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Review

Vehicle Routing Optimization for Pandemic Containment: A Systematic Review on Applications and Solution Approaches

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Abstract: The global spread of the novel coronavirus (COVID-19) has accounted for many deaths. The effective containment of the current COVID-19 epidemic calls for a fast and sustainable delivery strategy to minimize the impact of this crisis. As such, this study aimed to conduct a comprehensive review of research on the vehicle routing problem (VRP) from a sustainable viewpoint during the pandemic and explore viable delivery solutions that may aid in the containment of the COVID-19 pandemic. Through a systematic review of the selected articles, four broad themes of pandemic containment measures from the delivery aspect were identified: efficient pharmaceutical delivery strategy, contactless distribution, sustainable waste transportation strategy, and isolated and quarantine vehicle scheduling. Following that, the methodology utilized to execute the containment measures were analyzed, research gaps were hightlighted, and possibilities for future studies were suggested. In summary, the goal of this research is to provide an overview of the literature on the application of VRPs in pandemic control and to assist academics and practitioners in learning more about the performance metrics, models, and solution techniques utilized in pandemic control delivery operations.

Keywords: COVID-19; transportation planning; containment measures; VRP; sustainable development; literature review

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1. Introduction

Human history is full of public health crises that resulted in widespread pain and death. For example, epidemics of plagues with high mortality rates in late medieval Europe caused numerous deaths; the 1918–1919 Spanish influenza pandemic killed almost 50 million people globally [1,2]; and the influenza A(H1N1) virus outbreak in 2010 spread to 214 nations, killing 18,114 people [3]. Nevertheless, the novel coronavirus COVID-19 is distinct and has had far more severe, diverse, and dynamic consequences than recent disease outbreaks, such as the 2003 SARS outbreak or the 2009 H1N1 outbreak [4]. Since December 2019, the global spread has been so rapid that nearly 263,714,765 cases of infections have been confirmed worldwide as of the 1st of December, 2021, and around 5,228,255 people have perished [5]. Moreover, COVID-19 may come to coexist with humans [6,7], and continue to severely threaten public health [8]. Therefore, sustainable infection control measures are urgently needed in order to reduce the impact of COVID-19 and its dissemination.

In attempts to successfully combat an epidemic, logistics activities are essential [3]. In the field of epidemic control logistics operations, various different disease outbreaks have been investigated—For instance, Influenza [9], Ebola [10], Cholera [11] and Malaria [12] outbreaks, among others. In addition, two comprehensive surveys examining pandemic containment methods from a logistics operation standpoint [3,13] were discovered. These articles indicate that efficient resource allocation is crucial in controling epidemics or pandemics. Nevertheless, the allocation of resources cannot be accomplished unless these resources (such as medical suppliers, drugs, and vaccines) are available at the right time and place, and in the right quantity. In this regard, optimizing resource distribution may provide valuable insights into how to approach this complex scenario; however, surveys systematically reporting state-of-the-art delivery practices and solutions that can be used in dealing with infectious disease remains scarce. As such, our study intends to shed more light on this topic, providing valuable insights that will assist decision-makers in developing a rapid and sustainable (e.g., low infectious risk and emission gas) transportation plan for the COVID-19 pandemic.

One of the most important applications within logistics operation is vehicle routing. The first Vehicle Routing Problem (VRP) was introduced in Dantzig and Ramser [14], where the authors' goal was to enhance the responsiveness of logistics movements. As shown in Table 1, research on VRPs has advanced rapidly over the last sixty years. Currently, many variations of VRP are being studied. The first time-dependent VRP (TDVRP) was introduced in Cooke and Halsey [15], who considered the fluctuation in the travel time between a pair of points, while the first multi-depot VRP was studied in Tillman [16], who showed that demand customers could be assigned to more than one depot. The first study of stochastic VRP appeared in 1969 [16]; in this study, the customer demand was random. To handle more complex operational problems, a number of VRP variants have emerged since 1973, such as the location routing problem [17], periodic VRP [18], dynamic VRP [19], VRP with time window [20], inventory routing problem [21], fuzzy VRP [22], open VRP [23], multi-echelon VRP [24], and share VRP [25]. Over the past two decades, it seems that there has been a trend for scholars to pay more attention to sustainable VPR, incorporating economic, environmental, and social concerns [26,27]. Many variants of sustainable VRP, such as green VRP [28], electric-vehicle VRP [29], pollution routing problem [30], drones routing problem [31], and crowdsourced deliveries [32], appeared after the year 2000. For a comprehensive study of VRPs, Laporte [33] and Braekers et al. [34] provided detailed categorizations of VRP variants and their corresponding solution methods.

Table 1. A landscape of VRP variants.

1959	Capacitated VRP [14]
1966–1969	Time-dependent VRP [15]; multi-depot [16]; stochastic VRP [16]
1973–1977	Location routing problem [17]; periodic VRP [18]; dynamic VRP [19]; pickup and delivery problem [35]; VRP with time windows [20]
1983–1989	Inventory routing problem [21]; fleet size and mix VRP [36]; generalized VRP [37]; humanitarian VRP [38]; split-delivery VRP [39]
1995–2000	Fuzzy VRP [22]; open VRP [23]
2001–2005	VRP for perishable goods [40]; VRP with loading constraints [41]
2006–2010	Multi-echelon VRP [24]; green VRP [28]
2011–2015	Pollution routing problem [30]; electric-vehicle VRP [29]; drones routing [31]; share VRP [25]
2016–2020	Hybrid VRP [42]; crowd-sourced deliveries [32]

Unlike traditional VRPs which focus on the economic impact of vehicle routes, there are applications of VRP where servicing a customer has the social benefit and all available information and resources must be mobilized to provide the best possible delivery service to control the spread of infectious disease. Such applications appeared in the COVID-19 pandemic, when the overarching goal was to avoid and alleviate human suffering. In this study, literatures on the applications of VRPs, with a focus on preventative methods for disease outbreak control, were reviewed.

The application of VRPs for pandemic containment belongs to the field of humanitarian logistics (HL). The first effort to address the humanitarian VRP occurred in 1988 [38].

Since 2010, four previous systematic reviews of humanitarian VRPs, as shown in Table 2, that focus on relief routing problem [43–45], the modeling and solution of humanitarian operations [46], and evacuation and rescue operations [45], have been identified. All of these review papers concentrate on rapid-onset disasters [47], such as tsunamis, earthquakes, and hurricanes; however, delivery problems in slow-onset disasters (such as pandemic or drought) have still not been adequately investigated [45]. Moreover, none of these reviews examined vehicle routing strategies with sustainability concerns, which are critical in the post-pandemic period in order to prevent another pandemic and preserve our environment [6]. As a result, this article focuses on VRPs during a slow-onset calamity, such as pandemic, to fill in these research gaps. Unlike those four peer-reviewed articles, our study focuses on optimizing epidemic control delivery from a sustainable standpoint.

Table 2. Review papers on VRPs related to disaster management.

Reference, Year	Research Content	Finding
[43], 2012	Disaster relief routing	Risk-averse behavior in VRPs has not been well investigated.
[44], 2014	Disaster relief routing	There is a need for a better understanding of the impact of humanitarian goals on various types of disaster assistance situations.
[46], 2016	Uncertainties in humanitarian operation	Modeling uncertainties should remain the focus of future research activities.
[45], 2021	Humanitarian operations: supply and delivery, evacuation, rescue operations	Slow onset disasters deserve more attention to contribute to humanitarian operations.

To the best of the authors' knowledge, this is the first literature review of VRPs that focuses on sustainable epidemic control practices. The aims of this study can be summarized as follows:

- To provide an exhaustive literature review of VRPs in the context of an epidemic.
- To identify state-of-the-art preventive measures to halt the spread of COVID-19 from the delivery perspective.
- To find the ideal methodologies for implementing epidemic containment delivery operations.
- To highlight the lack of the existing studies and explore potential topics for further research.

The rest of this paper is structured as follows. Section 2 concerns the review methodology used. Section 3 includes a descriptive and content analysis of the literature. Section 4 systematically reviews the preventive measures used in epidemic control delivery operations. The discussion of methodologies used in each containment measure and potential future research opportunities are given in Section 5. Finally, Section 6 describes our conclusion.

2. Research Methodology

In this study, a systematic literature review (SLR) strategy was undertaken. The SLR has been proven to be a holistic paradigm for use in literature reviews [48]. The first step in this method is to finalize the research scope before implementing the literature search. In step 2, several research databases (such as Scopus, Google Scholar, and Web of Science) are used to search for relevant and high-quality studies. The last step is to conduct a reference check of the selected articles to include additional relevant papers.

The search methodology used in this review paper is outlined in Figure 1. Initially, electronic searches were undertaken in the Scopus database using the keywords 'vehicle routing' and 'pandemic' for articles. In the first round of analysis, keywords with a similar meaning to 'vehicle routing' were discovered and then included in the second round. VRP are widely used in the transportation literature, since they enable the simulation of a wide range of delivery operations [49,50]. Instead of 'vehicle routing', some studies employed the terms 'transportation' [51] or 'delivery' [52]. Words that have a similar meaning to 'pandemic', such as 'epidemic', 'COVID-19', 'coronavirus', 'SARS', and 'virus' were also included in the search database. The search string utilized in the database is shown in Table 3, and the Boolean operator was used in the 'title or abstract or keywords' field of the search engine. To concentrate on the most pertinent research, only published journal articles and conference papers available online from 2010 to the 20 of December 2021 were considered, while book chapters, working papers, theses, dissertations, and technical reports were excluded. The first process yielded 5622 results.

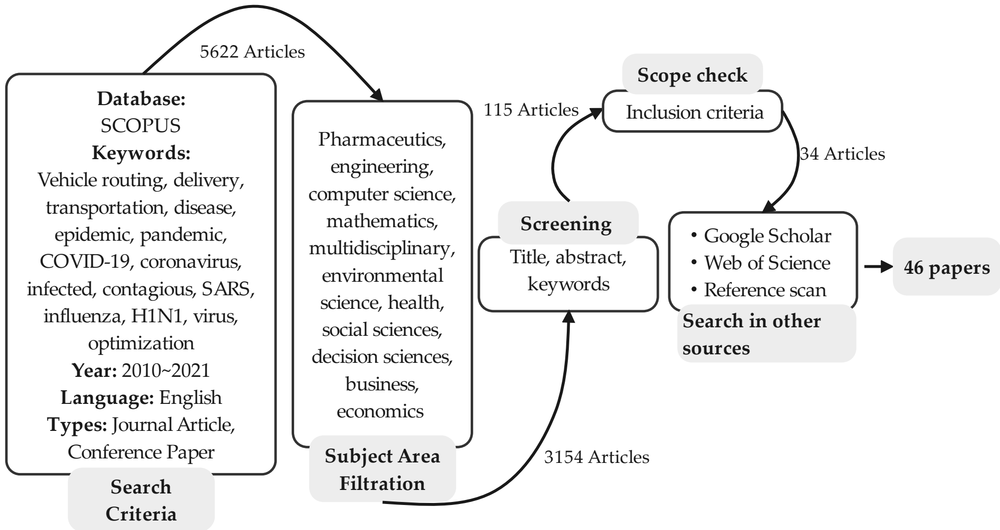

Figure 1. Search methodology.

Table 3. The search string utilized on the online database.

Database	Search String
Scopus	(TITLE-ABS-KEY ("vehicle routing") OR TITLE-ABS-KEY ("route") OR TITLE-ABS-KEY ("routing") OR TITLE-ABS-KEY ("delivery") OR TITLE-ABS-KEY ("transportation")) AND (TITLE-ABS-KEY ("disease") OR TITLE-ABS-KEY ("epidemic") OR TITLE-ABS-KEY ("pandemic") OR TITLE-ABS-KEY ("COVID-19") OR TITLE-ABS-KEY ("coronavirus") OR TITLE-ABS-KEY ("virus") OR TITLE-ABS-KEY ("contagious") OR TITLE-ABS-KEY ("infectious")) AND (TITLE-ABS-KEY ("optimization") OR TITLE-ABS-KEY ("algorithm") OR TITLE-ABS-KEY ("mathematic") OR TITLE-ABS-KEY ("heuristic"))
Web of Science	TS = st(("vehicle routing" OR "delivery" OR "transportation" OR "route" OR "routing") AND ("disease" OR "epidemic" OR "pandemic" OR "COVID-19" OR "coronavirus" OR "SARS" OR "infectious" OR "contagious" OR "influenza" OR "H1N1" OR "virus") AND ("optimization" OR "algorithm" OR "mathematic" OR "heuristic"))

Secondly, papers not related to the subject areas of pharmaceutics, engineering, computer science, mathematics, interdisciplinary, environmental science, public health, social sciences, decision sciences, business, and economics were omitted, leaving 3154 articles. Then, by screening titles, abstracts, and keywords, irrelevant publications were weeded out, leaving 115 articles for further investigation.

Thirdly, the titles, abstracts, introduction, and conclusions of the collected papers were analyzed in order to eliminate some of the studies. The inclusion criteria were (i) articles focused on VRPs in a pandemic or epidemic setting, and (ii) both the terms "vehicle routing" and "pandemic", or other similar words (as mentioned in Table 3), appearing in the body text. Hereby, VRP applications on animal disease control [53], agricultural route planning [54,55], home health care (HHC) [56–60], supply chain management [61,62], and production management [63] were excluded from consideration, since this review aims to focus on humanitarian delivery optimization and pandemic control. For a holistic review of the HHC routing problem and production routing problem, interested readers can refer to the surveys provided by Fikar and Hirsch [64] and Adulyasak et al. [65], respectively.

Finally, by repeating search in other databases (such as Google Scholar and Web of Science) and scanning the reference section of thirty-four included papers, additional works of interest were added to the shortlist, and relevant references were reviewed until no additional articles could be found. The whole process resulted in a total of forty-six articles.

The results of this screening method were organized into four groups. First, these 46 articles were comprehensively reviewed based on four aspects: their application scenarios, performance metrics, model characteristics, and solution approaches. This classification scheme was used to help focus on the applications of VRP and the corresponding characteristics of the problem. Second, the preventive measures of pandemic control used in the reviewed articles were examined and synthesized into four categories. Third, the methodologies (such as objectives, model constraints, solution procedures) employed in the epidemic control delivery operations were discussed and the research challenges associated with various optimization methodologies were highlighted. Finally, this study delivered suggestions for further research on epidemic control delivery operations. The framework of the entire process is displayed in Figure 2.

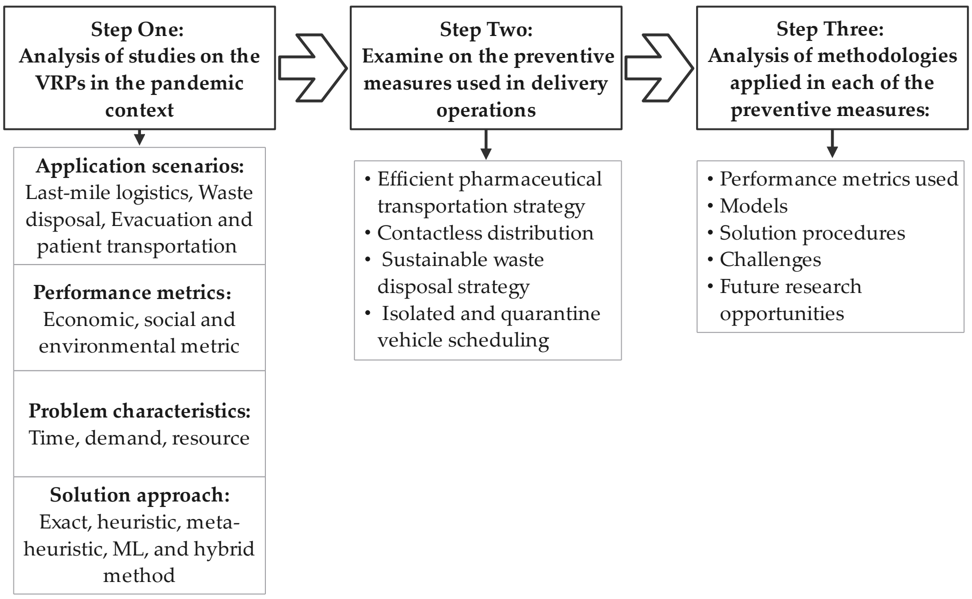

Figure 2. Research methodology.

3. A Review of Vehicle Routing Problem in the Pandemic Context

This section examines the theoretical underpinnings of the VRPs used in the 46 selected articles. Before investigating the main themes, a descriptive analysis is carried out to offer an overall picture of the articles found.

3.1. Descriptive Analysis

The distribution of these articles across different sources is illustrated in Table 4. This demonstrates that a diverse range of publications have contributed to the research in this field. Grouping the selected journal articles by their main subject areas, the result (see Figure 3) shows that the vast majority of the selected articles were published in logistics- and OR-related journals. However, the low number of articles published in environmental- and sustainability-related journals is unexpected.

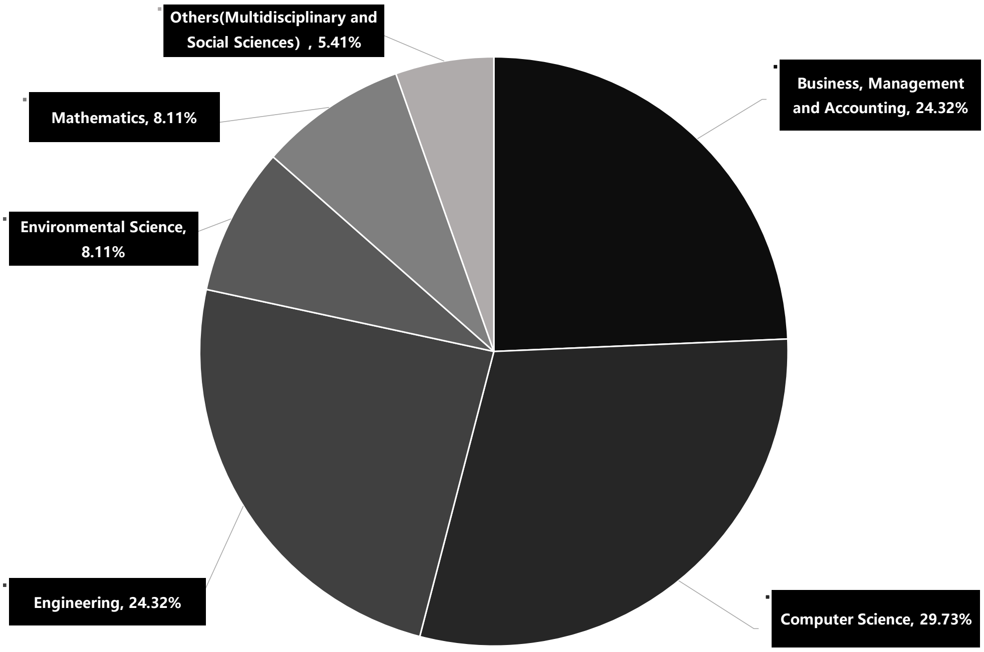

Figure 3. Subject areas of the analyzed articles.

Table 4. Distribution of articles across journals.

Source Title	Number of Articles
IEEE Transactions on Engineering Management	3
Mathematical Problems in Engineering	3
Computers & Industrial Engineering	2
Networks	2
International Transactions in Operational Research	2
Advances in Science, Technology and Engineering Systems	1
Discrete Applied Mathematics	1
European Journal of Operational Research	1
International Journal of Contemporary Hospitality Management	1
International Journal of Environmental Research and Public Health	1
International Journal of Intelligent Systems	1
Journal of Advanced Transportation	1
Journal of Cleaner Production	1
Journal of Combinatorial Optimization	1
Journal of Global Optimization	1
Journal of Heuristics	1
Journal of Humanitarian Logistics and Supply Chain Management	1
Journal of Traffic and Transportation Engineering (English Edition)	1

Table 4. *Cont.*

Source Title	Number of Articles
Omega	1
Optimization Letters	1
OR Spectrum	1
Production	1
Science of the Total Environment	1
Scientific Programming	1
Scientific Reports	1
Springer Optimization and Its Applications	1
Transportation Letters	1
Transportation Research Interdisciplinary Perspectives	1
Transportation Research Part E	1
Waste Management and Research	1
Conference	9
Total	46

Considering the distribution of articles by publication year, the trend in Figure 4 demonstrates that the number of papers published in this field increased dramatically after the year 2020 (39 out of 46 articles), while few studies on the use of VRP in controlling infectious disease were conducted during the period between 2009 and 2019, including some years in which no articles were published. It is worth mentioning that most of the research efforts before 2020 focused on VRPs in large-scale bioterrorism emergency [66–68], while after 2020 the study of VRPs for use in pandemic control started to attract the attention of researchers and became a hotspot.

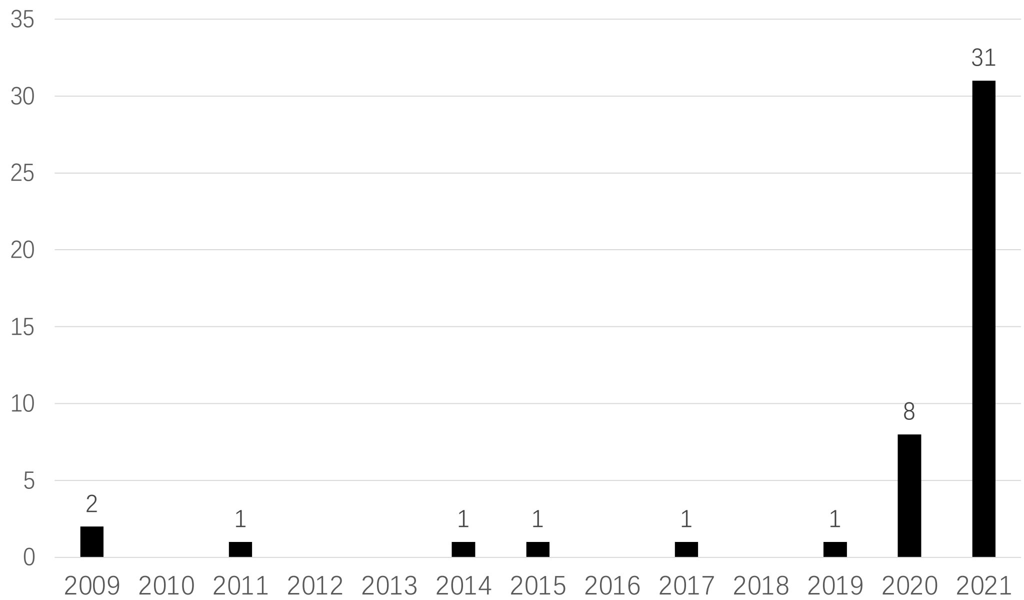

Figure 4. Distribution of articles over time.

Case studies were conducted in thirty-two articles (32 articles out of 46), with eleven studies considering real cases in China (See Table 5), showing that the greatest attention was focus on this country; this may be attributed to the fact that COVID-19 was discovered in China and spread rapidly within China and to other countries around the world. In terms of a particular continent, most of the review articles referred to the practices in Asian countries (19 papers out of 46), while a small number of articles considered practices in Oceania and American countries. Future research should provide more insights into developed countries with large numbers of confirmed cases [5].

Table 5. Distribution of articles by geographical area.

Area of Study	Number of Articles	References	Year
China	11	[69–71]	2020
		[72–79]	2021
Iran	2	[80,81]	2021
Turkey	2	[82,83]	2021
Hongkong	1	[84]	2015
India	1	[85]	2021
Indonesia	1	[86]	2021
Korea	1	[87]	2021
Total Asian countries	19		
France	1	[88]	2011
German	1	[89]	2021
Italy	1	[90]	2021
Spain	2	[91]	2020
		[92]	2021
Total European countries	5		
DR Congo	1	[93]	2017
Morocco	1	[94]	2020
Mozambique	1	[95]	2021
Nigeria	1	[96]	2020
Total African countries	4		
Brazil	1	[97]	2021
USA	1	[98]	2021
Colombia	1	[99]	2021
Total American countries	3		
Australia	1	[100]	2021
Total Oceania countries	1		
Others without indicating specific area	14	[66,67]	2009
		[68]	2014
		[101]	2019
		[102–104]	2020
		[51,52,105–109]	2021
Total	46		

In the following subsection, a content analysis for each theme was conducted in order to fulfill the target of this review.

3.2. Application Scenarios

A systematic analysis of the application scenario for the selected articles contributes to providing supplemental information about the nature of the problem, enabling the in-depth analysis of the problem. For example, each class of application scenario is revealed and accordingly, three groups of application themes are consolidated (see Table 6).

Table 6. Application scenarios of VRPs in the pandemic context.

Application Scenarios	Number of Articles	References
Last-mile logistics:	33	
• Vaccine or drug distribution	7	[68,80,93–95,97,107]
• Medical supplier distribution	10	[52,66,67,72,91,92,96] [71,79,99]
• Commodity distribution	8	[85,86,90,100,106,108] [103,104]
• Food distribution	5	[69,70,89,102,109]

Table 6. *Cont.*

Application Scenarios	Number of Articles	References
• Oil distribution	1	[76]
• Room service	1	[87]
• Testing specimen distribution	1	[83]
Waste disposal:	7	[73,74,77,78,81,82,105]
Patient transportation and evacuation:	6	
• Evacuation	1	[98]
• Patient transportation	5	[51,75,84,88,101]
Total	46	

The term "last-mile logistics" refers to the movement of goods from the last transportation center to their final destination. This theme has received significant attention (33 out of 46 articles), and seven sub-themes were identified. Our analysis revealed that the major focus in this theme is the distribution of the vaccine, drug, testing specimen, and medical supplier (18 papers). This finding makes sense, given the importance of using pharmaceutical interventions to control the pandemic. In addition, nine articles examined e-commerce logistics services, such as fresh food shipping [69,89,102] and parcel delivery [85,86,90,100,103,106], while four papers referred to on-demand transportation services [70,104,108,109], the use of which has been accelerated by the onset of COVID-19 in urban areas [92]. Among the rest of the articles in this area, one focused on oil distribution and one focused on ready meal delivery in hotels.

Regarding waste disposal, seven papers discussed the infectious waste (e.g., medical waste) collection activities during a pandemic scenario. These articles mainly explored various ways to mitigate the transmission risk presented by infectious medical waste, including the use of temporary facilities [74,77,78,81] and outsourcing [105].

The issue of evacuation and patient transportation gained the least attention (6 articles). Five references studied patient transportation from the viewpoint of emergency medical services, while one paper focused on social distancing and evacuation scheduling during the COVID-19 pandemic.

3.3. Performance Metrics

This section analyzes the performance indicators (i.e., objectives) used in the reviewed articles and discusses how they are related to sustainability in the operational vehicle routing field. The triple bottom line (TBL) approach [110], which stresses economic, social, and environmental dimensions, was adopted to examine the TBL objectives employed in the epidemic control delivery operation.

3.3.1. Economic Dimension

Economic performance metric measures the performance of VPRs in terms of costs. A summary of studies considering the economic metric is given in Table 7; our analysis reveals that nine articles took only economic factors into account, while twenty-one out of fourty-six articles (46%) considered both economic and other factors in the objectives. The most common economic factor was cost minimization. The often used cost elements were transportation [93,108], fixed and variable outsourcing [105], the use of vehicles [52,87,105], fuel consumption [109], penalty cost for arriving early or late [76], facility opening costs [77], and shortage costs for relief suppliers [79], etc.

Table 7. Performance metrics used in the selected articles.

Performance Metrics	Counts	Reference
Economic performance:	9	
Transport-related cost	9	[86–88,93,96,108] [71,99,102]
Social performance:	23	
(1) Response time	13	[73,83,89,100,106,107] [51,91,97,98,101,103,104]
(2) Public health (risk of infection)	2	[74,75]
(3) Customer demand	1	[68]
(4) Satisfaction	1	[69]
(5) Response time + customer demand	3	[66,67,72]
(6) Response time + public health	3	[81,82,108]
Multiple performance metrics:	14	
(1) Economic and social dimensions	8	
• Cost + time	(3)	[76,94,95]
• Cost + demand	(1)	[84]
• Cost + public health	(3)	[77,78,80]
• Cost + time + demand	(1)	[79]
(2) Economic and environmental dimensions	2	[74,90]
(3) Social and environmental dimensions	2	[85,92]
(4) Economic, social, and environmental dimensions	2	[105,109]
Total	46	

3.3.2. Social Dimension

Social metrics measure the social impact based on people, product, and time [26]. Out of 46 studies, the social dimension was the largest group of performance metrics in the reviewed articles (23 out of 46 articles). In this study, the social indicators (such as time, health effect, customer) proposed by Popovic et al. [111], was adapted to analyze the selected literature.

Response time was the factor used most often in the social dimension. The minimization of total time in the route was used in many articles [51,89,98,104,106,107]. In order to optimize the bottleneck route, Pacheco and Laguna [91] proposed an alternative objective function, aiming to minimize the longest route time and ignore all shorter routes. In contrast, Jiang et al. [70] suggested the minimization of average arrival time, taking into account all routes. If the travel time for a route is not directly available, the travel distance might be used to estimate it; therefore, another practical approach to measuring the response time is the minimization of the total travel distance [73,83,97,100].

Few papers considered health-oriented metrics to minimize the risk of infection during the pandemic. Similarly to Haolin et al. [74], Eren and Rıfat [82] and Tirkolaee et al. [81] studied the risk control of medical waste, while Jiang et al. [70] and M. Zhang et al. [75] focused on the risk of transmission between humans.

In customer-oriented studies, many articles [66–68,72] addressed the issue of minimizing unmet demand in an emergency situation, while D. Chen et al. [69] focused on maximizing customer satisfaction through improving the service level.

3.3.3. Multiple Dimensions

Among fourteen articles that took multiple sustainable factors into account, only six aimed to minimize the emission of pollutant gas together with other objectives. These studies addressed the problem of waste collection [105], parcel delivery [85,90], food distribution [109], and medical supplier transportation [52,92]. The other seven studies concerned with both cost and social factors.

Notably, three out of fourteen articles that considered health-related factors addressed the problem of waste collection [77,78,105]. A common assumption in these studies is that minimizing the total population exposed during medical waste transportation can reduce the risk of infection, thus improving public health.

3.4. Problem Characteristics

In contrast to the performance metrics, the problem characteristics embedded within the modeling frameworks in the reviewed papers varied substantially. In this section, humanitarian-centric attributes [112]: time, customer demand, and resource (e.g., available vehicles or depots used to meet the goal) were investigated. These frequently used attributes can be further categorized based on the scenario characteristics and problem characteristics proposed by Braekers et al. [34], as shown in Tables 8–10.

Time: Time windows (TW) were used in 56% of the selected articles (26 out of 46). These time windows were often imposed on the deadline of visiting each customer (26%) and the maximum duration of each route for each vehicle (32%). These two types of TW were quite often considered together in the reviewed articles, as many tasks are time-sensitive—e.g., fresh food distribution [89], patient transfer [84], or the provision of vaccines or drugs [68] must be finished within a certain time period. TW restrictions on depots, concerning when a vehicle has to return to its origin point, gained less attention (10%) in the reviewed papers, while multiple-period characteristics only appeared in six articles. Regarding the uncertain time parameter, few papers considered stochastic travel time (6%), and stochastic service time was not dealt with in any of the reviewed papers.

Table 8. Overview of time characteristics in absolute numbers.

Time Characteristics	Numbers	Reference
Time windows	26	
• Restriction on customer	12	[51,69,73,74,88,106] [66,67,76,81,84,109]
• Restriction on depot	5	[51,76,78,86,98]
• Restriction on vehicle/driver	15	[68,69,85,87,89,107] [76,81,83,84,95,102] [92,96,104]
Multi-horizon	6	[73,78,79,81,88,93]
Uncertain travel time	3	[66,67,85]

Customer demand satisfaction: Concerning the provision of service, precedence and coupling constraints, which may force the pickup site to be visited prior to the delivery site, appeared in 19% of the reviewed articles as presented in Table 9, while a range of articles considered subset-covering constraints (17%)—i.e., customers were assigned and served by intermediate facilities instead of the depot. This is a common assumption when implementing an efficient distribution strategy in order to cover as many visiting nodes as possible. In terms of visiting patterns, most reviewed papers assumed that each customer would be served once by a single vehicle, except in some cases [67,70,75] where split delivery—e.g., multiple visits to a demand node—was allowed to satisfy the strict requirements of fleet size in a large-scale epidemic context. In addition to the split delivery strategy, Shen et al. [67] introduced a strategy in which skipping low-demand customers was allowed in order to satisfy customers' demand as much as possible.

Table 9. Overview of demand characteristics in absolute numbers.

Demand Characteristics	Numbers	Reference
Uncertain demand quantity	8	[72,77,79–81,88,96,99]
Precedence and coupling constraint	9	[69,81,83,84,88,91,93,105,107]
Subset covering constraint	8	[68,73,74,77,79,94,99,106]
Split delivery	5	[67,70,72,75,78]

Resource: Regarding the characteristics of available resources (i.e., vehicles and depots), most of the reviewed papers considered capacitated vehicles, vehicles are seldom assumed uncapacitated, except in two cases where each vehicle could handle any quantity of small-sized goods [91,92]. In addition, most vehicles were assumed to be heterogeneous (32%) in the review articles. Some authors considered multiple-compartment VRP [76], where each kind of product could only be loaded into one vehicle compartment. Collaborative multiple depots were considered in some cases (19%) under emergency conditions. In particular, Pacheco and Laguna [91] and Babaee and Aydın [105] studied cases without a central depot; this enabled more flexibility in optimization and allowed vehicles to start and end their journeys at various locations.

Table 10. Overview of resource characteristics in absolute numbers.

Resource Characteristics	Numbers	Reference
Multiple depots	9	[52,68,71,76,78,83,94,96,99]
Rental vehicles	4	[52,88,105,109]
No depots	2	[91,105]
Heterogeneous vehicles	15	[66–68,75,77,78,81,83,85–88,90,96,102,105,106]

3.5. Solution Methods

Regarding the solution approach applied in the review articles, algorithms, as presented in Table 11, were categorized based on the classification provided by Lin et al. [113] and Laporte [33]. Machine learning (ML) is defined as a solution approach based on supervised, unsupervised, or reinforcement learning technique, and a hybrid solution is defined as a blend among ML, heuristic, metaheuristic, exact, and simulation solution.

Table 11. Solution methods used in the reviewed papers.

Solution Approach	Numbers	Publication Reference
Metaheuristics:	20	
• Local search	8	[51,66,67,86,88,91,97,108]
• Population search	12	[69–71,73–75,79,84,100,102,103,109]
Exact:	10	[68,72,77,78,80–83,87,105]
Heuristics:	4	[92,95,96,107]
Machine learning:	1	[98]
Simulation:	1	[101]
Hybrid:	10	
• Exact + heuristics	2	[93,106]
• Exact + meta	1	[90]
• Exact + ML	1	[89]
• Meta + heuristics	2	[52,76]
• Meta + ML	2	[85,94]
• Meta + simulation	1	[99]
• Heuristics + ML	1	[104]
Total	46	

Metaheuristic: Significant efforts have been made to develop meta-heuristic solution procedures to solve the VRPs in the pandemic context. The employed methods comprise a variety of population-based algorithms and local search-based procedures. The frequent used metaheuristics are tabu search, and evolutionary algorithm (such as genetic and memetic algorithms). Additionally, in several articles [69,70,75,76,84], multiple metaheuristic implementations were compared on a single data set. In most of the reviewed articles, real instances were used. However, computational comparisons are difficult due to the existence of major differences in performance metrics and problem characteristics. It can be seen that a common assumption for a practical planning problem in delivery operations during a pandemic includes less than 150 demand nodes. The computational run times varied significantly amongst the examined studies, ranging from a second to up to 30 min for each instance, depending on the problem size, programming language, and computing hardware.

Exact methods: Mix integer linear programming (MILP) was predominately implemented using optimization tools such as CPLEX [78,81,82,87,105]. As a result, instances with up to 100 demand nodes were addressed optimally in three hours or less [90]. Additionally, the branch-and-cut-and-price [68], and dynamic programming [80] technique were employed.

Hybrid methods: Combining the advantages of exact method and metaheuristic or heuristic, multiple authors developed hybrid methods, mainly by incorporating integer programming [93,106] to generate customer clusters and linear programming techniques [106] or local search-based methods [52,76] in order to reduce the computational time.

Other methods: Heuristics, simulation, and machine learning were rarely used in the reviewed articles. However, to provide a good solution for VRPs in real time, a biased-randomized heuristic with parallel computing was used to generate the solution within milliseconds [92,107], while deep reinforcement learning was implemented in Tsai et al. [98] to enhance the routing efficiency. To schedule multiple vehicles simultaneously in a dynamic traffic condition, Mook et al. [101] studied the simulation tool of Simio for the purpose of simulating autonomous cars after configuring the routing decision strategy in the road network.

Uncertainty: Considering the uncertainty in VRP operations during a pandemic, the focus was mainly placed on stochastic customer demand [77,79–81,88,99]. Therefore, fuzzy chance-constrained programming [81], scenario-based approaches [77], and Monte Carlo simulation [99] were utilized to address the severe demand uncertainty. Another stochastic parameter, travel time, was investigated in Shen et al. [66], and stochastic programming was used to determine the value of travel time. Dynamic events (such as new customer request) were seldom addressed and only mentioned in two articles [88,96]. The route plan was generated using the information available to the decision maker at the time; when new information became available, the route plan was updated via heuristic or metaheuristic techniques.

Multiple objectives: As presented in Table 7, multiple objectives were discussed in a range of articles. Most of these papers adopted a decomposition-based algorithm to transform multi-objectives into one equivalent objective, and the weight of each goal in the objective function can be derived from min-max normalization [70], ML [85], and the decision maker's experience [66,67,84,85,95]. Note that only one work introduced dynamism in the weights, which were dependent on the real-time information of customers' request [85]. Other decomposition-based methods such as Chebyshev method [52], Membership function [82] and Goal Programming(GP) [77,81,105] were also utilized to construct a compromising model for solving multi-objectives problems.

Compared with the aforementioned decomposition-based algorithm, Gamchi et al. [80] and Zhao et al. [77] proposed an ε-constraint method, which is efficient in converting multiple objectives into one, and other objectives become constraints. The numerical experiment indicated that the augmented ε-constraint method could deliver a better solution in less time compared to the Goal Programming method [77].

4. Pandemic Containment and Vehicle Routing Problem

Our analysis in Section 3.2 revealed that the selected studies on VRPs focused on three broad areas: last-mile logistics, medical waste disposal, and evacuation and patient transportation. In this section, preventive measurements of pandemic control implemented in these topic areas are systematically examined.

Various methods can be used for epidemic control, including quarantine, immunization, and treatment [114,115]. Based on these three control tools and the research topics in our study, four clusters of containment measures were identified. These refer to efficient pharmaceutical delivery, contactless delivery, sustainable waste transportation strategy, and isolated and quarantine vehicle scheduling. One study considering oil transportation [76] during the pandemic situation was excluded from these four themes, while the issue of transporting COVID-19 testing specimens [83] was included in the group of pharmaceutical delivery, since rapid response testing may result in more medications, preventing the further transmission of the virus. In Table 12, the allocation of the different preventive measures used in the selected papers is summarized.

Table 12. Preventive measures used to contain the pandemic.

Preventive Measures	Number of Articles	References
Efficient pharmaceutical delivery	21	[52,66–68,71,93,94,107] [72,80,83,85,91,95,96] [79,92,97,99,103,104]
Contactless delivery	18	[68,69,89,90,93,106,107] [52,70,83,85,87,108,109] [86,100,102,104]
Sustainable waste transportation	7	[73,74,77,78,81,82,105]
Isolated and quarantine vehicle scheduling	6	[51,75,84,88,98,101]

Our analysis shows that many articles discussed only one of these four measures. Others touched on two of the four measures. Among these measures, the majority of these articles (21 articles out of 46) discussed and reported potential medication and medical supplier distribution strategies to mitigate the pandemic's impact. In this paper, these strategies are grouped under the heading of efficient pharmaceutical delivery. In addition, contactless delivery was also frequently discussed, appearing in 18 articles. Seven of the included articles discussed sustainable transportation strategies for use in medical waste disposal. Finally, six articles discussed non-pharmaceutical interventions for controlling an epidemic, such as isolation, quarantine, and social distancing, when implementing vehicle scheduling. The following sub-sections summarize each of these four measures.

4.1. Efficient Pharmaceutical Delivery

Shortages of medical suppliers (such as face shields) and drugs put citizens and patients at risk during the pandemic. Many strategies have been suggested to significantly improve the responsiveness and efficiency of pharmaceutical distribution.

Given that the pandemic caused spikes in the demand of essential medical suppliers and medications, many researchers suggested using temporary healthcare facilities to distribute vaccines or drugs [68,79,94]. This strategy is effective in meeting the largest levels of demand with scarce resources, as citizens can travel by whatever means available to obtain treatments or medications in a temporary facility. In a low-resource setting (such as situations with a limited number of vehicles), Akwafuo et al. [96] suggested integrating new requests into the originally planned route and prioritizing new demand from the most vulnerable population. In addition, to address the issue of rapid delivery of medical items, especially personal protective equipment [91], some studies suggested employing external vehicles [52,91] or air transport [83,93].

Vaccine distribution is a challenging problem for governments around the world [95]. When vaccines are scarce, it is critical to establish the most effective strategy for prioritizing individual immunization. In addition, the time at which vaccines are delivered to each area has an effect on the regional demand, since any delay in obtaining a vaccine may result in an increase in infected people. In this regard, researchers have developed a route optimization tool [95,97] for efficiently distributing vaccines, as well as simulation tools [80] for estimating the amount of vaccines required based on the priority in each region.

4.2. Contactless Delivery

In the context of the normalization of the pandemic, contactless delivery, which aims to reduce personal contact during a delivery, is becoming more popular. In order to lessen the effect of the COVID-19 pandemic while also ensuring the availability of critical supplies in the last mile, various contactless delivery strategies have been proposed. Among these, home delivery [69,85,89,108] is a critical consideration in the case of lockdown, where goods are distributed to the designated location and customers pick them up themselves [52,69,108]. In addition, self-driving delivery robots have been used to avoid person-to-person contact [87,104,106,107]. In this strategy, having the optimal number of robots is crucial and this number should be determined by analyzing the relative costs and benefits [87]. Furthermore, in order to accelerate the response to the pandemic, traffic conditions in the delivery path must be taken into account [90,109], while cooperative unmanned ground and aerial vehicles [104], electricity-assisted bicycles [100], and joint distribution modes [89] have also been recommended.

4.3. Sustainable Medical Waste Transportation

In the era of COVID-19, the large amount of medical waste generated daily by hospitals is a source of infection, posing a significant threat of virus infection to the public [81]. Therefore, designing an efficient and sustainable transportation strategy for medical waste collection is necessary not only for the control of the current pandemic but also for the prevention of the next outbreak.

To ensure the effective transportation of infectious waste, some researchers have suggested establishing temporary facilities [77,78,81], such as collection, transfer, treatment, and disposal facilities, which may be swiftly changed from regular waste facilities at a low cost. Tirkolaee et al. [81] developed a decision support system (DSS) based on this method and the associated mathematical modeling to assure the harmless and effective disposal of pandemic-related medical waste. Along with implementing an effective waste disposal method, logistics providers also need to identify the least infectious transportation routes [74,78,82]. The risk can be quantified based on the population exposure alone the route. To achieve a more sustainable waste disposal strategy, the collection of contagious and non-infectious waste must be separated [78]; Gao et al. [73] recommended utilizing different visit frequencies for the waste collection according to the grades of the medical facilities involved.

4.4. Isolated and Quarantine Vehicle Scheduling

In an outbreak of a severe pandemic, confirmed and suspected cases must be isolated for medical care immediately to prevent the spread of the virus [75]. Therefore, efficient vehicle scheduling is crucial. When the demand for vehicles is high, Majzoubi et al. [51] suggested allowing emergency medical service vehicles to serve up to two patients instead of one, while Kergosien et al. [88] focused on scheduling vehicles based on the the urgency of demands. To prevent the spread of infectious disease, quarantine vehicles are needed to transfer the high-risk individuals [75,101]. After contagious transportation, the interior of the ambulances needs to be disinfected before another use [84,88]. Focusing on the example of evacuation, one study [98] suggested integrating social distancing strategy with transport operation—e.g., limiting the numbers of passengers allowed in one vehicle.

5. Discussion and Future Research Opportunity

In this section, the uses of VRPs in controlling infectious disease are summarized and critically assessed. Based on the assessment of the reviewed articles, some key areas that remain unexplored and uninvestigated are suggested. To the best of our knowledge, this is the first review article to systematically and methodologically evaluate the research status of pandemic containment measures from a delivery perspective.

5.1. Finding of Descriptive Analysis

Interesting findings emerged from our descriptive analysis, as presented in Table 13, preventive measures and performance metrics used in previous studies differed substantially in different countries.

Regarding studies in Asian countries, the data indicate that the majority of publications examined e-commerce and on-demand delivery strategies, as well as sustainable waste collection strategies, focusing on minimizing the pandemic's social impact; this was as expected, as most Asian countries have a high population density along with substantial demand for delivery and waste collection. Thus, route optimization is crucial, as it may enhance the transportation efficiency and reduce the risk of the transmission of the virus; however, environmental impacts are seldom discussed.

Studies in developed nations mainly focused on contactless distribution; the most frequently used performance metrics are delivery time and transportation cost. Surprisingly, even in these countries, only two papers used the environmental performance metric in developing their pandemic containment measures. The authors of [90] suggested that retail companies should change their urban mobility plans to deliver orders placed via e-channels. Additionally, they advocated for the promotion of using electric scooters to deliver grocery goods along alternative routes other than bicycles lanes to minimize the transmission risk.

Studies in African and South America countries placed more emphasis on pharmaceutical transportation issues in the context of the pandemic, with the primary challenge being maintaining a pharmacy with essential medications and supplies for the lowest transportation cost possible. Still, environmental issues received little attention.

In general, the transport systems of different countries encountered different challenges, as various nations experienced different infection rates and implemented different measures in response to the pandemic. As a result, adopting tailored distribution tactics for various geographic locations is necessary to combat the COVID-19 pandemic.

Table 13. Summary of the reviewed papers based on the countries, measures, and metrics used.

Country	Reference	Measures				Eco	Social				Env
		C	E	W	I		T	D	R	S	
China	[69]	✓								✓	
	[72]		✓				✓	✓			
	[73]			✓			✓				
	[78]			✓		✓			✓		
	[74]			✓					✓		
	[79]		✓			✓	✓	✓			
	[75]				✓				✓		
	[70]	✓				✓			✓		
	[71]		✓			✓					
	[77]			✓		✓			✓		
Iran	[80]		✓			✓			✓		
	[81]			✓			✓		✓		
Turkey	[82]			✓			✓		✓		
	[83]	✓	✓				✓				
Hongkong	[84]				✓	✓		✓			
India	[85]	✓	✓				✓	✓			✓
Indonesia	[86]	✓				✓					
Korea	[87]	✓				✓					

Table 13. *Cont.*

Country	Reference	Measures				Eco	Social				Env
		C	E	W	I		T	D	R	S	
Asia		6	6	6	2	9	7	4	8	1	1
Australia	[100]	✓					✓				
France	[88]				✓	✓					
German	[89]	✓					✓				
Italy	[90]	✓				✓					✓
Spain	[91]		✓				✓				
	[92]		✓				✓				✓
USA	[98]				✓	✓					
Developed countries		3	2	0	2	3	4	0	0	0	2
Brazil	[97]		✓				✓				
Colombia	[99]		✓			✓					
DR Congo	[93]	✓	✓			✓					
Morocco	[94]		✓			✓	✓				
Mozambique	[95]		✓			✓	✓				
Nigeria	[96]		✓			✓					
South America and Africa		1	6	0	0	5	3	0	0	0	0

C: contactless delivery; E: efficient pharmaceutical transportation; W: sustainable waste disposal policy; I: isolated and quarantine vehicle scheduling; Eco: economic; Env: environmental.

5.2. Efficient Pharmaceutical Delivery Methodology

As presented in Table 14, the considered performance metrics varied considerably across the different pharmaceutical transportation problems presented, with a clear emphasis being placed on social factors—e.g., the minimization of response time or the maximization of the unmet customer demand. Nevertheless, the risk factor was rarely considered in the reviewed articles. Additionally, only three articles included environmental factor in their objective function. Due to the critical nature of sustainability in the post-pandemic era, future studies should emphasize the importance of emission reduction or risk minimization.

Table 14. Methodologies used in pharmaceutical delivery.

Lead Author	C	Social				E	Model Characteristics							U	Solution				
		T	D	R	S		a	b	c	d	e	f	g		Ex	M	H	Ml	Hy
Shen (2009a) [66]		✓	✓				✓							✓		✓			
Shen (2009b) [67]		✓	✓				✓					✓		✓		✓			
Ceselli (2014) [68]			✓						✓		✓		✓		✓				
Clarke (2017) [93]	✓									✓					✓		✓		✓
Akwafuo (2020) [96]	✓								✓		✓			✓			✓		
EL Midaoui (2020) [94]	✓	✓									✓		✓			✓		✓	✓
Gao (2020) [104]		✓							✓								✓	✓	✓
Muslu (2020) [103]		✓														✓			
Pacheco (2020) [91]		✓														✓			
Calvet (2020) [92]		✓				✓			✓								✓		
Gai (2021) [72]		✓	✓									✓		✓	✓				
Gamchi (2021) [80]	✓			✓										✓	✓				
Huilin (2021) [52]	✓					✓					✓					✓	✓		✓
Long (2021) [79]	✓	✓	✓							✓			✓	✓		✓			

Table 14. *Cont.*

Lead Author	C	Social				E	Model Characteristics							U	Solution				
		T	D	R	S		a	b	c	d	e	f	g		Ex	M	H	Ml	Hy
Martinez-Reyes (2021) [99]	✓										✓		✓	✓		✓			✓
Martins (2021) [107]		✓							✓								✓		
Mehlawat (2021) [85]		✓	✓			✓			✓					✓		✓		✓	✓
Ozkan (2021) [83]		✓							✓		✓				✓				
Petroianu (2021) [95]	✓	✓							✓								✓		
Rodrigues (2021) [97]		✓														✓			
Wu (2021) [71]	✓										✓					✓			
Sum	9	14	6	1	0	3	2	0	8	2	7	2	4	5	8	11	7	3	6

C: cost; E: pollutant emission; T: response time; D: demand; R: transmission risk; S: customer satisfaction; a: time restriction on customers; b: time restriction on depot; c: time restriction on vehicle or route; d: multi-horizon; e: multi-depot; f: split delivery; g: multi-echelon; U: uncertain parameters; Ex: exact method; M: metaheuristic; H: heuristic; ML: machine learning; Hy: hybrid method.

With respect to model characteristics, most work considered pharmaceutical transportation as a VRPTW with a focus on the time limit of vehicles. Time restrictions on customer location and depot were still lacking in the reviewed papers within this area. While multiple depots were used in a range of articles, the concept of no depot was applied in [91], where volunteers (such as non-profit organizations and citizens) helped in the distribution of medical supplies without returning to the original departure location. To deal with uncertain parameters, the fuzzy method [81,85], robust optimization [79], and chance-constrained programming technique [66,67] were used to estimate the unknown demand and travel time. In terms of parameters that vary dynamically over time, Gamchi et al. [80] utilized a novel simulation model to estimate the amount of vaccine required to control the communicable disease, while Akwafuo et al. [96] applied a three-stage approach to incorporate real-time demand.

Regarding the solution approach, most work used metaheuristic and heuristic approaches to accelerate the generation of a routing plan. Population-based algorithms [52,71,79,85,94,97,103] prevailed in the pharmaceutical transportation problem; heuristics are often used to cluster customers [52,93] or develop a feasible solution first [96,104], followed by the implementation of exact solution procedures [68,80,83] or learning-based algorithms [104] to enhance the solution. Furthermore, the ML technique is utilized in [116] with a focus on the determination of potential depots. Since the performance metrics, problem settings, solution procedures, and test data differed substantially among the reviewed papers, there is no common benchmark that can be used to compare the solutions of the different methodologies.

5.3. Contactless Delivery Methodology

The contactless distribution strategy is able to cover a wide range of application scenarios of VRPs, including food, medication, and commodity transportation. Similar to the pharmaceutical transportation scheme discussed in Section 5.2, the majority of selected articles considered social and economic objectives (see Table 15); nevertheless, only Jiang et al. [70] focused on the minimization of infectious risk in food delivery. This is surprising, as the primary aim of contactless distribution is to prevent the spread of disease.

Table 15. Methodologies used in contactless delivery.

Lead Author	C	Social				E	Model Characteristics							U	Solution				
		T	D	R	S		a	b	c	d	e	f	g		Ex	M	H	Ml	Hy
Ceselli (2014) [68]			✓						✓		✓		✓		✓				
Clarke (2017) [93]	✓									✓					✓		✓		✓
D.Chen (2020) [69]					✓		✓		✓							✓			
Gao (2020) [104]		✓							✓								✓	✓	✓
Jin (2020) [102]	✓								✓							✓			
Y.Jiang (2020) [70]	✓			✓								✓				✓			
Ayu (2021) [86]	✓							✓								✓			
Breitbarth (2021) [89]		✓							✓						✓			✓	✓
Cerrone (2021) [90]	✓					✓									✓	✓			✓
C.Chen (2021) [106]		✓					✓						✓		✓				✓
Huilin (2021) [52]	✓					✓					✓					✓	✓		✓
Le (2021) [100]		✓							✓							✓			
Lee (2021) [87]	✓								✓						✓				
L.Jiang (2021) [108]	✓															✓			
Martins (2021) [107]		✓							✓								✓		
Mehlawat (2021) [85]		✓	✓			✓			✓					✓		✓		✓	✓
Ozkan (2021) [83]		✓							✓		✓				✓				
Wu (2021) [109]	✓				✓	✓	✓									✓			
Sum	9	7	2	1	2	4	3	1	10	1	3	1	2	1	7	10	4	3	7

C: cost; E: pollutant emission; T: response time; D: demand; R: transmission risk; S: customer satisfaction; a: time restriction on customers; b: time restriction on depot; c: time restriction on vehicle or route; d: multi-horizon; e: multi-depot; f: split delivery; g: multi-echelon; U: uncertain parameters; Ex: exact method; M: metaheuristic; H: heuristic; ML: machine learning; Hy: hybrid method.

Concerning problem characteristics, most works addressed the VRP with time windows (VRPTW), and time restrictions on vehicles were frequently used. However, only one work considered time limitation at the depot [86]. What is more, it is not common to see multiple periods being applied to address a more realistic long-term scenario rather than a short-term problem. Heterogeneous vehicles can be seen in a range of articles [68,83,85,87,106]; this is a common assumption that is made to cope with the complex requirements of routing operations during the pandemic, but split delivery is not commonly seen. Jiang et al. [70] pointed out that the use of split delivery might lead to diseases being spread, since it increases the frequency of contact between a vehicle and the community. Although multiple depots were mentioned in just three articles, employing external depots during an emergency pandemic situation is more realistic. The stochastic and dynamic problem settings were rarely considered. Only one study included fuzzy travel time in its model; unexpected events, such as new requested demand locations or demand surge through the expansion of the pandemic, were not found in any of the reviewed articles.

Regarding the solution approach, most works developed hybrid and metaheuristic procedures to generate a near-optimal solution for the contactless distribution problem. A combination of cluster heuristics and exact solutions was also frequently used as a hybrid solution procedure. Here, numerous clustering techniques were employed, such as k-means [89] and set partition [93]. Additionally, Mehlawat et al. [85] developed a hybrid technique integrating metaheuristics and machine learning in order to determine weights in multi-objective situations.

Implemented metaheuristics mainly focused on population-based algorithms, such as artificial bee colony algorithms [69], genetic algorithms [52,85,100], and ant colony algorithms [102,109]. To provide a real-time solution for distributing urgently needed drugs, Martins et al. [107] suggested the use of a constructive heuristic in combination with parallel computing; the outcome was then compared with the implemented metaheuristic when solving both small- and large-sized cases. Although plenty of solution approaches were adapted to solve the contactless delivery problem, there was no consensus regarding the optimal solution technique.

5.4. Sustainable Waste Transportation Methodology

Table 16 presents the metrics considered in each of the selected articles related to waste transportation. In contrast to the previous two application area, where most articles focused on cost reduction or time reduction, the majority of the examined articles in this subject tended to concentrate on risk reduction (6 out of 7 articles). However, since none of these publications incorporated factors such as unmet demand or customer satisfaction in their objective function, there is a scarcity of customer-centric evaluations in this research field. Furthermore, reducing vehicle emissions was only mentioned in one publication in this field. As a result, future research should focus more on environmental and human-centric issues in order to build a more sustainable waste transportation system.

Table 16. Methodologies used in sustainable waste transportation.

Lead Author	C	Social				E	Model Characteristics							U	Solution				
		T	D	R	S		a	b	c	d	e	f	g		Ex	M	H	Ml	Hy
Babaee (2021) [105]	✓			✓		✓					✓				✓				
Eren (2021) [82]		✓		✓											✓				
Gao (2021) [73]		✓					✓			✓			✓			✓			
Govindan (2021) [78]	✓			✓				✓		✓	✓	✓			✓				
Haolin (2021) [74]				✓			✓						✓			✓			
Tirkolaee (2021) [81]		✓		✓			✓		✓	✓				✓	✓				
Zhao (2021) [77]	✓			✓									✓	✓	✓				
Sum	3	3	0	6	0	1	3	1	1	3	2	1	3	2	5	2	0	0	0

C: cost; E: pollutant emission; T: response time; D: demand; R: transmission risk; S: customer satisfaction; a: time restriction on customers; b: time restriction on depot; c: time restriction on vehicle or route; d: multi-horizon; e: multi-depot; f: split delivery; g: multi-echelon; U: uncertain parameters; Ex: exact method; M: metaheuristic; H: heuristic; ML: machine learning; Hy: hybrid method.

In terms of model characteristics, the periodic VRP with time window was found to be frequently studied in the field of infectious waste transportation; often, the time window herein was specified as the priority of services for health clinics or hospitals with a different range of risks [74,81]. Given the dynamic nature of periodic planning, only two articles were discovered. Tirkolaee et al. [81] investigated uncertain demand (e.g., medical waste) using a fuzzy chance-constrained programming technique, while Zhao et al. [77] estimated uncertain demand using a set of scenarios according to the actual circumstances. Other dynamic problem settings such as new demand locations and dynamic traffic conditions were not reported in the reviewed articles.

Other commonly investigated mode in infectious waste transportation includes multi-echelon VRP [73,74,77] and location and routing VRP [77,78,81]. The former mode was applied when infectious waste generated in a small clinic was first transferred to collection stations and then transported to the disposal center. In contrast, the latter mode focused on locating temporary facilities to provide cost-efficient or timely waste collection services.

The exact solution procedure was predominately conducted (5 out of 7 articles) in studies on waste collection. Within seven hours of computing time, randomly created cases with up to 89 clients were solved until an optimal solution was found [105]. Additionally, the metaheuristic of particle swarm was employed to solve large-scale instances (up to 145 demand nodes). A good solution can be obtained with an average computation time of 6.5 min [74]. Notably, the hybrid solution procedure, which cannot be seen in the reviewed papers, may provide a more effective solution for a large-scale issue.

5.5. Isolated and Quarantine Transportation Methodology

As shown in Table 17, studies on passenger transportation have used various social and economic performance criteria to assess the quality of transportation strategies, including trip time, transport-related cost, customer demand, and infectious risk, to minimize the impact of infectious illness. Notably, the infectious risk formulation differed from that in Section 5.4; in this case, M. Zhang et al. [75] estimated the infectious risk based on the entire waiting time for suspected patients prior to loading them into a vehicle. In addition, it is worth mentioning that there was a lack of research on emission reduction in this field. As a result, future research may take the environmental factor into account in order to create a more sustainable transportation system.

Table 17. Methodologies used in isolated and quarantine vehicle scheduling.

Lead Author	C	Social				E	Model Characteristics							U	Solution				
		T	D	R	S		a	b	c	d	e	f	g		Ex	M	H	Ml	Hy
Kergosien (2011) [88]	✓						✓			✓				✓		✓			
Z.Zhang (2015) [84]	✓		✓				✓		✓							✓			
Mook (2019) [101]		✓												✓					
M.Zhang (2020) [75]				✓								✓				✓			
Majzoubi (2021) [51]		✓					✓	✓								✓			
Tsai (2021) [98]	✓							✓										✓	
Sum	3	2	1	1	0	0	3	2	1	1	0	1	0	2	0	4	0	1	0

C: cost; E: pollutant emission; T: response time; D: demand; R: transmission risk; S: customer satisfaction; a: time restriction on customers; b: time restriction on depot; c: time restriction on vehicle or route; d: multi-horizon; e: multi-depot; f: split delivery; g: multi-echelon; U: uncertain parameters; Ex: exact method; M: metaheuristic; H: heuristic; Ml: machine learning; Hy: hybrid method.

Regarding the problem characteristics and the solution methods, most articles modeled the patient transportation problem as a DARP, where each patient has pickup and drop-off points with associated service time frame. After transporting a patient with an infectious illness, a vehicle must be disinfected, which may be regarded as setup time for the subsequent transport assignment. To address real-time patient requests, Kergosien et al. [88] created a modeling framework based on adaptive memory and a tabu search technique, while Majzoubi et al. [51] devised a simulated annealing approach. Within five seconds, these two approaches can generate efficient solutions for large-size instances (between 132 and 200 demand nodes). In addition to DARP model, other articles in this scope of research used the Capacitated VRP model to capture the characteristics of the passenger transportation problem. A WWO (water wave optimization)-based metaheuristic [75] and DNN (Deep Neural Network)-based solution procedure [98] have been applied to implement transportation strategies. The former solution approach has shown success in controlling the pandemic, while the latter can provide a more efficient routing plan than the sweep algorithm. Notably, the general framework used for applying machine learning as a solution method is inadequate; this has resulted in some promising areas for future study.

5.6. Future Research Opportunities

Despite the fact that certain VRP applications have already been incorporated into pandemic control strategies, the field of epidemics control VRP remains a promising research area, since a plethora of research gaps has been identified. Several potential future directions for research activities could be considered including the following:

The development of customized strategies: During the containment effort of the COVID-19 pandemic, since different affected areas may encounter diverse transportation challenges, selecting an optimal combination of delivery strategies should be explored. For example, contactless strategies could be integrated with other epidemic control delivery approaches, and a better understanding of how contactless delivery strategies ultimately influence the social and environmental efficiency of pharmaceutical or garbage transportation is necessary. Furthermore, in the context of COVID-19, delivery strategies for epidemic control after natural catastrophes such as floods, hurricanes, and earthquakes should be explored.

The integration of risk performance metrics: The complex nature of epidemic containment efforts calls for an ideal combination of performance indicators, ensuring better disease mitigation measures. Although some research efforts have been undertaken with multiple performance metrics, a tailored epidemic control metric (e.g., reduction in infectious risk) is still lacking in most reviewed papers. Therefore, future research methodologies should include strategies for mitigating infectious risk alongside other success indicators (cost-oriented, time-oriented, environmental-centric metrics, etc.).

Sustainability considerations: Climate change could serve as a catalyst for the spread of the pandemic [117–119]. Therefore, the implementation of a green transportation system is critical in order to reduce the virus's spread. However, existing research often omits environmental criteria and fails to account for the three pillars of sustainability: economic, ecological, and social [110]. As a consequence, it would be beneficial to investigate the environmental impact of each delivery strategy studied in our work in order to develop a more sustainable vehicle routing operation.

VRP modeling with more realistic assumptions: Future research methodologies should contain more realistic characteristics. For example, multi-period planning is crucial for preventing pandemic transmission; thus, future modeling procedures should be based on a long-term framework. In addition, split delivery strategies may increase the frequency of contact between different parties, and future research can eliminate this unrealistic feature even if it may result in an increase in transportation cost. Furthermore, there are no generalizable methods for valuing transmission risk. Thus, future research should focus on developing particular measurement for transmission risk.

Stochasticity and dynamicity: Stochastic parameters (e.g., service time, travel time, and client demand) were overlooked in most of the studied publications. When no historical data exist for these uncertain parameters, fuzzy approaches are often utilized to estimate their values. On the other hand, if historical data for these parameters are given in advance, future research may be able to concentrate on how to include machine learning (such as supervised methods) into the estimation process. When dealing with dynamic parameters, it is necessary to establish a framework for dynamic modeling in order to develop a robust solution approach.

Combination of metaheuristics and ML: For rapidly addressing large-scale cases, several hybrid solutions have been developed using machine learning-based clustering algorithms (unsupervised approaches) and metaheuristics. However, clients are often clustered according to their geographical locations. When clustering algorithms are used to solve a real-world issue, it may be beneficial to integrate extra features (such as demand items or time frames).

Decision support system: During the post-pandemic era, establishing a user-friendly and comprehensive routing optimization tool may aid in the deployment of delivery operations for the purpose of containing a disease outbreak. The established DSS should give more insights into which preventative delivery strategies are most beneficial in particular application scenarios.

6. Conclusions

This literature review systematically examined the existing articles on VRPs during the epidemic. Our focus was on the application of VRPs in controlling the spread of the pandemic, and numerous themes emerged: efficient pharmaceutical delivery, contactless distribution, sustainable waste transportation, and isolated and quarantined vehicle scheduling. Following that, three criteria were utilized to assess the methodology used to carry out each delivery operation: I. Performance indicators for evaluating sustainability. II. Problem features and operational constraints used in pandemic containment delivery strategies. III. Approaches for solving different variants of VRPs. The results indicated that optimizing delivery operations is crucial during containment attempts because it mitigates transmission risk and strengthens the transportation system. Finally, based on the research gaps identified in the discussion section, a future study path was proposed.

While our research contributes to this field of study, it does have certain limitations. First, only English-language journal papers and conference proceedings, published before 20 December 2021, were considered. Theses, books, book chapters, and unpublished articles were omitted. As a consequence, the summary provided in this research may not accurately represent all available information on the issue. Second, online database searching for publications did not include particular publishers such as Elsevier. Hence, some additional items may be overlooked. Finally, VRP applications in home health care, supply chain management, inventory scheduling, production management, and animal disease control, was excluded in our research.

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References

1. Benedictow, O.J. Morbidity in historical plague epidemics. *Popul. Stud.* **1987**, *41*, 401–431. [CrossRef] [PubMed]
2. Tumpey, T.M.; Basler, C.F.; Aguilar, P.V.; Zeng, H.; Solórzano, A.; Swayne, D.E.; Cox, N.J.; Katz, J.M.; Taubenberger, J.K.; Palese, P.; et al. Characterization of the reconstructed 1918 Spanish influenza pandemic virus. *Science* **2005**, *310*, 77–80. [CrossRef] [PubMed]
3. Dasaklis, T.K.; Pappis, C.P.; Rachaniotis, N.P. Epidemics control and logistics operations: A review. *Int. J. Prod. Econ.* **2012**, *139*, 393–410. [CrossRef]
4. Koonin, L.M. Novel coronavirus disease (COVID-19) outbreak: Now is the time to refresh pandemic plans. *J. Bus. Contin. Emerg. Plan.* **2020**, *13*, 298–312.
5. Johns Hopkins University and Medicine. Global Deaths. 2021. Available online: https://coronavirus.jhu.edu/ (accessed on 1 December 2021).
6. Ivanov, D. Viable supply chain model: Integrating agility, resilience and sustainability perspectives—Lessons from and thinking beyond the COVID-19 pandemic. *Ann. Oper. Res.* **2020**, 1–21. [CrossRef] [PubMed]
7. Ivanov, D. Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (COVID-19/SARS-CoV-2) case. *Transp. Res. Part Logist. Transp. Rev.* **2020**, *136*, 101922. [CrossRef] [PubMed]
8. Chinazzi, M.; Davis, J.T.; Ajelli, M.; Gioannini, C.; Litvinova, M.; Merler, S.; Y Piontti, A.P.; Mu, K.; Rossi, L.; Sun, K.; et al. The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science* **2020**, *368*, 395–400. [CrossRef] [PubMed]
9. Mamani, H.; Chick, S.E.; Simchi-Levi, D. A game-theoretic model of international influenza vaccination coordination. *Manag. Sci.* **2013**, *59*, 1650–1670. [CrossRef]
10. Büyüktahtakın, İ.E.; des Bordes, E.; Kıbış, E.Y. A new epidemics–logistics model: Insights into controlling the Ebola virus disease in West Africa. *Eur. J. Oper. Res.* **2018**, *265*, 1046–1063. [CrossRef]

11. Anparasan, A.; Lejeune, M. Analyzing the response to epidemics: Concept of evidence-based Haddon matrix. *J. Humanit. Logist. Supply Chain. Manag.* **2017**, *7, 266–283.* [CrossRef]
12. Parvin, H.; Beygi, S.; Helm, J.E.; Larson, P.S.; Van Oyen, M.P. Distribution of medication considering information, transshipment, and clustering: Malaria in Malawi. *Prod. Oper. Manag.* **2018**, *27*, 774–797. [CrossRef]
13. Chowdhury, P.; Paul, S.K.; Kaisar, S.; Moktadir, M.A. COVID-19 pandemic related supply chain studies: A systematic review. *Transp. Res. Part Logist. Transp. Rev.* **2021**, *148*, 102271. [CrossRef] [PubMed]
14. Dantzig, G.B.; Ramser, J.H. The truck dispatching problem. *Manag. Sci.* **1959**, *6*, 80–91. [CrossRef]
15. Cooke, K.L.; Halsey, E. The shortest route through a network with time-dependent internodal transit times. *J. Math. Anal. Appl.* **1966**, *14*, 493–498. [CrossRef]
16. Tillman, F.A. The multiple terminal delivery problem with probabilistic demands. *Transp. Sci.* **1969**, *3*, 192–204. [CrossRef]
17. Watson-Gandy, C.; Dohrn, P. Depot location with van salesmen—A practical approach. *Omega* **1973**, *1*, 321–329. [CrossRef]
18. Beltrami, E.J.; Bodin, L.D. Networks and vehicle routing for municipal waste collection. *Networks* **1974**, *4*, 65–94. [CrossRef]
19. Speidel, V. EDP-assisted fleet scheduling in tramp and coastal shipping. In Proceedings of the 2nd International Ship Operation Automation Symposium, Washington, DC, USA, 30 August–2 September 1976; Volume 5.
20. Russell, R.A. An effective heuristic for the m-tour traveling salesman problem with some side conditions. *Oper. Res.* **1977**, *25*, 517–524. [CrossRef]
21. Bell, W.J.; Dalberto, L.M.; Fisher, M.L.; Greenfield, A.J.; Jaikumar, R.; Kedia, P.; Mack, R.G.; Prutzman, P.J. Improving the distribution of industrial gases with an on-line computerized routing and scheduling optimizer. *Interfaces* **1983**, *13*, 4–23. [CrossRef]
22. Cheng, R.; Gen, M.; Tozawa, T. Vehicle routing problem with fuzzy due-time using genetic algorithms. *J. Jpn. Soc. Fuzzy Theory Syst.* **1995**, *7*, 1050–1061. [CrossRef]
23. Sariklis, D.; Powell, S. A heuristic method for the open vehicle routing problem. *J. Oper. Res. Soc.* **2000**, *51*, 564–573. [CrossRef]
24. Crainic, T.G.; Ricciardi, N.; Storchi, G. Models for evaluating and planning city logistics systems. *Transp. Sci.* **2009**, *43*, 432–454. [CrossRef]
25. Fatnassi, E.; Chaouachi, J.; Klibi, W. Planning and operating a shared goods and passengers on-demand rapid transit system for sustainable city-logistics. *Transp. Res. Part B Methodol.* **2015**, *81*, 440–460. [CrossRef]
26. Dündar, H.; Ömürgönülşen, M.; Soysal, M. A review on sustainable urban vehicle routing. *J. Clean. Prod.* **2021**, *285*, 125444. [CrossRef]
27. Ghorbani, E.; Alinaghian, M.; Gharehpetian, G.B.; Mohammadi, S.; Perboli, G. A survey on environmentally friendly vehicle routing problem and a proposal of its classification. *Sustainability* **2020**, *12*, 9079. [CrossRef]
28. Kara, I.; Kara, B.Y.; Yetis, M.K. Energy minimizing vehicle routing problem. In Proceedings of the International Conference on Combinatorial Optimization and Applications, Big Island, HI, USA, 18–20 December 2007; pp. 62–71.
29. Gonçalves, F.; Cardoso, S.R.; Relvas, S.; Barbosa-Póvoa, A. Optimization of a distribution network using electric vehicles: A VRP problem. In Proceedings of the IO2011-15 Congresso da Associação Portuguesa de Investigação Operacional, Coimbra, Portugal, 18–20 April 2011; pp. 18–20.
30. Bektaş, T.; Laporte, G. The pollution-routing problem. *Transp. Res. Part B Methodol.* **2011**, *45*, 1232–1250. [CrossRef]
31. Levy, D.; Sundar, K.; Rathinam, S. Heuristics for routing heterogeneous unmanned vehicles with fuel constraints. *Math. Probl. Eng.* **2014**, *2014*, 131450. [CrossRef]
32. Arslan, A.M.; Agatz, N.; Kroon, L.; Zuidwijk, R. Crowdsourced delivery—A dynamic pickup and delivery problem with ad hoc drivers. *Transp. Sci.* **2019**, *53*, 222–235. [CrossRef]
33. Laporte, G. Fifty years of vehicle routing. *Transp. Sci.* **2009**, *43*, 408–416. [CrossRef]
34. Braekers, K.; Ramaekers, K.; Van Nieuwenhuyse, I. The vehicle routing problem: State of the art classification and review. *Comput. Ind. Eng.* **2016**, *99*, 300–313. [CrossRef]
35. Wilson, N.H.; Weissberg, R.W.; Hauser, J. Advanced Dial-a-Ride Algorithms Research Project: Final report. In *Technical Report. Department of Civil Engineering*; MIT: Cambridge, MA, USA, 1976; pp. 76–120.
36. Golden, B.; Assad, A.; Levy, L.; Gheysens, F. The fleet size and mix vehicle routing problem. *Comput. Oper. Res.* **1984**, *11*, 49–66. [CrossRef]
37. Tsiligirides, T. Heuristic methods applied to orienteering. *J. Oper. Res. Soc.* **1984**, *35*, 797–809. [CrossRef]
38. Knott, R. Vehicle scheduling for emergency relief management: A knowledge-based approach. *Disasters* **1988**, *12*, 285–293. [CrossRef]
39. Dror, M.; Trudeau, P. Savings by split delivery routing. *Transp. Sci.* **1989**, *23*, 141–145. [CrossRef]
40. Tarantilis, C.; Kiranoudis, C. A meta-heuristic algorithm for the efficient distribution of perishable foods. *J. Food Eng.* **2001**, *50*, 1–9. [CrossRef]
41. Iori, M.; Gonzalez, J.S.; Vigo, D. *An Exact Approach for the Symmetric Capacitated Vehicle Routing Problem with Two-Dimensional Loading Constraints*; Università di Bologna, DEIS, Operations Research: Bologna, Italy, 2003.
42. Mancini, S. The hybrid vehicle routing problem. *Transp. Res. Part C Emerg. Technol.* **2017**, *78*, 1–12. [CrossRef]
43. Luis, E.; Dolinskaya, I.S.; Smilowitz, K.R. Disaster relief routing: Integrating research and practice. *Socio-Econ. Plan. Sci.* **2012**, *46*, 88–97.
44. Golden, B.L.; Kovacs, A.A.; Wasil, E.A. Chapter 14: Vehicle Routing Applications in Disaster Relief. In *Vehicle Routing: Problems, Methods, and Applications*, 2nd ed.; SIAM: Pennsylvania, PA, USA, 2014; pp. 409–436.

45. Anuar, W.K.; Lee, L.S.; Pickl, S.; Seow, H.V. Vehicle Routing Optimisation in Humanitarian Operations: A Survey on Modelling and Optimisation Approaches. *Appl. Sci.* **2021**, *11*, 667. [CrossRef]
46. Grass, E.; Fischer, K. Two-stage stochastic programming in disaster management: A literature survey. *Surv. Oper. Res. Manag. Sci.* **2016**, *21*, 85–100. [CrossRef]
47. Van Wassenhove, L.N. Humanitarian aid logistics: Supply chain management in high gear. *J. Oper. Res. Soc.* **2006**, *57*, 475–489. [CrossRef]
48. Tranfield, D.; Denyer, D.; Smart, P. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *Br. J. Manag.* **2003**, *14*, 207–222. [CrossRef]
49. Faulin, J.; Gilibert, M.; Juan, A.A.; Vilajosana, X.; Ruiz, R. SR-1: A simulation-based algorithm for the capacitated vehicle routing problem. In Proceedings of the 2008 Winter Simulation Conference, Miami, FL, USA, 7–10 December 2008; pp. 2708–2716.
50. Juan, A.A.; Faulin, J.; Ruiz, R.; Barrios, B.; Gilibert, M.; Vilajosana, X. Using oriented random search to provide a set of alternative solutions to the capacitated vehicle routing problem. In *Operations Research and Cyber-Infrastructure*; Springer: Berlin/Heidelberg, Germany, 2009; pp. 331–345.
51. Majzoubi, F.; Bai, L.; Heragu, S.S. The EMS vehicle patient transportation problem during a demand surge. *J. Glob. Optim.* **2021**, *79*, 989–1006. [CrossRef] [PubMed]
52. Li, H.; Xiong, K.; Xie, X. Multiobjective Contactless Delivery on Medical Supplies under Open-Loop Distribution. *Math. Probl. Eng.* **2021**, *2021*, 1–7. [CrossRef]
53. Vernieuwe, H.; Ducheyne, E.; Hendrickx, G.; De Baets, B. Efficient management of transportation logistics related to animal disease outbreaks. *Comput. Electron. Agric.* **2010**, *71*, 148–157. [CrossRef]
54. Mahmud, M.S.A.; Abidin, M.S.Z.; Mohamed, Z.; Abd Rahman, M.K.I.; Iida, M. Multi-objective path planner for an agricultural mobile robot in a virtual greenhouse environment. *Comput. Electron. Agric.* **2019**, *157*, 488–499. [CrossRef]
55. Zangina, U.; Buyamin, S.; Abidin, M.; Mahmud, M. Agricultural rout planning with variable rate pesticide application in a greenhouse environment. *Alex. Eng. J.* **2021**, *60*, 3007–3020. [CrossRef]
56. Nasir, J.A.; Kuo, Y.H. A decision support framework for home health care transportation with simultaneous multi-vehicle routing and staff scheduling synchronization. *Decis. Support Syst.* **2020**, *138*, 113361. [CrossRef]
57. Guevara, C.; Peñas, M.S. Surveillance Routing of COVID-19 Infection Spread Using an Intelligent Infectious Diseases Algorithm. *IEEE Access* **2020**, *8*, 201925–201936. [CrossRef]
58. Bazirha, M.; Kadrani, A.; Benmansour, R. Daily scheduling and routing of home health care with multiple availability periods of patients. In Proceedings of the International Conference on Variable Neighborhood Search, Rabat, Morocco, 3–5 October 2019; pp. 178–193.
59. Shahnejat-Bushehri, S.; Tavakkoli-Moghaddam, R.; Momen, S.; Ghasemkhani, A.; Tavakkoli-Moghaddam, H. Home health care routing and scheduling problem considering temporal dependencies and perishability with simultaneous pickup and delivery. *IFAC-PapersOnLine* **2019**, *52*, 118–123. [CrossRef]
60. Kim, S.J.; Lim, G.J.; Cho, J.; Côté, M.J. Drone-aided healthcare services for patients with chronic diseases in rural areas. *J. Intell. Robot. Syst.* **2017**, *88*, 163–180. [CrossRef]
61. Mondal, A.; Roy, S.K. Multi-objective sustainable opened-and closed-loop supply chain under mixed uncertainty during COVID-19 pandemic situation. *Comput. Ind. Eng.* **2021**, *159*, 107453. [CrossRef]
62. Sazvar, Z.; Zokaee, M.; Tavakkoli-Moghaddam, R.; Salari, S.A.s.; Nayeri, S. Designing a sustainable closed-loop pharmaceutical supply chain in a competitive market considering demand uncertainty, manufacturer's brand and waste management. *Ann. Oper. Res.* **2021** , 1–32. [CrossRef] [PubMed]
63. Pasha, J.; Dulebenets, M.A.; Kavoosi, M.; Abioye, O.F.; Wang, H.; Guo, W. An Optimization Model and Solution Algorithms for the Vehicle Routing Problem with a 'Factory-in-a-Box'. *IEEE Access* **2020**, *8*, 134743–134763. [CrossRef]
64. Fikar, C.; Hirsch, P. Home health care routing and scheduling: A review. *Comput. Oper. Res.* **2017**, *77*, 86–95. [CrossRef]
65. Adulyasak, Y.; Cordeau, J.F.; Jans, R. The production routing problem: A review of formulations and solution algorithms. *Comput. Oper. Res.* **2015**, *55*, 141–152. [CrossRef]
66. Shen, Z.; Ordóñez, F.; Dessouky, M.M. The stochastic vehicle routing problem for minimum unmet demand. *Springer Optim. Appl.* **2009**, *30*, 349–371. [CrossRef]
67. Shen, Z.; Dessouky, M.M.; Ordóñez, F. A two-stage vehicle routing model for large-scale bioterrorism emergencies. *Networks* **2009**, *54*, 255–269. [CrossRef]
68. Ceselli, A.; Righini, G.; Tresoldi, E. Combined location and routing problems for drug distribution. *Discret. Appl. Math.* **2014**, *165*, 130–145. [CrossRef]
69. Chen, D.; Pan, S.; Chen, Q.; Liu, J. Vehicle routing problem of contactless joint distribution service during COVID-19 pandemic. *Transp. Res. Interdiscip. Perspect.* **2020**, *8*, 100233. [CrossRef] [PubMed]
70. Jiang, Y.; Bian, B.; Liu, Y. Integrated multi-item packaging and vehicle routing with split delivery problem for fresh agri-product emergency supply at large-scale epidemic disease context. *J. Traffic Transp. Eng.* **2021**, *8*, 196–208. [CrossRef]
71. Wu, L.; Xiang, X. Emergency Resource Scheduling during COVID-19. *E3S Web Conf.* **2021**, *253*, 1–6. [CrossRef]
72. Gai, L.; Jin, Y.; Zhang, B. An integrated method for hybrid distribution with estimation of demand matching degree. *J. Comb. Optim.* **2021**, 1–27. [CrossRef] [PubMed]

73. Gao, J.; Li, H.; Wu, J.; Lyu, J.; Tan, Z.; Jin, Z. Routing Optimisation of Urban Medical Waste Recycling Network considering Differentiated Collection Strategy and Time Windows. *Sci. Program.* **2021**, *2021*, 5523910. [CrossRef]
74. Li, H.; Hu, Y.; Lyu, J.; Quan, H.; Xu, X.; Li, C. Transportation Risk Control of Waste Disposal in the Healthcare System with Two-Echelon Waste Collection Network. *Math. Probl. Eng.* **2021**, *2021*, 5580083. [CrossRef]
75. Zhang, M.X.; Yan, H.F.; Wu, J.Y.; Zheng, Y.J. Quarantine vehicle scheduling for transferring high-risk individuals in epidemic areas. *Int. J. Environ. Res. Public Health* **2020**, *17*, 2275. [CrossRef]
76. Xu, G.; Lyu, Q. Vehicle Routing Problem for Collaborative Multidepot Petrol Replenishment under Emergency Conditions. *J. Adv. Transp.* **2021**, *2021*, 5531500. [CrossRef]
77. Zhao, J.; Wu, B.; Ke, G.Y. A bi-objective robust optimization approach for the management of infectious wastes with demand uncertainty during a pandemic. *J. Clean. Prod.* **2021**, *314*, 127922. [CrossRef]
78. Govindan, K.; Nasr, A.K.; Mostafazadeh, P.; Mina, H. Medical waste management during coronavirus disease 2019 (COVID-19) outbreak: A mathematical programming model. *Comput. Ind. Eng.* **2021**, *162*, 107668. [CrossRef]
79. Long, S.; Zhang, D.; Liang, Y.; Li, S.; Chen, W. Robust Optimization of the Multi-Objective Multi-Period Location-Routing Problem for Epidemic Logistics System with Uncertain Demand. *IEEE Access* **2021**, *9*, 151912–151930. [CrossRef]
80. Gamchi, N.S.; Torabi, S.A.; Jolai, F. A novel vehicle routing problem for vaccine distribution using SIR epidemic model. *OR Spectr.* **2021**, *43*, 155–188. [CrossRef]
81. Tirkolaee, E.B.; Abbasian, P.; Weber, G.W. Sustainable fuzzy multi-trip location-routing problem for medical waste management during the COVID-19 outbreak. *Sci. Total Environ.* **2021**, *756*, 143607. [CrossRef]
82. Eren, E.; Tuzkaya, U.R. Safe distance-based vehicle routing problem: Medical waste collection case study in COVID-19 pandemic. *Comput. Ind. Eng.* **2021**, *157*, 107328. [CrossRef] [PubMed]
83. Ozkan, O.; Atli, O. Transporting COVID-19 testing specimens by routing unmanned aerial vehicles with range and payload constraints: The case of Istanbul. *Transp. Lett.* **2021**, *13*, 482–491. [CrossRef]
84. Zhang, Z.; Liu, M.; Lim, A. A memetic algorithm for the patient transportation problem. *Omega* **2015**, *54*, 60–71. [CrossRef]
85. Mehlawat, M.K.; Gupta, P.; Khaitan, A. Multiobjective fuzzy vehicle routing using Twitter data: Reimagining the delivery of essential goods. *Int. J. Intell. Syst.* **2021**, *36*, 3566–3595. [CrossRef]
86. Ayu, T.; Nahry. Optimizing the Heterogeneous Ft Vehicle Routing Problem with Time Window on Urban Last Mile Delivery. *IOP Conf. Ser. Earth Environ. Sci.* **2021**, *830*, 012100. [CrossRef]
87. Lee, W.; Ko, Y.D. Operation policy of multi-capacity logistic robots in hotel industry. *Int. J. Contemp. Hosp. Manag.* **2021**, *33* . [CrossRef]
88. Kergosien, Y.; Lenté, C.; Piton, D.; Billaut, J.C. A tabu search heuristic for the dynamic transportation of patients between care units. *Eur. J. Oper. Res.* **2011**, *214*, 442–452. [CrossRef]
89. Breitbarth, E.; Groβ, W.; Zienau, A. Protecting vulnerable people during pandemics through home delivery of essential supplies: A distribution logistics model. *J. Humanit. Logist. Supply Chain. Manag.* **2021**, *11*, 227–247. [CrossRef]
90. Cerrone, C.; Cerulli, R.; Sciomachen, A. Grocery distribution plans in urban networks with street crossing penalties. *Networks* **2021**, *78*, 248–263. [CrossRef]
91. Pacheco, J.; Laguna, M. Vehicle routing for the urgent delivery of face shields during the COVID-19 pandemic. *J. Heuristics* **2020**, *26*, 619–635. [CrossRef]
92. Calvet, L.; Alvarez-Palau, E.J.; Viu, M.; Castillo, C.; Copado, P.; Juan, A.A. Promoting Sustainable and Intelligent Freight Transportation Systems in the Barcelona Metropolitan Area. *Transp. Res. Procedia* **2021**, *58*, 408–415. [CrossRef]
93. Clarke, J.; Gascon, V.; Ferland, J.A. A Capacitated Vehicle Routing Problem With Synchronized Pick-Ups and Drop-Offs: The Case of Medication Delivery and Supervision in the DR Congo. *IEEE Trans. Eng. Manag.* **2017**, *64*, 327–336. [CrossRef]
94. EL Midaoui, M.; Qbadou, M.; Mansouri, K. A novel approach of smart logistics for the health-care sector using genetic algorithm. *Adv. Sci. Technol. Eng. Syst.* **2020**, *5*, 1143–1152. [CrossRef]
95. Petroianu, L.P.G.; Zabinsky, Z.B.; Zameer, M.; Chu, Y.; Muteia, M.M.; Resende, M.G.; Coelho, A.L.; Wei, J.; Purty, T.; Draiva, A.; et al. A light-touch routing optimization tool (RoOT) for vaccine and medical supply distribution in Mozambique. *Int. Trans. Oper. Res.* **2021**, *28*, 2334–2358. [CrossRef] [PubMed]
96. Akwafuo, S.E.; Ihinegbu, C.; Urbanovsky, J.; Mikler, A.R. A Dynamic Heuristic Algorithm for Management of Public Health Emergencies in Unreliable Settings. In Proceedings of the 2020 IEEE International Conference on Healthcare Informatics, ICHI 2020, Oldenburg, Germany, 30 November–3 December 2020. [CrossRef]
97. Rodrigues, A.J.D.S.; Lima, G.L. A metaheuristic to support the distribution of COVID-19 vaccines. *Production* **2021**, *31*, 1–12. [CrossRef]
98. Tsai, Y.L.; Rastogi, C.; Kitanidis, P.K.; Field, C.B. Routing algorithms as tools for integrating social distancing with emergency evacuation. *Sci. Rep.* **2021**, *11*, 1–40. [CrossRef] [PubMed]
99. Martínez-Reyes, A.; Quintero-Araújo, C.L.; Solano-Charris, E.L. A Decision Support Tool for the Location Routing Problem During the COVID-19 Outbreak in Colombia. *Commun. Comput. Inf. Sci.* **2021**, *1408*, 33–46. [CrossRef]
100. Le, D.; Men, Y.; Luo, Y.; Zhou, Y.; Nguyen, L. An efficient multi-vehicle routing strategy for goods delivery services. In Proceedings of the IEEE Workshop on Advanced Robotics and its Social Impacts, ARSO, Virtual, 8–10 July 2021; pp. 188–193. [CrossRef]
101. Mook, M.; Kloth, E.; Lee, J. Isolation and quarantine policy for connected vehicles routing. In Proceedings of the IISE Annual Conference and Expo 2019, Orlando, FL, USA, 18–21 May 2019.

102. Jin, X.; Wang, C.; Hu, W. A Study on the Optimization of Distribution Routes for Fresh Food under Epidemic Situation. In Proceedings of the 2020 2nd International Conference on Big Data and Artificial Intelligence, Johannesburg, South Africa, 28–30 April 2020; pp. 81–85. [CrossRef]
103. Muslu, M.T.; Dogan, Y. Improved Genetic Algorithm and Mobile Application for an Up-to-date Traveling Salesman Problem. In Proceedings of the 4th International Symposium on Multidisciplinary Studies and Innovative Technologies, ISMSIT 2020-Proceedings, Istanbul, Turkey, 22–24 October 2020. [CrossRef]
104. Gao, W.; Luo, J.; Zhang, W.; Yuan, W.; Liao, Z. Commanding Cooperative UGV-UAV with Nested Vehicle Routing for Emergency Resource Delivery. *IEEE Access* **2020**, *8*, 215691–215704. [CrossRef]
105. Babaee Tirkolaee, E.; Aydın, N.S. A sustainable medical waste collection and transportation model for pandemics. *Waste Manag. Res.* **2021** , 0734242X211000437. [CrossRef]
106. Chen, C.; Demir, E.; Huang, Y.; Qiu, R. The adoption of self-driving delivery robots in last mile logistics. *Transp. Res. Part E Logist. Transp. Rev.* **2021**, *146*, 102214. [CrossRef] [PubMed]
107. do C. Martins, L.; Hirsch, P.; Juan, A.A. Agile optimization of a two-echelon vehicle routing problem with pickup and delivery. *Int. Trans. Oper. Res.* **2021**, *28*, 201–221. [CrossRef]
108. Jiang, L.; Zang, X.; Dong, J.; Liang, C.; Mladenovic, N. A variable neighborhood search for the last-mile delivery problem during major infectious disease outbreak. *Optim. Lett.* **2022**, *16*, 333–353. [CrossRef]
109. Wu, F. Contactless Distribution Path Optimization Based on Improved Ant Colony Algorithm. *Math. Probl. Eng.* **2021**, *2021*, 5517778. [CrossRef]
110. Elkington, J. The triple bottom line for 21st century business. In *The Earthscan reader in business and sustainable Development*; Earthscan: London, UK, 2001; pp. 20–43.
111. Popovic, T.; Barbosa-Póvoa, A.; Kraslawski, A.; Carvalho, A. Quantitative indicators for social sustainability assessment of supply chains. *J. Clean. Prod.* **2018**, *180*, 748–768. [CrossRef]
112. Beamon, B.M.; Balcik, B. Performance measurement in humanitarian relief chains. *Int. J. Public Sect. Manag.* **2008**, *21*, 4–25. [CrossRef]
113. Lin, C.; Choy, K.L.; Ho, G.T.; Chung, S.H.; Lam, H.Y. Survey of Green Vehicle Routing Problem: Past and future trends. *Expert Syst. Appl.* **2014**, *41*, 1118–1138. [CrossRef]
114. Tognotti, E. Lessons from the history of quarantine, from plague to influenza A. *Emerg. Infect. Dis.* **2013**, *19*, 254. [CrossRef]
115. Laarbi, H.; Abta, A.; Rachik, M.; Labriji, E.; Bouyaghroumni, J.; Labriji, E. Stability Analysis and Optimal Vaccination Strategies for an SIR Epidemic Model with a Nonlinear Incidence Rate. *Int. J. Nonlinear Sci.* **2013**, *16*, 323–333.
116. El Midaoui, M.; Qbadou, M.; Mansouri, K. Logistics chain optimization and scheduling of hospital pharmacy drugs using genetic algorithms: Morocco case. *Int. J. Web-Based Learn. Teach. Technol.* **2021**, *16*, 54–64. [CrossRef]
117. Engler, J.O.; Abson, D.J.; von Wehrden, H. The coronavirus pandemic as an analogy for future sustainability challenges. *Sustain. Sci.* **2021**, *16*, 317–319. [CrossRef] [PubMed]
118. Nath, D.; Sasikumar, K.; Nath, R.; Chen, W. Factors affecting COVID-19 outbreaks across the globe: Role of extreme climate change. *Sustainability* **2021**, *13*, 3029. [CrossRef]
119. Fuentes, R.; Galeotti, M.; Lanza, A.; Manzano, B. COVID-19 and climate change: A tale of two global problems. *Sustainability* **2020**, *12*, 8560. [CrossRef]