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A Concise Review of Home Health Care Routing and Scheduling Problem

Soumen Atta [a,b,*], Vítor Basto-Fernandes [b], Michael Emmerich [a]

[a] Faculty of Information Technology, University of Jyväskylä, P.O. Box 35, (Agora), Jyväskylä, 40014, Finland

[b] Instituto Universitário de Lisboa (ISCTE-IUL), University Institute of Lisbon, ISTAR, Av. das Forças Armadas, Lisboa, 1649-026, Portugal

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ABSTRACT

The Home Health Care Routing and Scheduling Problem (HHCRSP) plays a crucial role in optimizing the delivery of home-based healthcare services by efficiently allocating caregivers to patient locations while adhering to logistical, operational, and regulatory constraints. This concise review provides an analysis of HHCRSP, discussing its key objectives, constraints, and solution methodologies. The study examines various optimization approaches, including exact algorithms, heuristics, and metaheuristic techniques. Furthermore, the impact of HHCRSP on healthcare delivery efficiency is explored, highlighting its role in reducing operational costs, improving service quality, and ensuring continuity of care. The article also discusses the regulatory requirements affecting HHCRSP, addressing compliance with legal and organizational requirements, quality assurance frameworks, economic constraints, and patient prioritization mandates. The challenges associated with HHCRSP, including logistical complexities, workload balancing, and technological barriers, are also reviewed. To align HHCRSP with regulatory frameworks, this review discusses various strategies such as adaptive scheduling, advanced algorithmic solutions, and the integration of environmental and social sustainability considerations. Additionally, emerging technological advancements, including the use of Artificial Intelligence (AI), Internet of Things (IoT), and intelligent transport systems, are evaluated for their potential to enhance HHCRSP efficiency. The article concludes by summarizing key findings, discussing the practical implications of HHCRSP for healthcare providers, and outlining future research directions. Addressing existing gaps, such as AI explainability, blockchain integration for secure scheduling, and sustainable healthcare logistics, remains a critical avenue for further exploration. As the demand for home healthcare services grows, innovative HHCRSP solutions will be essential to ensuring high-quality, cost-effective, and patient-centered care.

1. Introduction

Home healthcare (HHC) services are becoming increasingly vital as healthcare systems shift towards patient-centered care models. With aging populations and a growing preference for at-home medical assistance, healthcare providers face significant challenges in efficiently routing and scheduling home visits. The Home Health Care Routing and Scheduling Problem (HHCRSP) emerges as a crucial optimization challenge aimed at ensuring timely, cost-effective, and high-quality care delivery [1]. This article explores the fundamental aspects of HHCRSP, including its importance, impact on healthcare logistics, and strategies for addressing its challenges.

HHCRSPs are a domain of complex combinatorial optimization problems that involve efficiently scheduling and routing healthcare professionals, such as nurses, doctors, and therapists, to visit and provide medical services to patients at home. It is an extension of the Vehicle Routing Problem (VRP) [2] but incorporates additional healthcare-specific constraints such as time windows, caregiver skill requirements, synchronized visits, and continuity of care [1].

There is a rising demand for home-based healthcare services due to an aging population, limited budgets for expanding hospital capacity, and ongoing challenges such as managing dispersed populations with little access to central hospitals and beds (i.e., 'healthcare deserts') [3–5]. Efficient routing and scheduling directly impact patient satisfaction, caregiver workload balance, and the overall operational cost of healthcare service providers [1,6]. Effective HHCRSP solutions can minimize travel distances, reduce operational expenses, enhance caregiver efficiency, and improve the quality of healthcare services provided to patients in need.

HHC services play a significant role in modern healthcare systems by offering personalized care to patients who may have mobility

* Corresponding author at: Faculty of Information Technology, University of Jyväskylä, P.O. Box 35, (Agora), Jyväskylä, 40014, Finland.
E-mail addresses: soumen.s.atta@jyu.fi, soumen.atta@iscte-iul.pt (S. Atta), vitor.basto.fernandes@iscte-iul.pt (V. Basto-Fernandes), michael.t.m.emmerich@jyu.fi (M. Emmerich).

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limitations, chronic illnesses, or post-surgical recovery needs. Unlike traditional hospital settings, home healthcare operations require strategic planning to address patient-specific constraints while ensuring optimal resource utilization [7–9].

From a logistical perspective, HHCRSP aims to optimize the allocation of healthcare professionals to patient locations, considering factors such as travel time, time windows for care, and continuity of service. Unlike standard logistics problems, HHCRSP integrates human-centric factors, such as caregiver fatigue, work-life balance, and adherence to medical regulations, into the optimization models [10–12].

From a patient-centered care perspective, HHCRSP ensures that patients receive timely, high-quality medical attention. For instance, a well-optimized routing and scheduling system reduces patient wait times, ensures that skilled caregivers are matched to appropriate patients, and improves service consistency by maintaining continuity of care. Furthermore, compliance with regulatory guidelines ensures equitable access to home healthcare services while upholding ethical standards in care delivery [13–15].

The existing review articles by Fikar and Hirsch [16],Cissé et al. [17] on HHCRSP are almost a decade old. They do not cover recent developments in HHCRSP and its various variants. This concise review aims to provide a comprehensive study of the HHCRSP, summarizing the latest research, methodologies, and applications. Other more recent review articles by Euchi et al. [18],Masmoudi et al. [19] on HHCRSP do not address the impact of HHCRSP on healthcare delivery efficiency, the influence of regulatory requirements, or the key challenges in optimizing routing and scheduling for home healthcare services. Review articles by Di Mascolo et al. [20] and Alves et al. [21] do not address the regulatory impacts, among other factors, on home health care management. A comprehensive review on a related problem, the appointment scheduling problem in complex healthcare services, can be found in [22]. The key objectives of this review article are as follows:

- **To analyze key challenges:** Identify logistical, operational, and patient-centric challenges in optimizing HHCRSP, including uncertainties in travel time, workload balance, and caregiver availability.
- **To review solution methodologies:** Examine mathematical models, heuristic and metaheuristic approaches, and advanced optimization techniques used to solve HHCRSP efficiently.
- **To investigate regulatory impacts:** Discuss how healthcare regulations influence routing and scheduling decisions, including compliance with labor laws, patient prioritization policies, and financial constraints.
- **To explore strategies and real-world applications:** Assess how home healthcare providers implement routing and scheduling strategies while ensuring regulatory compliance and operational efficiency.
- **To highlight technological advancements:** Evaluate the role of artificial intelligence, multi-objective optimization, machine learning, and Internet of Things (IoT)-based solutions in improving HHCRSP efficiency.
- **To identify future research directions:** Provide insights into gaps in existing research and propose future advancements for improving HHCRSP optimization models.

This review connects recent theoretical research with practical HHCRSP implementations for the Operations Research community. It aids in developing efficient and sustainable planning tools for home healthcare logistics and understanding key challenges. We highlight optimization model features like decision variables, objective functions, constraints, and solution methods, discussing their strengths and limitations.

The selection of papers for this review on the HHCRSP was conducted using a systematic search strategy on Scopus, ensuring the inclusion of high-quality and relevant literature. The search was performed on February 24, 2025 using the following query:

```
TITLE-ABS-KEY ( "Home Health Care Routing and Scheduling Problem" OR "HHCRSP" )
AND ( LIMIT-TO ( SUBJAREA , "COMP" ) OR LIMIT-TO ( SUBJAREA , "ENGI" ) OR
LIMIT-TO ( SUBJAREA , "MATH" ) OR LIMIT-TO ( SUBJAREA , "DECI" ) OR
LIMIT-TO ( SUBJAREA , "BUSI" ) OR LIMIT-TO ( SUBJAREA , "MEDI" ) )
AND ( LIMIT-TO ( DOCTYPE , "ar" ) OR LIMIT-TO ( DOCTYPE , "cp" ) )
AND ( LIMIT-TO ( LANGUAGE , "English" ) )
```

This query was designed to identify research papers explicitly focused on HHCRSP by searching for relevant terms in the title, abstract, and keywords. To ensure a broad yet relevant scope, publications were limited to specific subject areas, including Computer Science, Engineering, Mathematics, Decision Sciences, Business, and Medicine, as these disciplines contribute significantly to HHCRSP research. Furthermore, only journal articles ("ar") and conference papers ("cp") were considered, ensuring that only peer-reviewed and high-impact publications were included. Additionally, only English-language papers were selected to maintain consistency and accessibility in the review. The execution of this query resulted in the identification of 66 relevant papers (published between 2014 and 2024), which serve as the foundation of this review, providing insights into the optimization models, methodologies, challenges, and recent advancements in HHCRSP. Since this article presents a concise review of the HHCRSP, only the most significant works are cited from these 66 identified papers. To illustrate the growing research interest in the HHCRSP, we analyzed these 66 publications indexed in Scopus over the past decade. As shown in Fig. 1, there has been a notable increase in the number of publications since 2020, with 13 papers published in both 2023 and 2024. This trend reflects the rising significance of HHCRSP in the context of operational healthcare logistics and the increasing complexity of home health care service delivery. In addition to core articles, we enhanced the review by including literature quantifying home healthcare's importance and challenges, and we point to promising computational solution techniques for planners.

To better understand the thematic landscape of the literature on HHCRSP, we performed a bibliometric keyword co-occurrence analysis using VOSviewer[1] [23]. The VOSviewer is a free, Java-based tool for building and exploring bibliometric maps (e.g., visual networks of publications, authors, keywords, or journals) using data from sources like Web of Science or Scopus. Fig. 2 shows the resulting network visualization, where each node represents a frequently occurring (at least five times) keyword extracted from the data of the 66 Scopus-indexed publications reviewed in this study. The size of each node indicates the frequency of the keyword, and the proximity and thickness of links between nodes reflect their co-occurrence strength. The visualization highlights research themes like optimization, scheduling, home health care, vehicle routing, multi-objective optimization, integer programming, uncertainty, and metaheuristics. These themes pertain either to problem definition (scheduling, routing) or solution methods (integer programming, multi-objective optimization, metaheuristics). The clustering of keywords (three clusters are shown in Fig. 2) suggests the presence of sub-domains within the HHCRSP research community. The green cluster could be characterized as being focused on metaheuristic approaches, and benchmarking forms an integral part of this cluster. The red and blue keyword clusters overlap significantly, emphasizing different aspects of problem formulations with a focus on modeling rather than solution methods.

The rest of this article is structured as follows: Section 2 outlines key objectives, decision variables, and constraints of HHCRSPs. Section 3 reviews various solution approaches, including exact mathematical programming models, heuristic and metaheuristic techniques, multi-objective optimization solvers, and real-time adaptive scheduling strategies. The impact of HHCRSP on healthcare delivery efficiency is discussed in Section 4, focusing on cost reduction, service quality improvement, patient satisfaction, and environmental considerations.

[1] https://www.vosviewer.com/

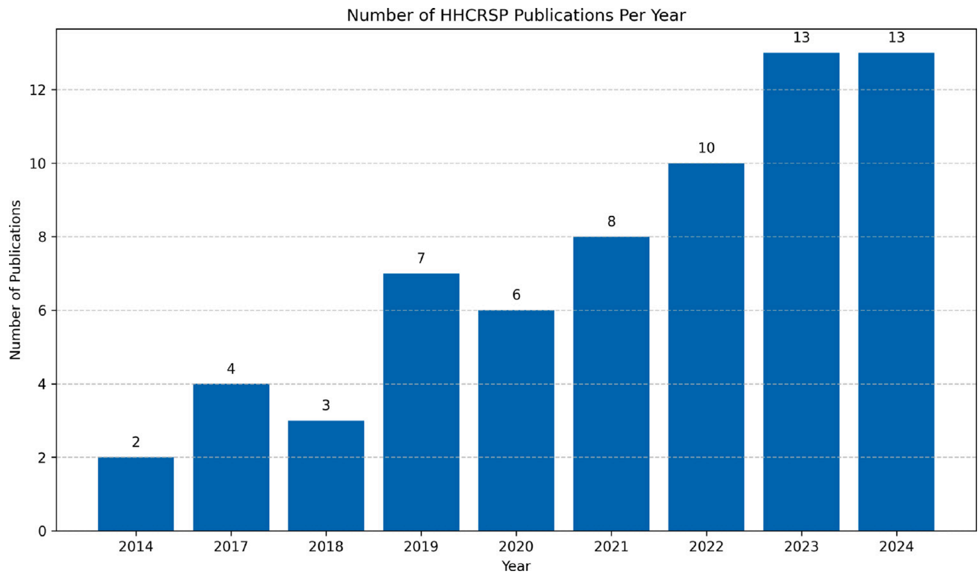

Fig. 1. Annual number of HHCRSP publications indexed in Scopus (2014–2024).

Section 5 explores the regulatory landscape affecting HHCRSP, covering compliance with legal and organizational regulations, quality assurance frameworks, economic constraints, and patient prioritization policies. In Section 6, we examine key challenges in optimizing routing and scheduling for home healthcare, including logistical complexities, operational constraints, and patient-centric concerns. Strategies for aligning HHCRSP with regulatory frameworks, including adaptive scheduling, caregiver workload balancing, and sustainability considerations, are discussed in Section 7. Finally, Section 8 summarizes key findings, highlights practical implications for healthcare service providers, and outlines open research challenges in the HHCRSP, emphasizing the need for further advancements in AI-driven optimization, blockchain-based secure scheduling, and sustainable healthcare logistics. The list of abbreviations used in this article, along with their respective full forms, is provided in Table A.6.

2. Decision variables, objectives, and constraints

The HHCRSP is a complex and practical extension of the VRP, specifically designed to address the unique challenges of HHC services. It involves assigning and routing caregivers, including nurses, medical doctors, and other health professionals, to provide medical and paramedical services at the homes of patients. The primary objectives of the HHCRSP are to minimize travel costs, maximize patient satisfaction, and ensure compliance with various operational constraints and requirements.

In general, at least on the lower levels of decision making, tools from mathematical optimization can play a vital role. They work with problems formulated as optimization or operations research (OR) models, typically in the form

$$\begin{aligned} &\min_{x\in X} \left(f_1(x),\ f_2(x),\ \ldots,\ f_m(x)\right) \\ \text{s.t.}\quad & g_i(x)\ \le\ b_i, \qquad\qquad i = 1,\ldots,p, \\ & h_j(x)\ =\ d_j, \qquad\qquad j = 1,\ldots,q, \end{aligned} \tag{1}$$

where

- $x = (x_1,\ldots,x_n)^\top$ is the vector of decision variables (continuous, integer, or mixed);
- $f_k : X \to \mathbb{R}$, $k = 1,\ldots,m$, are objective functions to be minimized (replace *min* by *max* if required);
- $g_i : X \to \mathbb{R}$ and $h_j : X \to \mathbb{R}$ are the constraint functions;
- $b_i \in \mathbb{R}$ and $d_j \in \mathbb{R}$ are constant upper bounds and target values, respectively;
- $X \subseteq \mathbb{R}^n$ is the decision space (bounds, integrality, logical restrictions, etc.).

Often, there are various different ways the problem can be formulated, and for a given OR model, there are various different solvers (gradient-based, branch-and-bound, evolutionary, etc.) [24–27].

2.1. Decision variables and decision levels

In HHCRSPs, the decisions, ultimately expressed as quantitative decision variables in OR models, can be organized into several hierarchical levels [28].

- Strategic level (long-term)
  - **Service portfolio**: Specification of the categories of care the organization will deliver.
  - **Admission policy**: Eligibility criteria, prioritization rules, and associated acceptance thresholds.
  - **Capacity planning**: Sizing of human and material resources and definition of employment contracts, based on aggregated demand forecasts and budget constraints.
  - **Geographical coverage**: Delimitation of the service region(s) to maximize accessibility while controlling travel effort.
  - **Partnership configuration**: Selection of long-term collaborators (hospitals, laboratories, pharmacies, third-party logistics, peer HHC providers) and the make-or-buy split of service components.
- Tactical level (mid-term)
  - **Workforce structure**: Number of mobile teams, team sizes, and corresponding skill profiles.
  - **Districting and team assignment**: Partitioning the coverage area into districts (known as the districting problem [29, 30]) and allocating each team to a district while considering urban/rural context, transport modes, and (de)centralized control policies.
  - **Tactical partnerships**: Identification of medium-term collaborators that support operations within each district.
- Operational level (short- and very short-term)

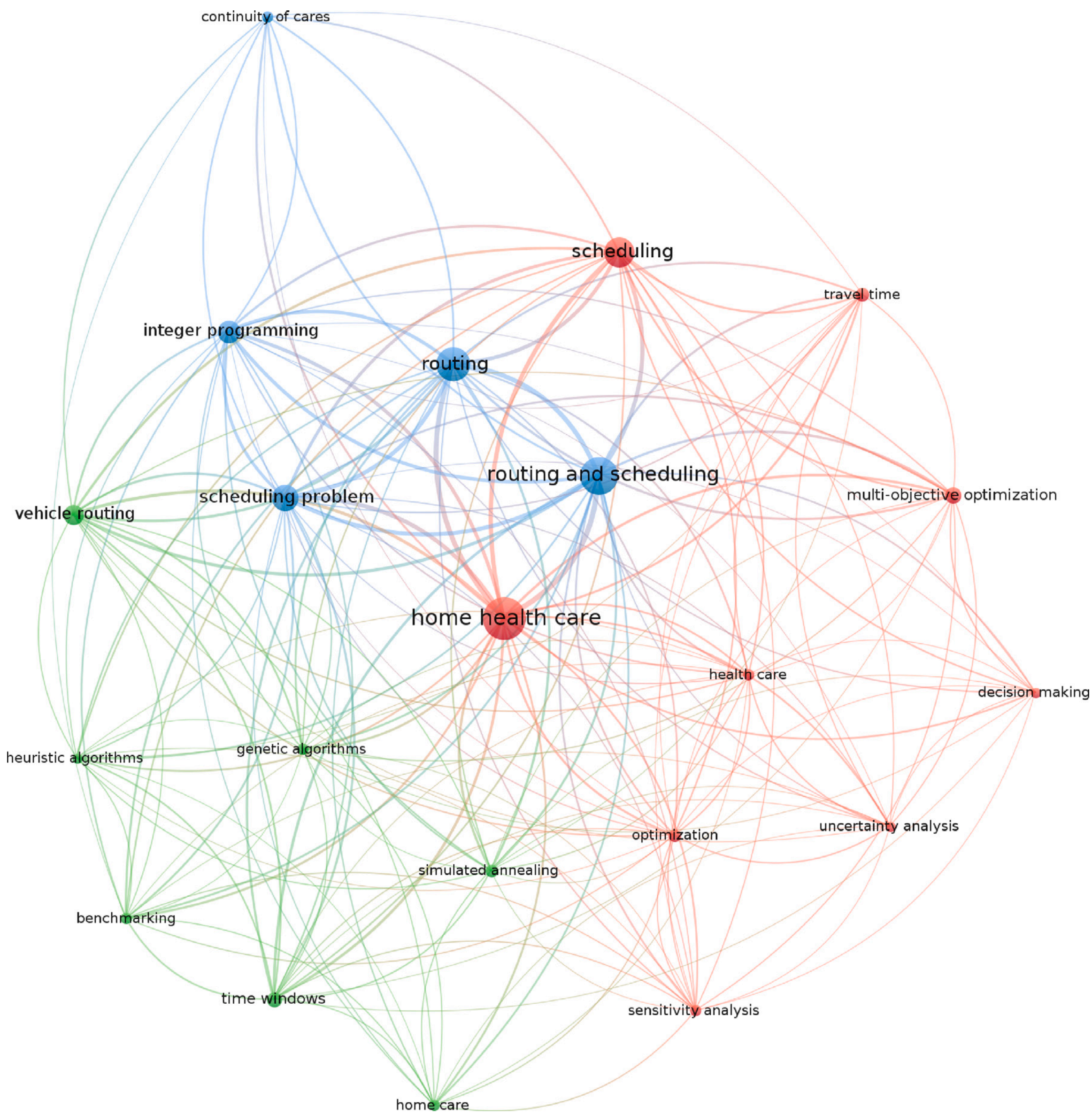

Fig. 2. Network visualization of co-occurring keywords in HHCRSP literature based on Scopus data analyzed using VOSviewer.

- **Routing and scheduling**: Construction of daily/weekly caregiver routes and service start times under time-window, periodic-visit, and multi-depot constraints.
- **Assignment variables**: (Typically binary) allocation of caregivers to visits.
- **Material flow control**: Inventory level of items required for visits at times and associated replenishment decisions.
- **Contingency set**: Predefined operational responses to unexpected events such as unavailability of personnel, road closures, emergency admissions, or patient cancellations.

Decisions at the strategic, tactical, and operational levels are ordered by time horizon and influenced by the management plan, uncertainty, and their impact on objectives. High-level decisions often involve political processes, whereas operational decisions can be managed by local healthcare providers and are best supported by optimization software and operations research tools.

A typical daily schedule for home health care services is illustrated in Fig. 3. Each horizontal line represents a patient's time window for receiving care, and the white rectangles indicate the duration of service at each location. The figure includes three staff members, each assigned a sequence of patient visits visualized using different line styles: solid (staff member 1), dotted (staff member 2), and dashed (staff member 3). Arrows depict the direction and order of visits, starting and ending at the central office (node 0). The diagram also highlights instances where patients require synchronized visits from multiple caregivers, as seen in the overlapping routes. This representation is useful for analyzing caregiver coordination, time window feasibility, and route planning in the HHCRSP context [1].

2.2. Objectives

Addressing the HHCRSP involves considering various objectives and constraints. Note that in OR modeling, constraints and objectives might be interchangeable, as they can often be formulated as either. Let us first focus on some typical objectives. These include minimization of operational costs, travel costs, service costs, and overall system costs [31–39]. Maximization of patient satisfaction ensures high-quality service delivery and the accommodation of patient preferences [6,31,33,34,36,40,41]. A specific aspect of HHCRSP, as opposed to some other problems, is that patient satisfaction can crucially depend on continuity of care, e.g., whether the same person serves as a caregiver for

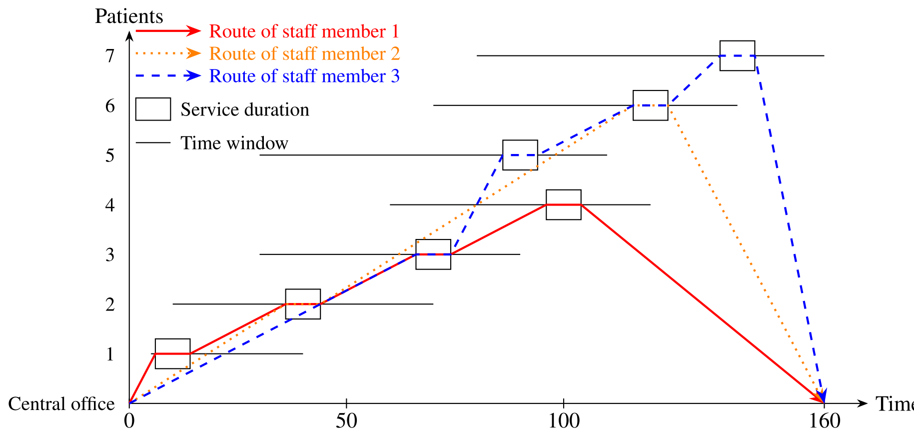

Fig. 3. Service time diagram with services that require two caregivers jointly present at some locations [1].

a longer period. Workload balancing distributes the workload evenly among caregivers to avoid overburdening [31,34,39,42]. Minimization of travel distance and CO_2 emissions reduces the environmental impact of home healthcare services [9]. Maximization of caregiver satisfaction ensures that caregiver preferences and working conditions are met [34, 37]. Minimization of unscheduled visits ensures that all planned visits are completed [35]. These objectives collectively contribute to the optimization of HHCRSP, ensuring cost-effectiveness, service quality, sustainability, and workforce efficiency.

2.3. Constraints

Various real-world constraints are also considered in the HHCRSP to ensure practical applicability and feasibility. Time-window constraints in the HHCRSP ensure that visits are scheduled within predefined time frames [6,31,33,37,39–41,43–46]. Continuity of care ensures that the same caregiver consistently visits the same patient [31,34,35,43, 47]. Caregiver qualifications are an important aspect of HHC systems. Assigning caregivers based on their skills and qualifications is considered in [6,31,32,40,44,48,49]. Synchronized visits refer that some patients require simultaneous visits from multiple caregivers [6,32,34, 44,45,50]. Scheduling mandatory breaks (such as lunch breaks) for caregivers is also incorporated as a constraint in the HHCRSP [6,32, 34,44,51]. Under flexible departure modes, caregivers can start their routes from home or the HHC center [6,31]. Patient preferences for specific caregivers are considered in [41,44]. Limiting the working hours (workload) and overtime of caregivers is also common in the HHCRSP [32,35,37,52]. Certain tasks must be completed before others in the HHCRSP. This is known as precedence constraints [36,38,44, 53]. Environmental constraints such as reducing CO_2 emissions and considering green logistics are considered in [36]. These objectives and constraints (summarized in Table 1) ensure that the HHCRSP is addressed comprehensively, balancing cost efficiency, patient satisfaction, and caregiver well-being while adhering to practical and logistical constraints.

3. Solution approaches and datasets

In this section, we discuss various solution approaches, provide guidelines for selecting HHCRSP solution methods, and present publicly available datasets for HHCRSP.

3.1. Solution approaches

The HHCRSP involves assigning and routing care workers to provide services at patients' homes, often under various constraints. Different solution methodologies are used to address the HHCRSP based on the objective functions and constraints. A branch-and-price (B&P)

Table 1
Objective functions and constraints.

Objective functions	References
Minimization of Operational Costs	[31–39]
Maximization of Patient Satisfaction	[6,31,33,34,36,40,41]
Workload Balancing	[31,34,39,42]
Minimization of Travel Distance and CO_2 Emissions	[9]
Maximization of Caregiver Satisfaction	[34,37]
Minimization of Unscheduled Visits	[35]
Constraints	**References**
Time Windows	[6,31,33,37,39–41,43,44]
Continuity of Care	[31,34,35,43]
Caregiver Qualifications	[6,31,32,40,44,48,49]
Synchronized Visits	[6,32,34,44,50]
Lunch Breaks	[6,32,34,44,51]
Flexible Departure Modes	[6,31]
Patient Preferences	[41,44]
Workload and Overtime	[32,35,37,52]
Precedence Constraints	[36,38,44,53]
Environmental Constraints	[36]

algorithm that combines a route-based mathematical model with a discrete approximation method to handle stochastic travel and service times, ensuring on-time service probability, is proposed in [54]. A Branch-and-Price-and-Cut algorithm is proposed in [55] for solving the HHCRSP with multiple prioritized time windows. Mixed integer linear programming (MILP) is frequently used in combination with other heuristics or metaheuristics to solve the HHCRSP, ensuring continuity of care and handling practical constraints [34,43,56–59]. In [43], MILP is combined with greedy algorithms to quickly find feasible solutions for large instances. Matheuristic combines heuristics with mathematical programming solvers (e.g., Gurobi) to efficiently solve large-scale instances. Examples include Adaptive Large Neighborhood Search (ALNS) integrated with MILP [34,56]. In [60], a stochastic programming model with recourse is employed to solve the HHCRSP, where uncertainties in traveling and caring times as well as synchronization of services are considered. In [61], the gossip algorithm is used to solve the HHCRSP. In the gossip algorithm, each node exchanges information with a neighboring node, ensuring that computations are performed in a decentralized manner [62]. In [63,64], a column generation-based improved gossip algorithm is employed to solve the HHCRSP. Recently, a new variant of the HHCRSP was solved using a constraint programming solver in [65].

Cluster-assign algorithms are used in a two-stage approach where the first stage clusters tasks based on location and time, and the second stage constructs routes and schedules [66,67]. Variable Neighborhood Search (VNS) and Variable Neighborhood Descent (VND) are applied in a two-stage solution approach to handle large-scale problems, focusing

Table 2
Key solution methodologies for HHCRSP.

Solution methodology	Reference
Branch-and-Price (B&P) Algorithm	[54]
Branch-and-Price-and-Cut Algorithm	[55]
Mixed-Integer Linear Programming (MILP)	[34,43,56–59]
MILP with Greedy Algorithms	[43]
Column Generation-Based Gossip Algorithm	[64]
Matheuristic (ALNS with MILP)	[34,56]
Stochastic programming model with recourse	[60]
Cluster-Assign Algorithms	[66,67]
Variable Neighborhood Search (VNS) and Variable Neighborhood Descent (VND)	[67]
Adaptive Large Neighborhood Search	[68]
Adaptive Large Neighborhood Search embedded in an Enhanced Multi-Directional Local Search	[48]
Greedy Randomized Adaptive Search Procedure (GRASP)	[57]
Distributed Algorithms with AI Techniques	[69]
Spatial–Temporal Decomposition with Patient Filtering (STDPF)	[70]
Simulated Annealing	[71,72]
Genetic Algorithm (GA)	[58,73]
Three-Step Algorithm	[74]
Multi-Objective Evolutionary Algorithms (NSGA-II, SPEA2)	[75,76]
AMOALNS (Archived Multi-Objective Simulated Annealing with Adaptive Large Neighborhood Search)	[77]
Multi-Objective Artificial Bee Colony Metaheuristic	[10]
Enhanced NSGA-II with VND and MILPs (Green HHCRSP)	[36]
Multi-Objective Migrating Birds Optimization Algorithm	[78]
Knowledge-based multi-objective evolutionary algorithm	[79]
Augmented Epsilon Constraint and Fuzzy Goal Programming	[80]
Discrete Multi-Objective Grey Wolf Optimizer	[81]
Multi-Objective Cooperative Evolutionary Algorithm with Stochastic Simulation	[82]
NSGA-II with Multidirectional Local Search	[83]

on clustering and route constructions [67]. Adaptive Large Neighborhood Search (ALNS) embedded in an Enhanced Multi-Directional Local Search framework is used for solving a bi-objective HHCRSP under uncertainty in [48]. An enhanced ALNS is used to solve the electric HHCRSP with time windows and fast chargers [68]. The objective is to plan the daily routes of healthcare nurses to efficiently deliver a series of services to patients distributed across a scattered area [68]. Greedy Randomized Adaptive Search Procedure (GRASP) is a metaheuristic method that is combined with MILP to enhance scheduling and routing efficiency [57]. In [69], the solution approach integrates artificial intelligence techniques in a distributed optimization method to optimize appointment assignments. Spatial–Temporal Decomposition with Patient Filtering (STDPF) is a solution approach that combines multi-dimensional temporal and spatial decomposition with a prioritization scheme to handle large problem instances efficiently [70]. In [71], simulated annealing is used for multi-constraint personnel allocation by dividing tasks and caregivers into groups based on geographical location to reduce computation time for finding the global optimal solution. In [58], a genetic algorithm (GA) is used alongside MILP and hybrid approaches to solve operational planning problems, focusing on cost-efficiency and service quality. In [74], a three-step algorithm is developed that involves route scheduling, resource selection, and local improvement to optimize daily service routes and caregiver dispatch.

Multi-objective evolutionary algorithms such as Non-dominated Sorting Genetic Algorithm (NSGA-II) [84] and Strength Pareto Evolutionary Algorithm (SPEA2) [85], are often hybridized with clustering techniques to improve solution quality in HHCRSP [75,76]. In [77], HHC scenarios in pandemics are solved as HHCRSP. It focuses on minimizing travel costs, workload differences, and negative patient preferences. It uses a customized algorithm, AMOALNS, which combines Archived Multi-objective Simulated Annealing (AMOSA) with adaptive large neighborhood search (ALNS) [77]. In [10], Multi-objective Consistent HHCRSP (MoConHHCRSP) is considered, where the aim is to minimize routing cost, improve service consistency, and balance workload. It also incorporates uncertain travel and service times, and is solved using an improved multi-objective artificial bee colony metaheuristic. A Green Home Health Care (GHHC) framework is considered in [36], which aims to minimize travel distance and CO_2 emissions while balancing caregiver workload. An enhanced NSGA-II algorithm with VND and MILPs is developed to solve multi-objective GHHC problem [36]. A multi-objective HHCRSP with uncertainties in service and travel times is considered in [78]. A stochastic programming method and a multi-objective migrating birds optimization algorithm are proposed for solving the HHCRSP [78]. In [79], a multi-objective HHCRSP with multiple HHC centers is considered and solved using a knowledge-based multi-objective evolutionary algorithm. In [80], a patient-oriented multi-objective HHCRSP is considered. It focuses on emergency patients, nurses' proficiency, and patients' preferences. An augmented epsilon constraint and fuzzy goal programming approaches are developed in [80] for solving this multi-objective HHCRSP. A fuzzy multi-objective HHCRSP that maximizes the total priority of visited customers and minimizes service cost is considered in [81]. A discrete multi-objective grey wolf optimizer is used to solve this problem [81]. A multi-center, multi-objective HHCRSP that minimizes total operation cost and penalty cost due to earliness and delay is considered in [82]. A multi-objective cooperation evolutionary algorithm with stochastic simulation is utilized to solve this problem [82]. Another multi-objective HHCRSP with Practical constraints having objectives of minimizing tardiness of services, caregivers' waiting times, and balanced workload is considered in [83]. NSGA-II with multidirectional local search is proposed to solve this problem [83].

The summary of the key solution methodologies used for the HHCRSP is given in Table 2. These methodologies (summarized in Table 2) highlight the diverse approaches used to tackle the complexities of HHCRSP, each offering unique advantages in terms of efficiency, scalability, and solution quality.

3.2. Guidelines for selecting HHCRSP solution methods

The suitability of a solution approach often depends on specific instance features such as size, uncertainty, and objective complexity. For example, MILP and exact methods are best suited for small- to medium-scale deterministic instances, especially when precision is critical [43,57]. In contrast, metaheuristics and hybrid approaches, such as ALNS or GRASP, are more effective for large-scale or highly constrained problems due to their scalability and flexibility [34,57]. When uncertainty in travel and service times is present, stochastic programming or scenario-based heuristics are appropriate, as demonstrated in [10, 78]. For multi-objective HHCRSP, evolutionary algorithms like NSGA-II, SPEA2, or hybrid AMOALNS are commonly adopted to navigate trade-offs between cost, quality, workload balance, and environmental impact [36,76]. This taxonomy provides a foundation for selecting solution methods aligned with instance characteristics and problem types (e.g., deterministic vs. stochastic), offering practical guidance for modelers and practitioners.

3.3. Datasets for HHCRSP

Here, we provide the details of some publicly available datasets for the HHCRSP.

- **HHCRSP Dataset 2014**: This dataset [86] comprises benchmark instances originally generated by Mankowska et al. [1]. It has served as the foundation for many other benchmark instances developed in subsequent studies.
- **HHCRSP Dataset 2021**: This dataset [87] includes instances for the daily home health care routing and scheduling problem with multiple service types, multiple visits, and route inter-dependency constraints. It was introduced by Mankowska et al. [1] and generated using a modified version of the OVIG (Open Source Vehicle Routing Instance Generator) tool proposed by Sartori [88].
- **HHCRSP Data and Toolbox Repository**: This repository [89] contains instances, selected solutions, and a toolbox for generating instances and validation. It was presented by Ceschia et al. [90].
- **Dataset for Stochastic HHCRSP with Multiple Synchronized Services**: This dataset focuses on the stochastic HHCRSP with multiple synchronized services [60,91]. These test instances were randomly generated based on the benchmark instances from Mankowska et al. [1]. Two distinct sets of instances were created: Single Services and Multiple Synchronized Services. Each set comprises three subsets of varying sizes [91].
- **Dataset for Stochastic HHCRSP with Multiple Hard Time Windows**: These test instances [92] were randomly generated by Bazirha et al. [93] using the benchmark instances from Mankowska et al. [1].
- **Multi-day HHCRSP Dataset**: This dataset [94] consists of 60 instances generated by Grenouilleau et al. [47].
- **C-HHCRSP Dataset**: This dataset [95] was generated by Wang et al. [96], where the collaborative HHCRSP (C-HHCRSP) is treated as a variant of the multi-depot heterogeneous vehicle routing problem with time windows. In this dataset, patient locations were randomly generated following the methodologies described by Solomon [97].

4. Impact of HHCRSP on healthcare delivery efficiency

In this section, we discuss the key ways in which HHCRSP enhances healthcare delivery. The HHCRSP significantly impacts the efficiency of healthcare delivery by optimizing the allocation and scheduling of caregivers to patients' homes. Here are the key ways in which HHCRSP enhances healthcare delivery:

- **Cost Reduction:** Cost reduction can be achieved by minimizing either operational costs or logistics expenses. Efficient routing and scheduling reduce the overall operational costs for home healthcare organizations. For instance, algorithms like an approximation algorithm (APA), genetic algorithm (GA), and tabu search (TS) have been shown to reduce costs by 45.75%, 53.01%, and 57.74%, respectively [7]. By minimizing travel distances and optimizing routes, HHCRSP helps in cutting down logistics expenses, which is crucial for maintaining budget constraints [8].
- **Improved Service Efficiency:** Service efficiency can be improved by providing timely service and balanced workload. HHCRSP ensures that caregivers can reach patients in a timely manner by optimizing travel routes and schedules, which is particularly important during emergencies or for patients with critical needs [8]. The problem also addresses the issue of workload balance among caregivers, ensuring that no single caregiver is overburdened, which can lead to better service quality and caregiver satisfaction [9].
- **Enhanced Patient Satisfaction:** Enhanced patient satisfaction can be achieved by providing continuity of care and high service quality. By considering factors like continuity of care and patient preferences, HHCRSP helps in maintaining consistent caregiver-patient relationships, which is crucial for patient satisfaction and quality of care [67,98]. The integration of patient satisfaction as an objective function in the optimization models ensures that the quality of service is not compromised even under uncertain conditions [99,100].
- **Environmental Impact:** By optimizing travel routes, HHCRSP contributes to reducing CO_2 emissions, making home health care services more environmentally friendly [36].
- **Handling Uncertainties:** HHCRSP models that incorporate uncertainties such as travel time variability and service processing time help in creating more robust schedules that can adapt to real-world disruptions and variability, thereby maintaining service efficiency [101,102].
- **Technological Integration:** The integration of IoT and intelligent transport systems in HHCRSP can further enhance route optimization and service delivery, ensuring that medical supplies and caregivers reach patients efficiently [103].
- **Multi-objective optimization:** Multi-objective optimization models in HHCRSP allow for balancing various factors such as travel distance, caregiver workload, and patient satisfaction, leading to more comprehensive and effective solutions [36,104,105].

The HHCRSP plays a crucial role in enhancing the efficiency of healthcare delivery by reducing costs, improving service efficiency, ensuring patient satisfaction, and addressing environmental concerns. By incorporating advanced optimization techniques and considering real-world uncertainties, HHCRSP models provide robust and practical solutions for home healthcare services.

5. Key impacts of regulatory requirements

To understand how regulatory requirements impact the optimization of routing and scheduling for HHC services, it is essential to consider various factors highlighted in this section.

5.1. Compliance with legal and organizational regulations

Regulatory requirements often include adherence to legal and organizational working regulations, which are crucial for practical application in home health care (HHC) routing and scheduling. These regulations are already widely incorporated in nurse rostering problems for stationary institutions and must be adapted for home care providers [13]. Failure to consider these regulations can lead to a high number of violations, emphasizing the importance of modeling working regulations in optimization problems [13].

5.2. Quality assurance and accountability

Regulatory frameworks often emphasize quality assurance and accountability. For instance, the Home Health Prospective Payment System (HHPPS) updates include changes to quality reporting program requirements and therapy reassessment time-frames, which directly impact how services are scheduled and delivered [14]. Accountability requirements from various stakeholders can lead to unintended

Table 3
Key impacts of regulatory requirements.

Impact area	Description	Reference
Legal and Organizational Compliance	Adherence to working regulations and legal requirements.	[13]
Quality Assurance and Accountability	Emphasis on quality reporting and accountability, affecting service delivery.	[14,15]
Economic and Financial Constraints	Influence of financing and reimbursement on service delivery and cost optimization.	[107,108]
Patient Prioritization	Prioritizing patients based on urgency and critical needs.	[8]
Optimization Model Complexity	Inclusion of various regulatory constraints in optimization models.	[33,109]

consequences, such as shifting care time away from patients and dissuading innovation, which can affect the efficiency of routing and scheduling [15,106].

5.3. Economic and financial constraints

Regulatory requirements related to financing and reimbursement can significantly impact the delivery and quality of home care services. For example, the system funded by Medicare, Medicaid, and other sources affects how services are scheduled and delivered, with implications for cost optimization and quality assurance [107]. Economic constraints and the need to meet client (patient) needs better are also influenced by local public authorities' disposable incomes, which can affect the distribution and scheduling of home care services [108].

5.4. Patient prioritization and service delivery

Regulations may necessitate prioritizing patients based on urgency and critical needs, which impacts the routing and scheduling strategies. For example, models that prioritize patients with urgent needs ensure that those with severe conditions are serviced first, affecting the overall scheduling and routing optimization [8]. The need to balance workload among caregivers while ensuring good patient care is another regulatory consideration that impacts routing and scheduling [9].

5.5. Impact on optimization models

Regulatory requirements add complexity to optimization models, necessitating the inclusion of various constraints such as blood sampling requirements, caregiver qualifications [48,49], and continuity of care [109]. Models must also consider soft and hard time windows, temporal dependencies, and patient preferences, which are influenced by regulatory standards [33]. In modeling terms, regulatory constraints in HHCRSP can be categorized as hard or soft depending on their enforceability and flexibility. Hard constraints are mandatory and must not be violated, for instance, legal working hours, caregiver qualifications, and required visit time windows enforced by labor laws or healthcare standards. In contrast, soft constraints are desirable but can be violated at a cost, such as caregiver or patient preferences, continuity of care, and equitable workload distribution. These are typically modeled using penalty terms in the objective function. Clearly distinguishing between hard and soft constraints is essential for developing robust and realistic optimization models that balance compliance with flexibility in real-world operations.

5.6. Modeling regulatory requirements in optimization frameworks

To strengthen the integration of regulatory impacts with optimization modeling, we can explicitly map regulatory requirements to corresponding mathematical constructs. Legal and organizational regulations, such as caregiver working hour limits and mandatory rest periods, are typically modeled as hard constraints that must not be violated in MILP formulations [57]. Caregiver qualifications are also encoded as hard constraints to ensure skill matching between caregivers and required patient services [48]. Patient prioritization policies, particularly those driven by urgency and clinical severity, are implemented as priority-based routing rules or via weighted objectives in multi-objective models [8]. Continuity of care, while essential for service quality [109], can be treated as a soft constraint, modeled via penalty terms to encourage, but not strictly enforce, consistent caregiver assignments. Optimization frameworks can also model stakeholder satisfaction using constraints that ensure compliance with time windows and quality expectations, thereby embedding quality assurance and accountability as soft constraints [110]. In [33], the model includes caregiver skill-matching and patient preferences through constraints, balancing legal compliance with patient-centric flexibility. This mapping of regulatory requirements to optimization components enables the development of realistic models that support both compliance and operational efficiency. By explicitly linking regulatory requirements to optimization components, such as hard constraints (legal limits, qualifications), soft constraints (preferences, continuity), and objective penalties (cost, emissions), these models demonstrate how regulatory compliance is operationalized within the HHCRSP framework.

From the above discussions, we can conclude that the regulatory requirements (summarized in Table 3) significantly impact the optimization of routing and scheduling for HHC services by introducing legal, quality, economic, and patient prioritization constraints that must be carefully integrated into optimization models to ensure compliance and efficiency. Regulatory compliance in HHCRSP often introduces trade-offs that can conflict with cost or efficiency objectives. For example, strict adherence to labor regulations may limit scheduling flexibility, leading to increased travel distances or the need for additional staff. Similarly, prioritizing high-need patients or ensuring continuity of care can reduce routing efficiency by restricting caregiver assignments. These constraints, while essential for quality and equity, can impose higher operational costs or compromise optimal resource utilization, requiring careful balancing in model design.

6. Key challenges in optimizing routing and scheduling for home health care services

Optimizing routing and scheduling for HHC services involves addressing several complex and interrelated challenges. These challenges can be broadly categorized into logistical, operational, and patient-centric issues.

6.1. Logistical challenges

The key logistical challenges include travel and service time uncertainty [10], geographic distribution of patients [11], and cost minimization [36,39]. Uncertain travel and service times complicate the planning process. These uncertainties need to be accounted for to ensure reliable service delivery [10]. The wide geographical distribution of patients, especially in rural areas, increases travel distances and complicates route planning [11]. Reducing the total cost of operations, including travel costs and service delivery costs, is a primary objective. This involves optimizing routes to minimize travel distances and fuel consumption [36,39].

6.2. Operational challenges

Operational challenges in HHC services include workload balance among caregivers [6,10,48], caregiver skills [46] and availability [9,10], and dynamic re-planning [111,112]. Ensuring a balanced workload among caregivers is crucial to prevent burnout and maintain

Table 4
Challenges in optimizing routing and scheduling for HHC services.

Challenge	Description	References
Travel and Service Time Uncertainty	Unpredictable travel and service times affecting reliability.	[10]
Geographical Distribution	Wide distribution of patients, especially in rural areas.	[11]
Cost Minimization	Reducing operational costs, including travel and service delivery costs.	[36,39]
Workload Balance	Ensuring even distribution of workload among caregivers.	[6,10]
Caregiver Skills and Availability	Matching skills and managing availability, including synchronized visits.	[6,9]
Dynamic Re-planning	Frequent re-planning while maintaining continuity of care.	[111,112]
Patient Preferences and Priorities	Incorporating patient preferences and prioritizing urgent cases.	[12,41,114]
Service Consistency	Maintaining consistent caregiver assignments.	[10,36]
Accessibility and Equity	Ensuring equitable access to care for all patients.	[11,113]
Integration of Advanced Algorithms	Using advanced algorithms to solve complex optimization problems.	[7,42,69]
Environmental Considerations	Minimizing environmental impact while optimizing routes.	[36]

service quality. This involves distributing visits evenly and considering caregivers' working hours and breaks [6,10,48]. Matching caregivers' skills with patient needs and managing their availability is essential [46]. This includes handling synchronized visits where multiple caregivers are required simultaneously [9,10]. The need for frequent re-planning due to changes in patient conditions or caregiver availability adds complexity. Continuity of care must be preserved during re-planning to maintain patient satisfaction [111].

6.3. Patient-centric challenges

Patient-centric challenges in HHC services include patient preferences and priorities [12,41], service consistency [10,36], accessibility, and equity [11,113]. Incorporating patient preferences for specific caregivers and prioritizing urgent cases are critical for patient satisfaction. This requires a flexible scheduling system that can adapt to individual needs [12,41,114]. Maintaining consistency in caregiver assignments to build trust and ensure high-quality care is important. However, achieving this consistency can conflict with other objectives like cost minimization and workload balance [10,36,48]. Ensuring equitable access to care for all patients, including those in remote areas, is a significant challenge. This involves optimizing routes to cover all patients efficiently while considering their specific needs [11,113].

6.4. Technological and methodological challenges

Utilizing advanced algorithms like genetic algorithms, tabu search, and other artificial intelligence techniques to solve the NP-hard nature of the problem is necessary. These algorithms help in finding near-optimal solutions within a reasonable time frame [7,42,69]. Minimizing environmental impact, such as reducing CO_2 emissions, while optimizing routes adds another layer of complexity to the problem [36].

Addressing these challenges (summarized in Table 4) requires a multi-faceted approach that balances logistical efficiency, operational feasibility, and patient satisfaction.

7. Strategies for aligning home health care routing and scheduling with regulations

To align routing and scheduling with regulatory requirements, home health care providers can implement several strategies. These strategies ensure compliance with legal and organizational regulations while optimizing service delivery.

7.1. Incorporate working regulations

In HHC services, it is important to integrate legal and organizational working regulations into the routing and scheduling models and algorithms (see Section 5.6). This includes adhering to labor laws, break times, and maximum working hours [6,13,115]. Mixed-integer programming models and heuristic approaches can be used to handle the complexity of these regulations efficiently [6,13].

7.2. Prioritize patients based on needs

In HHC services, a prioritization scheme can be developed to ensure that patients with urgent or critical needs are serviced first. This can be achieved using methods like the *Best-Worst Method* (BWM) and *Technique for Order of Preference by Similarity to Ideal Solution* (TOPSIS) [8]. A bi-objective optimization model can be implemented to balance patient priorities with logistical constraints [8].

7.3. Flexible and adaptive scheduling

We can utilize adaptive large neighborhood search and other heuristic algorithms to dynamically adjust schedules based on real-time data and regulatory constraints [6,13,112]. We can also implement spatial–temporal decomposition approaches to manage multi-period planning horizons and synchronize visits when multiple caregivers are required [70].

7.4. Consideration of caregiver constraints

It is important to ensure that caregiver schedules include mandatory breaks and comply with labor regulations. This can be managed through hybrid metaheuristics and mixed-integer programming models [6,115,116]. It is also better to allow flexible departure modes, enabling caregivers to start their routes from home or the HHC company office [6].

7.5. Use of advanced algorithms

We can apply artificial intelligence techniques, such as genetic algorithms and tabu search, to optimize routing and scheduling while considering regulatory constraints [7,69]. Multi-objective algorithms can be implemented to balance cost, service consistency, and workload distribution [10].

7.6. Integration of environmental and social factors

In HHC services, it is very important to incorporate environmentally sustainable transport systems and consider social sustainability in planning. This includes using walking routes and car-sharing concepts to reduce the number of required vehicles and comply with environmental regulations [117,118].

By implementing the above-mentioned strategies (also summarized in Table 5), HHC providers can ensure that their routing and scheduling processes are compliant with regulatory requirements while optimizing service delivery and operational efficiency.

8. Conclusion

The Home Health Care Routing and Scheduling Problem (HHCRSP) is a critical optimization challenge that directly impacts the efficiency, cost-effectiveness, and quality of home healthcare services. This review has examined various aspects of HHCRSP, including its key constraints, optimization methodologies, regulatory implications, and emerging technological advancements.

Table 5
Strategies for aligning HHC routing and scheduling with regulations.

Strategy	Description	References
Incorporate Working Regulations	Adhere to labor laws, break times, and working hours.	[6,13,115]
Prioritize Patients	Use BWM and TOPSIS for prioritization.	[8]
Flexible and Adaptive Scheduling	Adaptive large neighborhood search, spatial–temporal decomposition.	[6,13,70]
Consideration of Caregiver Constraints	Include mandatory breaks, flexible departure modes.	[6,115]
Use of Advanced Algorithms	Genetic algorithms, tabu search, multi-objective algorithms.	[7,10,69]
Integration of Environmental Factors	Use walking routes, car-sharing concepts.	[117,118]

8.1. Summary of findings

HHCRSP extends the classical Vehicle Routing Problem (VRP) by incorporating unique constraints such as time windows [6,33,119,120], skill-matching requirements [9,40,119,121], synchronized visits [6, 70], continuity of care [43], multi-depot operations [6,43], and multi-period planning [9,37,70]. The key challenges associated with HHCRSP include:

- **Logistical Challenges:** Travel time uncertainties, geographic distribution of patients, and cost minimization.
- **Operational Challenges:** Workload balance, caregiver availability, and dynamic re-planning.
- **Patient-Centric Challenges:** Personalized care, service consistency, and equitable accessibility.
- **Regulatory Challenges:** Compliance with labor laws, patient prioritization frameworks, and quality assurance requirements.

To address these challenges, researchers have developed various optimization models, including:

- **Mathematical Approaches:** Utilizes Mixed Integer Linear Programming (MILP) and other mathematical formulations to model the problem [6,33,40,43,120].
- **Heuristic and Metaheuristic Techniques:** Employs various heuristic and metaheuristic methods such as General Variable Neighborhood Search (GVNS), Iterated Local Search (ILS), Genetic Algorithm (GA), and Tabu Search (TS) to find near-optimal solutions efficiently [6,7,33,109,119].
- **Multi-objective optimization models:** Multi-objective optimizations [76–78] tackles the conflicting objectives often arise in the HHCRSP.
- **Hybrid Approaches:** Combines different algorithms and techniques to improve solution quality and computational efficiency [6,43,122].

Furthermore, technological advancements such as IoT, AI-driven decision-making, and intelligent transport systems are transforming HHCRSP by enabling real-time optimization and predictive analytics.

8.2. Practical implications for healthcare service providers

Optimizing HHCRSP presents several practical benefits for healthcare providers, including:

- **Cost Reduction:** Efficient routing minimizes operational expenses such as transportation costs and caregiver overtime.
- **Enhanced Service Quality:** Adaptive scheduling ensures timely visits, reducing patient wait times and improving healthcare outcomes.
- **Regulatory Compliance:** AI-driven compliance frameworks help providers align with labor laws, safety guidelines, and insurance reimbursement policies.
- **Sustainability in Healthcare Logistics:** Environmentally friendly routing strategies and electric vehicle integration reduce carbon emissions in HHC operations.
- **Workforce Management:** Fair workload distribution improves caregiver job satisfaction and reduces burnout.

Implementing HHCRSP solutions can improve the overall efficiency of healthcare logistics, leading to higher patient satisfaction, optimized resource utilization, and better adherence to regulatory requirements.

8.3. Future perspectives and open research challenges

Despite significant advancements in HHCRSP, several research gaps and challenges remain that require further exploration:

- **AI Explainability and Trustworthiness:** The use of AI in HHCRSP decision-making must be interpretable and transparent to ensure regulatory compliance and trust among stakeholders. In the context of HHCRSP, explanations may identify and highlight bottlenecks, such as unusual service costs or unfulfilled services, and their impact on objectives and constraint satisfaction.
- **Blockchain Integration for Secure Scheduling:** Decentralized and partially encrypted scheduling systems can improve data security and enhance patient privacy.
- **Personalized and Interactive Decision Making:** Future research should focus on optimizing caregiver-patient matching based on historical interactions and patient preferences. Moreover, interactive multi-objective optimization could be used to find solutions that meet the preferences of both patients and caregivers in a better way.
- **Dynamic and Uncertainty-Aware Optimization Models:** More robust frameworks are needed to handle real-time disruptions such as emergency visit requests and last-minute caregiver unavailability, and long-term planning in case of uncertain future demand and availability considerations.
- **Sustainable Home Healthcare Logistics:** Explore and integrate fossil-fuel saving strategies and alternative transport models like bicycle healthcare delivery and electro-mobility in routing. Consider combining pickup-and-delivery routing with home visits to create multi-purpose rides for restocking medical supplies in local healthcare centers and pharmacies, and visiting patients.

Furthermore, big Data and context-aware systems enable effective responses to the large-scale, complex, dynamic, and real-time decision-making processes involved in HHCRSP [123]. The design of information systems capable of handling such challenges requires a multi-layered architecture: a Perception Layer for real-time data collection using IoT and Digital Twin technologies; a Comprehension Layer supported by semantic integration standards and techniques; a Projection Layer equipped with predictive analytics; and a Pragmatics Layer for decision-making based on prescriptive analytics techniques [124, 125]. Additionally, important challenges such as privacy assurance, cybersecurity, and trustworthiness in HHCRSP can be addressed through emerging technologies like homomorphic encryption, multi-party computation, and blockchain infrastructures [126,127]. These approaches, technologies, and techniques are expected to play a critical role in the successful deployment of HHCRSP solutions in real-world applications.

8.4. Final remarks

As home healthcare services continue to expand globally, optimizing HHCRSP remains essential for improving service efficiency, cost reduction, and patient-centered care. Future advancements in AI,

Table A.6
List of abbreviations used in this article.

Abbreviation	Full form
AI	Artificial Intelligence
ALNS	Adaptive Large Neighborhood Search
AMOSA	Archived Multi-objective Simulated Annealing
B&P	Branch-and-Price
BWM	Best-Worst Method
C-HHCRSP	Collaborative Home Health Care Routing and Scheduling Problem
CP	Constraint Programming
GA	Genetic Algorithm
GHHC	Green Home Health Care
GRASP	Greedy Randomized Adaptive Search Procedure
GVNS	General Variable Neighborhood Search
HHC	Home Health Care
HHCRSP	Home Health Care Routing and Scheduling Problem
HHPPS	Home Health Prospective Payment System
ILS	Iterated Local Search
IoT	Internet of Things
MILP	Mixed-Integer Linear Programming
ML	Machine Learning
MoConHHCRSP	Multi-objective Consistent Home Health Care Routing and Scheduling Problem
NSGA-II	Non-dominated Sorting Genetic Algorithm II
OR	Operations Research
OVIG	Open Source Vehicle Routing Instance Generator
SA	Simulated Annealing
SPEA2	Strength Pareto Evolutionary Algorithm 2
STDPF	Spatial–Temporal Decomposition with Patient Filtering
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TS	Tabu Search
VND	Variable Neighborhood Descent
VNS	Variable Neighborhood Search
VRP	Vehicle Routing Problem

IoT, blockchain, and intelligent transport systems will further enhance HHCRSP solutions, enabling smarter and more adaptive healthcare logistics. By integrating innovative optimization techniques with regulatory frameworks, home healthcare providers can achieve more efficient, equitable, and sustainable service delivery.

CRediT authorship contribution statement

Soumen Atta: Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Vítor Basto-Fernandes:** Writing – review & editing, Supervision, Resources, Conceptualization. **Michael Emmerich:** Writing – review & editing, Supervision, Resources, Conceptualization.

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Declaration of competing interest

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Appendix. List of abbreviations

See Table A.6.

Data availability

No data was used for the research described in the article.

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