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A Genetic Algorithm-Based Traffic Light Optimization Model for Efficient Home Healthcare Service Delivery in Türkiye

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ABSTRACT Home healthcare (HHC) has become a crucial service model to address the rising needs of aging populations and patients with chronic conditions. However, efficient planning and resource allocation remain major challenges, especially in geographically dispersed regions. This study proposes a novel optimization-based operational model incorporating a traffic light algorithm to prioritize patient visits based on health status in Diyarbakır, Türkiye. The algorithm classifies patients into three categories (green, yellow, and red) allowing proactive and dynamic care management. A genetic algorithm is applied to solve the complex multi-objective routing and scheduling problem while considering numerous real-world constraints such as minimum team size, gender composition, and vehicle capacity. The model integrates demographic data from 2011–2023 and minimizes total visit duration while maximizing the number of patients served. Key decision variables include team size, staff gender distribution, patient condition, location, and travel time. The optimization process demonstrates significant improvements in performance metrics across generations, reducing penalty values and achieving more balanced, efficient outcomes. Results indicate that the model effectively aligns healthcare delivery with patient needs, operational limitations, and service quality goals. Unlike previous studies focusing mainly on cost or time, this model uniquely emphasizes clinical prioritization through color-coded patient conditions, integrating cultural and practical constraints. The study highlights the importance of tailored, region-specific solutions and offers a framework that can be adapted for broader applications. Future work should explore integrating machine learning for dynamic risk scoring and incorporating logistical elements such as traffic and real-time availability.

KEYWORDS
Traffic light algorithm
Health informatics
Optimization
Home healthcare services

INTRODUCTION

Home health care (HHC) has expanded rapidly in recent years as an alternative to hospital care in many countries due to aging populations and limited healthcare resources (TÜİK 2024). The global population aging is causing a rise in chronic diseases, ill health, and dependence, particularly among the elderly. This is a significant challenge for healthcare delivery systems due to rising healthcare and long-term care expenditures, necessitating alternative care options to address the unique needs of the elderly and their families (World Health Organization 2015; Çınar *et al.* 2025).

Home care refers to professional care delivered to individuals in their residences, aiming to enhance their quality of life and functional health status while substituting hospital care for societal considerations. It encompasses a broad spectrum of activities, ranging from preventive visits to end-of-life care (Genet *et al.* 2013; Pacal and Cakmak 2025). It involves providing medical supplies and services directly to patients inside the community, targeting many illnesses and therapy areas. Services may encompass medical, psychological, or social evaluations, wound care, medication education, pain management, illness information, physical therapy, speech therapy, medication reminders, and health promotion and prevention empowerment. Home health care is frequently more cost-efficient, convenient, and equally effective as care provided in a healthcare facility. It alleviates the burden on family members serving as caregivers and represents the most economical method to enhance access to primary healthcare services (Özüpak 2025; Cakmak *et al.* 2026). In 2020, 3 million patients received home healthcare services in the U.S.; of the 11.400 home health agencies registered, about 83.5% were classified for profit (U.S. Centers for Disease Control and Prevention 2024).

Home healthcare services require careful planning and organization to allocate nurses, schedule working hours, and manage travel routes. However, manual routing and scheduling often lead to suboptimal outcomes (Fikar and Hirsch 2017). A survey in two

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Norwegian municipalities found that driving time accounts for 18-26% of total working hours, with an overestimation of routes (Holm and Angelsen 2014). Numerous municipalities seek cost-effective solutions to ensure home care maintains adequate quality while remaining affordable (Holm and Angelsen 2014).

In recent years, HHC routing and scheduling challenges have gained significant attention (Fikar and Hirsch 2017). Therefore, designing effective home health care routing and scheduling management is essential to alleviate the conflict between high-quality home health care and limited resources. Planning home health services involves multiple variables, including travel time to clients (parking, entering and exiting the home, supplies), visit duration (including documentation), alignment of nurses' skills with patients' expectations (medical, language, and social skills), continuity of care, staff workload balance, time sensitivity (e.g., timely insulin injections), visit sequencing, planning timelines (ranging from one day to several months), and cost assessments (Fikar and Hirsch 2017; Holm and Angelsen 2014; Yalçındağ *et al.* 2016). Consequently, numerous researchers focus on a multi-objective home healthcare routing and scheduling problem defined by conflicting objectives: reducing routing costs while improving service consistency and balancing workloads. Home healthcare managers must develop effective route plans for caregivers to provide in-person care to clients. Geographically dispersed customers must be considered, daily routes for caregivers must be determined, and the planned routes must deliver services. Home healthcare administrators prioritize reducing operational costs in formulating route plans (Trautsamwieser and Hirsch 2011).

Numerous studies have concentrated on the modeling and optimization of distributed flexible job shop scheduling problems within different systems (Luo *et al.* 2022; Du *et al.* 2022). However, studies on these problems assume that machines are always available (Xie *et al.* 2023; Zhang *et al.* 2024) and neglect the transportation activities of jobs. The methods used are diverse, paralleling the studied problem settings, and encompassing various population-based algorithms alongside local search-based procedures. Most researchers address meta-heuristic solution procedures for single-period home health care problems. The home healthcare worker scheduling challenge is complicated since it includes both the hard vehicle routing and personnel assignment issues (Mutingi and Mbohwa 2014). Koeleman *et al.* (2012) used the Markov decision process, which leads to a high-dimensional control problem. Castillo *et al.* (2024) utilized an agile algorithm to optimize route planning for providing home healthcare in Spanish rural areas. Belhor *et al.* (2023) utilizes a hybrid algorithm to enhance the routing of in-home healthcare services.

Traffic light visualizations might enhance clinical decision-making by leveraging the proven correlation between colors and corresponding therapeutic signals, which have been utilized across various therapeutic domains (Saposnik 2020). The implementation of traffic light coding for patient management has been effective in an emergency room context, where a three-tier urgency code facilitated the prioritization of patients for care (Leppäniemi and Jousela 2014; Araújo *et al.* 2021). Despite the significant importance of patient and caregiver's satisfaction, limited literature on this topic underscores the need to create a multi-objective routing and scheduling model that incorporates the interests of various stakeholders in home healthcare services (Wirnitzer *et al.* 2016). This study seeks to formulate optimization-based techniques for visit planning and vehicle routing in home healthcare services, specifically in Diyarbakır province, southeastern Türkiye.

MATERIALS AND METHODS

The section outlines the research framework employed to develop an operational plan for home healthcare services in Diyarbakır, Turkey, from 2011 to 2023. This section integrates demographic data, system variables, constraints, and a mathematical framework to optimize patient visits while minimizing visit duration. The methodology is structured into three key components: the dataset, which provides demographic and operational context; the mathematical model, which formalizes the optimization problem; and the proposed model, which details the operational strategy and constraints for service delivery. This structured approach ensures a comprehensive analysis of the home healthcare system, prioritizing patient satisfaction and operational efficiency.

Dataset

The research leverages demographic data from the Turkish Statistical Institute (TUIK) Report of 2024, which indicates that Diyarbakır province had a population of 1,818,133 in 2024, with a growth rate of 0.73% and a population density of 119 individuals per square kilometer. The demographic composition reveals that individuals aged 5-9 constitute 11.15% of the population, while older age groups show a significant decline: those aged 60-64 represent 2.60%, 65-69 account for 1.86%, 70-74 comprise 1.44%, 75-79 make up 0.94%, 80-84 constitute 0.56%, and those aged 90 and above represent 0.18%. The research population encompasses individuals receiving home healthcare services in Diyarbakır from 2011 to 2023. This retrospective study utilizes operational data from this period, focusing on patient visits and service delivery protocols.

This paper presents an operational plan for home healthcare services, a distributed healthcare system. Figure 1 illustrates home healthcare services registered in Turkey. It shows a visit protocol for patients who have received and/or are currently receiving services from 2011 to 2023. The research utilized a retrospective design.

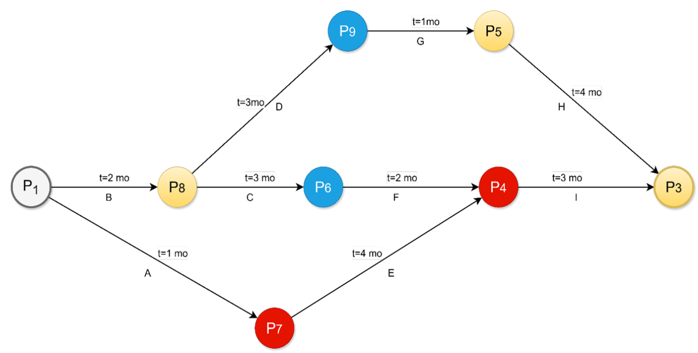

Figure 1 Home Healthcare Services Diagram

Fig 1 shows the location of the patients (P), the time between locations (t) and the possible paths (A-I) to be used during the visit. Fig 1 is a small virtual demonstration of the considered optimization problem. Teams or groups located within a healthcare facility deliver home healthcare services to individuals residing at designated addresses, whose overall health conditions differ. The variables of the system depicted in Figure 1 are as follows:

- Number of teams
- Patient's gender, Patient's overall condition (Green/Yellow/Red)
- Quantity of vehicles
- Number of male employees

- Number of female employees
- Locations of patients

The specified variables need the consideration of the following constraints in the delivery of home healthcare services:

- Teams departing from the health center must return upon the conclusion of their visits.
- Each team must comprise a minimum of four individuals.
- Each team is required to include a minimum of one female and one male staff member.
- Teams' ought to evaluate the patient's comprehensive condition during the appointment.
- Patients with like conditions ought to be attended to base on their proximity.

The traffic light-based patient classification system, adapted from established emergency triage protocols, categorizes patients according to the urgency of their health condition:

- Red: Patients with life-threatening conditions requiring immediate intervention.
- Yellow: Patients with serious but non-life-threatening conditions that can tolerate a short delay.
- Green: Patients with stable, minor conditions that can wait longer without risk of deterioration.

This classification enables proactive prioritization, ensuring critical patients are visited first while optimizing resource allocation.

Considering the specified variables and limits, the minimum visit duration must be achieved. In this setting, patient visits should occur at the most appropriate moment. The primary objective is to enhance patient satisfaction with the service. Table 1 presents the variables associated with the optimization problem modeled in the context of Home Health Services.

Mathematical framework

The mathematical framework aims to maximize patient visits while minimizing visit duration, contingent upon variables such as the patient's overall condition, location, number of teams, vehicles, and personnel. The objective function is designed to identify the optimal route and minimal visit duration for each team. Key variables are defined in Table 2, including the number of teams (E), number of patients (H), number of vehicles (C), number of male (Pm) and female (Pf) staff, patient location (Li), patient condition (Si), travel time (Tij), visit status (xek), and presence of female (yef) and male (yem) staff. The cost function incorporates these decision variables to optimize service delivery.

The objective function seeks to maximize patient visits while minimizing visit duration. The duration of the visit is contingent upon the patient's overall condition, the patients' locations, the number of teams, the number of cars, the personnel count, and the teams' locations. A cost function can be formulated in which specific variables are contingent upon decision variables. Our objective is to identify the optimal route and the minimal visit length for each team. Representation of the objective function can be formulated as follows:

$$\text{Min } Z = \sum_{e=1}^{E} \sum_{i=1}^{H} \sum_{j=1}^{H} T_{ij} \cdot x_{ei} \cdot x_{ej} \quad (1)$$

Constraints

- Each team must comprise a minimum of 4 individuals.

$$\sum_{f=1}^{P_f} y_{ef} + \sum_{m=1}^{P_m} y_{em} \geq 4, \quad \forall e \in \{1, 2, 3, \ldots, E\} \quad (2)$$

- Each team is required to include a minimum of one female and one male staff,

$$\sum_{f=1}^{P_f} y_{ef} \geq 1, \quad \forall e \in \{1, 2, 3, \ldots, E\} \quad (3)$$

$$\sum_{m=1}^{P_m} y_{em} \geq 1, \quad \forall e \in \{1, 2, 3, \ldots, E\} \quad (4)$$

- Each patient shall be attended by no more than one team;

$$\sum_{e=1}^{E} x_{ek} \leq 1, \quad \forall k \in \{1, 2, 3, \ldots, H\} \quad (5)$$

- Teams should prioritize based on the overall condition of the patients,

$$x_{ek} \geq x_{el} \quad \text{if } S_k > S_l \text{ and } L_k \text{ near } L_l \quad (6)$$

- Teams must reconvene in the center upon the conclusion of their visits,

$$\sum_{i=1}^{H} x_{ei} = \sum_{j=1}^{H} x_{ej}, \quad \forall e \in \{1, 2, 3, \ldots, E\} \quad (7)$$

- Vehicle capacity constraint,

$$\sum_{k=1}^{H} x_{ek} \leq C, \quad \forall e \in \{1, 2, 3, \ldots, E\} \quad (8)$$

EXPERIMENTAL RESULTS FINDINGS

The study's findings indicate that the penalty levels in the first population are high and show considerable variation. The optimal penalty value is 510.1, whereas the mean penalty value is 735.8. This scenario suggests that the solution is anomalous and that the system has not attained an optimal resolution. Figure 2 indicates that the initial hints of progress are evident in generation 10. The optimal penalty value decreases to 440.0, whilst the mean penalty diminishes to 648.0. This reduction signifies that the model is generating superior answers and that the optimization process has improved in efficiency compared to the the initial stage.

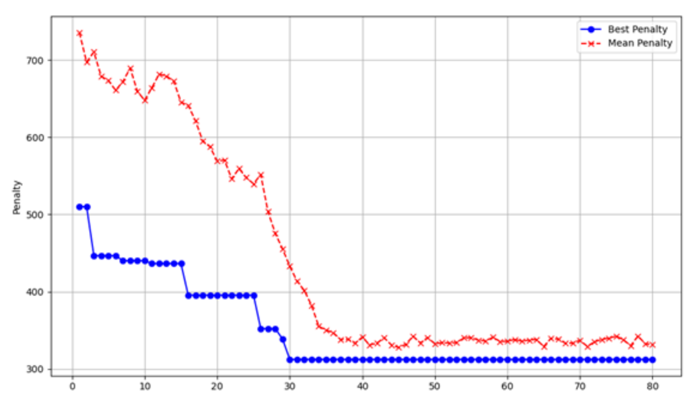

Figure 2 Optimization curve

Table 1 Key Variables Used in Home Health Services Optimization Model

Variable Name	Symbol	Definition
Number of teams	E	The total number of teams in a healthcare facility.
Number of patients	H	The total number of patients in the dataset.
Number of vehicles	C	The total number of vehicles owned by the teams.
Number of male staff	P_m	The total number of male staff in the team.
Number of female staff	P_f	The total number of female staff in the team.
Patient's location	L_i	The location of patient i.
The patient's general condition	S_i	The general condition of patient i.
Travel time	T_{ij}	Travel time from location i to location j.
Visit status	x_{ek}	The e-th team's visit status for patient k; a binary variable indicating whether team e visited patient k (1: visit, 0: no visit).
Presence of female staff	y_{ef}	Variable indicating whether female staff f is present in team e (1: present, 0: not present).
Presence of male staff	y_{em}	Variable indicating whether male staff m is present in team e (1: present, 0: not present).

In Generation 20, the penalty value decreased to 395.6, although the mean penalty was recorded at 569.1. This scenario suggests that an increase in iterations yields better solutions. Notably, from the 20th generation onward, there has been a considerable reduction in both the optimal and mean penalty values, suggesting that the model is more adeptly managing the constraints and yielding more appropriate solutions within the search space. In generation 29, the optimal penalty value declined to 338.6, while the mean penalty value fell to 455.5, signifying that the optimization process is progressing well and the model is yielding more precise solutions. The substantial reduction in the 29th generation signifies that the algorithm has transitioned into the exploitation phase and is generating solutions nearer to the optimal. In Generation 30, the penalty value was 312.2, however the mean penalty value was 433.0. This setting signifies that the model has achieved equilibrium during the optimization process, resulting in a stable optimal solution.

In the final stage, the optimal penalty value is maintained at 312.2, but the mean penalty value drops to 331.5. This condition signifies that the optimization procedure was executed with exceptional performance and that superior efficiency was attained in the model's final stage. The persistent decline in the average penalty value signifies that the solution quality has reached a stable high across the population. The data validate that the algorithm has enhanced both individual and collective solution efficacy, yielding significant efficiency. Table 2 illustrates that the quality of the solution in the optimization process enhances with advancing generations, ultimately stabilizing from the originally elevated penalty values.

To evaluate the performance of the proposed model, the random initial solution (Generation 1), where no optimization was applied, was taken as the baseline. The reduction of the best penalty value from an initial 510.1 to 312.2 in the 30th generation demonstrates that the model produces approximately 38.7% more efficient results compared to the baseline scenario.

Table 3 presents the optimized home healthcare service model's results, showing patient-to-team assignments and total visit duration for Diyarbakır (2011–2023). The sequence 1-2-3-3-1-1-1-2-3-3-1-2-3-1-1 assigns 15 patients to three teams: Team 1 (6 patients), Team 2 (3 patients), Team 3 (6 patients). This distribution optimizes patient condition prioritization, proximity, and constraints like minimum team size (four members, including one male and one female) and single-team visits. The total visit duration of 312.2146 (likely minutes) reflects minimized travel and visit times across 15 patients, averaging 20.81 minutes per visit. This efficiency, achieved via MATLAB-based optimization, aligns with the goal of enhancing patient satisfaction. The model effectively balances resource use and patient needs, but lacks baseline comparison, patient condition details, and time unit clarity. Future work should include these for robust validation.

Table 3 Solution of the new model

Definition	Assignment
Best individual (Assignment of patients to teams)	1-2-3-3-1-1-1-2-3-3-1-2-3-1-1
Best fit value (Total visit duration)	312.2146

The "Best fit value" (312.2146) presented in Table 3 represents the total visit and travel duration in minutes calculated by the model. Penalty values incorporate both the total operational time and theoretical cost points arising from violations of constraints, such as staff gender balance or vehicle capacity.

DISCUSSION

The planning and management of Home Health Services (HHS) is a multi-dimensional optimization problem that focuses on the effort to provide high quality care with limited resources. This study aims to maximize patient visits and minimize visit duration using an optimization model developed specifically for Diyarbakır province, with the aim of increasing patient satisfaction and optimizing operational efficiency in the process. The model priori-

Table 2 Optimization Output

Generation	Best Penalty	Mean Penalty	Note
1	510.1	735.8	Initial population; high penalty values, significant variance.
10	440.0	648.0	The initial indicators of improvement; a notable reduction in penalty values.
20	395.6	569.1	Substantial enhancement in solution quality; the team and restrictions are efficient.
29	338.6	455.5	A crucial phase of iterative improvement; a notable enhancement was noted.
30	312.2	433.0	The penalty value has stabilized; equilibrium has been attained in the optimization process.
80	312.2	331.5	Consistent reduction in average penalty value; exceptional performance in the model's final stage.

tized the health status of patients by classifying them into 'green', 'yellow' and 'red' categories, and planned team routes and staff assignments in an integrated manner using a genetic algorithm-based approach. This section compares the results with similar studies in the literature, discusses the innovative aspects and limitations of the model, and provides recommendations for future work. Table 4 provides detailed information on further studies and summarizes important details from the literature.

The proposed model significantly outperforms previous approaches by reducing travel distance, time, cost, and waiting time while improving fairness and health condition prioritization. Its hybrid structure, integrating a genetic algorithm with a traffic light–based prioritization system, ensures both operational efficiency and patient-centered optimization.

TD: Travel Distances, TT: Travel Time, TC: Travel Cost, WA: Waiting Time, PN: Personal Number, HC: Health Condition, FA: Fairness, NoS: Number of Nurses

The main difference of our study is that it places patients' health states at the center of the optimization process. While many studies on HHS in the literature often focus on parameters such as distance, travel time or cost, (Fikar and Hirsch 2015), the prioritization of the dynamic health status of patients is often neglected. For example, Akjiratikarl *et al.* (2007) only considered travel time and staff preferences when optimizing staff scheduling with a particle swarm optimization (PSO) algorithm; no parameters for patient health status were included in the model. Similarly, Allaoua *et al.* (2013) optimized HHS by combining staff assignment and vehicle routing problems, but did not consider patient status as a variable. In contrast, our model provides a proactive approach to care by ensuring that patients in the 'yellow' category are visited more frequently before their condition becomes 'red'. While this shows a similar flexibility to the work of (Lanzarone and Matta 2014), which considers variability in patient demands, our approach offers a more intuitive and feasible prioritization through traffic light coding.

Another important contribution of the model is the consideration of realistic constraints on the composition of teams. The requirement that each team consists of at least four people and includes at least one female and one male staff member is an approach that reflects gender balance and team dynamics. This is one of the few studies to consider the social and cultural dimensions of HHS. In the literature, studies such as Allaoua *et al.* (2013) and Braekers *et al.* (2016) have integrated staff assignment and routing problems, but such specific constraints on team composition are often ignored. In this respect, our model has a framework that is more appropriate for real-world applications.

The use of the genetic algorithm in the optimization process has shown effective results in complex and multi-objective problems. The results show that the algorithm significantly reduces the penalty values as the generations progress: the best penalty value decreased from 510.1 in the first generation to 312.2 in the 30th generation and the average penalty value decreased to 331.5 in the final stage. This confirms that the algorithm is finding better solutions in the search space and managing the constraints effectively. A similar improvement was reported by (Akjiratikarl *et al.* 2007) using PSO; however, our model provided a more comprehensive optimization by taking into account the patient's health status. Furthermore, while our initial solution showed high and variable penalty values (average 735.8), the system reached a balanced and optimal solution as iterations progressed. This proves that the model improves both individual and collective solution quality.

The model developed in this study brings together several innovative elements of HHS optimization that have not been adequately addressed in the literature. First, traffic light coding (green, yellow, red) has facilitated patient prioritization by using the association of colors with therapeutic signals in clinical decision-making processes (Bredström and Rönnqvist 2008). This approach was inspired by triage systems in emergency departments Lanzarone and Matta (2014) and adapted to the HHS context, providing a proactive strategy in patient care. Second, the fact that the model simultaneously optimizes the objective of maximizing patient visits and minimizing time provides a multi-objective optimization framework. This represents a more balanced approach compared to single objective models in the literature (e.g. studies focusing only on cost reduction). Finally, testing with demographic data specific to a particular geographic region, such as Diyarbakır, demonstrates the adaptability of the model to local conditions.

The limitations of the model are that it may not be sufficient for real-world applications as it only classifies the health status of patients into three categories of "green", "yellow" and "red"; this simple classification, which does not take into account factors such as age, chronic diseases, etc., can be improved to more precise risk scores using machine learning; furthermore, the lack of practical factors such as vehicle capacity, traffic conditions and parking

Table 4 HHS optimization studies in the literature

Author(s)	Solution	TD	NoS	TT	TC	WA	PN	FA	HC
Akjiratikarl *et al.* (2007)	Min.	↓							
Allaoua *et al.* (2013)	Min.			↓				↓	
Braekers *et al.* (2016)	Max.								↑
Fikar and Hirsch (2015)	Min.				↓				
Bredström and Rönnqvist (2008)	Min.			↓		↓			
Lanzarone and Matta (2014)	Max.								↑
Proposed Model	Max/Min	↓	↓	↓	↓	↓		↑	

space in the model limits its applicability and the integration of these dynamics; finally, the general model can be improved to more precise risk scores using machine learning, This simple classification, which does not take into account factors such as age, chronic diseases, etc., can be improved to more accurate risk scores using machine learning; furthermore, the lack of practical factors such as vehicle capacity, traffic conditions, and parking space in the model limits its applicability and the integration of these dynamics is recommended; finally, the generalizability of the model developed with data specific to Diyarbakır is limited and needs to be tested in different regions.

This study presents an innovative approach to the optimization of HHS that focuses on the health status of patients. The model, supported by a genetic algorithm, aims to increase patient and caregiver satisfaction while considering operational efficiency and integrates patient prioritization, team composition and route planning. The results show that the model overcomes the initial suboptimal solutions (high penalty values) and achieves a stable and efficient optimization process. However, to address the limitations, future work could focus on more detailed patient classifications, modelling logistical factors, and testing the model in different regions. A comprehensive and flexible optimization framework developed in this direction could contribute to a more effective implementation of HHS on a global scale.

Although the proposed optimization framework was tested specifically for Diyarbakır, its modular structure allows it to be easily adapted to other provinces with different demographic data and geographic characteristics. By updating variables such as staff count and patient density, the parametric nature of the model proves its usability as a general tool for planning home healthcare services on both a national and international scale.

CONCLUSION

This study proposed an innovative optimization-based operational model for improving the efficiency and equity of home healthcare services in Diyarbakır, Türkiye. By integrating a genetic algorithm with a traffic light prioritization mechanism, the model effectively addressed the multi-objective challenge of minimizing visit durations while maximizing the number of patients served. The algorithm classified patients into green, yellow, and red categories, ensuring that care delivery dynamically aligned with patients' clinical urgency and operational constraints. The optimization process achieved significant performance improvements across generations, reducing penalty values from 735.8 to 331.5, which indicates enhanced model stability and convergence. The findings highlight that integrating demographic data, staff composition constraints, and patient condition prioritization into a unified optimization framework can substantially enhance service quality and resource utilization in home healthcare systems. Moreover, incorporating gender-balanced team structures add a realistic and culturally sensitive dimension to service delivery. While the model demonstrated robust optimization outcomes, future research should incorporate additional real-world parameters such as traffic dynamics, vehicle capacity, and real-time patient data alongside machine learning-based dynamic risk scoring to enhance adaptability. Ultimately, the proposed framework presents a promising foundation for the development of intelligent, region-specific, and patient-centered home healthcare planning systems applicable to diverse geographic and demographic contexts.

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Ethical standard

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and material

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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