact logistics performance.

Second, the data for this study came from the drivers participating in crowd logistics in China. Crowd logistics platforms in other countries may have different functions. This might lead to different influence mechanisms of platform support on logistics performance. Therefore, future research is needed to determine whether the findings reported here are valid in other countries.

Third, considering the difficulty of gathering data from hundreds of managers from crowd logistics companies, our study used drivers who used the crowd logistics platforms to collect data. However, the managers and technicians managing these platforms may have more knowledge of platform support and could give us more accurate and profound data. Future research might be undertaken to collect data from multiple informants, thus enhancing the validity of the findings [24].

7. Conclusions

Grounded in organization information processing theory, we construct and test a model that explains how a platform's informative support affects logistics performance. After developing scales for platform's informative support and logistics resources-demand match, we find that logistics resources-demand match and logistics agility can mediate a positive relationship between a platform's informative support and logistics performance. In addition, a platform's ease of use plays a moderating role in both the effect of platform's informative support on logistics resources-demand match and indirectly affects logistics performance. However, the moderating effect of a platform's ease of use on the positive relationship between a platform's informative support and logistics agility is not significant. Overall, this paper contributes to the crowd logistics literature by exploring the theoretical mechanisms through which a platform's informative support predicts logistics performance.

In addition, this paper also indicates that crowd logistics, which is a new business model, predicts logistics performance and contributes to sustainable urban transport. In particular, with platform's informative support, crowd logistics increases efficiency of vehicle usage and reduces empty mileage, which leads to reduction of emissions and traffic. Furthermore, crowd logistics companies need to focus on platforms' informative functions to promote the development of crowd logistics and transport sustainability.

Author Contributions: All authors contributed extensively to the study. M.Z. proposed the theoretical model, planned the questionnaire and provided research support. Y.X. contacted the respondents, conducted the survey, and collected data. S.L. analyzed the data and wrote this paper. Both W.W. and S.W. planned the questionnaire, provided research support, guidance and advice throughout the study.

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Appendix A

Table A1. Construct items (items, factor loadings and Cronbach's alpha).

Construct	Item	Factor Loading	Cronbach's Alpha
Platform's informative support			0.930
PIS1	The platform provides me with an access method to locate logistics service requests *.	0.886	
PIS2	The platform gathers and categorizes information and constructs an integrated database *.	0.857	
PIS3	The platform will assign appropriate logistics service requests for me *.	0.824	
PIS4	The platform provides me with delivery solutions *.	0.828	
PIS5	The platform provides me with real-time GPS navigation *.	0.801	
PIS6	The platform will help me adjust the delivery routes and solutions in case of changes *.	0.789	
Logistics resources-demand match			0.943
LRDM1	The platform can help me to find matched logistics service requests *.	0.931	
LRDM2	The match is very good between the logistics service requests and my capability *.	0.912	
LRDM3	The match is very good between the logistics service requests and my preference *.	0.882	
LRDM4	The platform can help me to find matched logistics service requests quickly *.	0.865	
Logistics agility			0.923
LA1	Speed in adjusting delivery solutions	0.794	
LA2	Speed in improving customer service	0.888	
LA3	Speed in improving delivery reliability	0.912	
LA4	Speed in improving responsiveness to customers' needs	0.881	
Logistics performance			0.935
LP1	Lower costs	0.846	
LP2	Better customer service	0.839	
LP3	Quicker delivery results	0.825	
LP4	Reduced cycle time or lead time	0.875	
LP5	Improved quality	0.869	
LP6	Improved value to our customers	0.789	
Platform's ease of use			0.969
PEU1	My interaction with this platform is clear and understandable.	0.949	
PEU2	Interacting with this platform does not require a lot of mental effort.	0.943	
PEU3	I find this platform easy to use.	0.945	
PEU4	I find it easy to locate the information that I need in this platform.	0.935	

* refers to the items which have been retained in the process of scale development.

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