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Optimizing palliative home healthcare: A routing and scheduling model with emotional burden and patient-caregiver preferences

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Abstract

The increasing demand for personalized and human-centered care in home-based palliative services necessitates efficient yet empathetic healthcare logistics solutions. This study addresses the Palliative Home Healthcare Caregiver Routing and Scheduling Problem with Emotional Consideration (PHHCRSP-E), aiming to optimize the daily assignment and routing of nurses visiting patients in home-based palliative care. The model minimizes a weighted sum of total travel time and emotional imbalance among nurses, subject to operational constraints such as service durations, time windows and nurse workload limits. A mixed-integer linear programming (MILP) formulation is proposed, incorporating subtour elimination and emotional burden balancing. The model is implemented on a synthetic dataset consisting of five patients and two nurses, with each patient characterized by spatial coordinates, service requirements, time preferences, and an emotional burden score. Results demonstrate the model's capability to provide feasible and balanced nurse–patient assignments while respecting logistical and psychosocial constraints. By embedding emotional dynamics directly into care planning, this study contributes a novel and human-centered perspective to healthcare logistics and supports more empathetic, data-driven decisions in palliative home care services.

Keywords: *Palliative Care, Healthcare Logistics, Emotional Burden, Optimization, MILP*

Palyatif evde sağlık hizmetlerinin optimize edilmesi: Duygusal yük ve hasta-bakıcı tercihleriyle yönlendirme ve zamanlama modeli

Öz

Evde sunulan palyatif hizmetlerde kişiselleştirilmiş ve insan odaklı bakım talebinin artması, verimli ama aynı zamanda empatik sağlık lojistiği çözümlerini gerekli kılmaktadır. Bu çalışma, Duygusal Yük Göz Önünde Bulundurularak Palyatif Evde Sağlık Hizmeti Bakıcı Yönlendirme ve Zamanlama Problemi (PHHCRSP-E) ile ilgilenmektedir. Amaç, evde palyatif bakım hizmeti alan hastaları ziyaret eden hemşirelerin günlük görev ve güzergâhlarını optimize etmektir. Model, toplam seyahat süresi ile hemşireler arasındaki duygusal dengesizliğin ağırlıklı toplamını minimize etmektedir. Bu süreçte hizmet süreleri, zaman pencereleri ve hemşire iş yükü sınırları gibi operasyonel kısıtlar dikkate alınmıştır. Çalışmada alt-tur engelleme (subtour elimination) ve duygusal yük dengesi içeren bir karma tamsayılı doğrusal programlama (MILP) formülasyonu önerilmiştir. Model, her biri konum bilgileri, hizmet gereksinimleri, zaman tercihleri ve duygusal yük puanlarıyla tanımlanan beş hasta ve iki hemşireden oluşan sentetik bir veri kümesi üzerinde uygulanmıştır. Sonuçlar, modelin lojistik ve psikososyal kısıtlamalara saygılı biçimde uygulanabilir ve dengeli hemşire–hasta atamaları sağlayabildiğini göstermektedir. Duygusal dinamikleri doğrudan bakım planlamasına yerleştirerek, bu çalışma sağlık lojistiğine yeni ve insan merkezli bir bakış açısı kazandırmakta ve palyatif evde bakım hizmetlerinde daha empatik, veri odaklı kararları desteklemektedir.

Anahtar Kelimeler: *Palyatif Bakım, Sağlık Lojistiği, Duygusal Yük, Optimizasyon, MILP*

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INTRODUCTION

Palliative care has significantly evolved over the past two decades, expanding beyond institutional end-of-life services to encompass integrated, home-based, and community-centered care models. This evolution is driven by the increasing prevalence of chronic illnesses, the aging global population, and a growing recognition of patients' emotional and existential needs alongside clinical concern. This evolution is reflected in policy shifts, technological integration, and an increased emphasis on holistic, interdisciplinary approaches. As highlighted in recent literature, palliative care now aims to improve quality of life through the management of physical symptoms, psychosocial distress, and caregiver support mechanisms (Mercadante et al., 2025; YinHu et al., 2024). Moreover, increasing global attention has been drawn to the accessibility and equity of these services, especially in rural and underserved populations where home-based models offer a critical lifeline (Sítima et al., 2024).

In Türkiye, the landscape of palliative care reflects both global inspirations and context-specific challenges. While national guidelines and institutional efforts have expanded service coverage, structural limitations such as data infrastructure, workforce distribution, and inter-sectoral coordination remain central concerns (Özçelik, 2020; Erel & Tural-Büyük, 2021).

Several studies emphasize the need for improved communication between primary and tertiary care units, and for home-based care models that integrate family dynamics and local cultural expectations (Jersak et al., 2024). Additionally, the adoption of digital tools, such as e-visit platforms and mobile documentation systems, shows promise in enhancing continuity of care and clinical follow-up (YinHu et al., 2024), although implementation varies regionally. Overall, palliative care is evolving into a dynamic field that blends compassionate care with system-level innovation and responsiveness.

Home-based palliative care (HBPC) has emerged as a preferred modality for patients with advanced illnesses, primarily due to its potential to enhance quality of life, preserve patient autonomy, and align care with personal preferences. In a large-scale longitudinal study, Busquet-Duran et al. (2024) found that approximately 60% of patients under palliative home care died at home, indicating that structured home care programs—especially those with strong team-based exosystem support—are highly effective in honoring patients' end-of-life wishes. This finding is reinforced by observations that systemic strengths at the caregiver and patient level are significantly correlated with the likelihood of dying at home. Additionally, home care reduces the frequency of unnecessary hospitalizations and provides psychosocial continuity, as shown in research by Huu and Gandhi (2025), who emphasized the cultural and emotional relevance of home-based death, particularly in rural communities where hospital access is limited. Furthermore, Ritchie and Leff (2018) report that HBPC can reduce unnecessary hospitalizations, lower healthcare expenditures, and enhance patient satisfaction when structured through interdisciplinary teams. Pask et al. (2025) complement these findings by noting that effective communication, caregiver support, and timely symptom control in the home setting foster both quality of life and a dignified death experience. Collectively, these studies highlight HBPC's potential to combine cost-effectiveness with patient-centered outcomes.

However, HBPC also presents notable limitations. Challenges such as inadequate caregiver support, high physical and emotional burden on families, and uneven access to trained palliative professionals are consistent across diverse settings. The review by Huu and Gandhi (2025) identified geographical disparities, limited infrastructure, and cultural taboos as major obstacles to equitable palliative care in rural India, resulting in delayed access and suboptimal symptom control. Busquet-Duran et al. (2023) caution that complexity in family dynamics, caregiver exhaustion, and variability in care delivery may hinder service continuity. Additionally, García-López et al. (2023), while focusing on pediatric cases, identify that even with trained personnel, home environments may lack necessary infrastructure for safe symptom management, especially in marginalized or rural areas. Ritchie and Leff (2018) also underscore that without adequate integration between primary care and palliative teams, home-based services may suffer from coordination lapses, leading to missed visits or inconsistent follow-up. The evidence thus points to a dual reality: while HBPC offers patient-centered benefits, its scalability and safety hinge on robust systemic planning, resource availability, and caregiver preparedness.

To fill this gap, this study proposes a new model for the Palliative Home Health Care Routing and Scheduling Problem (PHHCRSP-E). The model has the following novel contributions:

• Incorporates emotional burden dynamics of patients and caregivers.

• Balances nurse satisfaction across the planning horizon.

• Integrates patient time-window preferences and route continuity.

• Offers a scalable framework usable in synthetic datasets.

This research offers both theoretical and practical contributions to the literature by adapting complex logistics planning tools to the unique psychosocial environment of palliative care. This model may serve as a blueprint for future human-centric service designs in Türkiye and other emerging healthcare systems.

METHOD

As HBPC continues to evolve, the need for optimization-based planning has become increasingly apparent. Traditional models—largely reliant on clinician availability and geographical convenience—often fall short in balancing multiple, sometimes conflicting, objectives such as minimizing travel time, ensuring continuity of care, and respecting patient preferences. Recent research has proposed optimization frameworks that tackle these constraints in a formalized, data-driven manner. Parreño-Torres et al. (2024) developed an integer linear programming model to simultaneously address routing and scheduling of HBPC visits, demonstrating how mathematical optimization can reduce logistical inefficiencies without compromising service quality. Atta et al. (2025) further emphasize that heuristic and metaheuristic approaches are essential to navigating the complexity of home health care routing problems, especially in settings where resources are constrained or demand fluctuates.

Beyond logistical efficiency, optimization models also play a pivotal role in enhancing the ethical and emotional quality of end-of-life care. Crape et al. (2024) highlight that frequency and timing of nurse home visits are strongly associated with outcomes measured via the Good Death Inventory, suggesting that optimization efforts must integrate human-centric indicators. Meanwhile, the rising integration of artificial intelligence (AI) into palliative care underscores the importance of transparency and interpretability. Migiddorj et al. (2025) argue that explainable AI (XAI) is critical when deploying decision models in such sensitive contexts, reinforcing the need for frameworks that are not only efficient but also trustworthy. On a systemic level, Isenberg et al. (2019) identify that optimization-driven interventions at the HBPC level can lead to cost savings while also reducing caregiver burnout. Finally, Kumar et al. (2025) show that machine learning strategies—when aligned with operational research—enable dynamic labor allocation models that outperform static scheduling in unpredictable healthcare environments. Collectively, these findings advocate for embedding optimization into both policy and practice to ensure that HBPC systems remain scalable, equitable, and patient-centered.

This research applies a model-driven simulation strategy to address the Palliative Home Health Care Routing and Scheduling Problem with Emotional Burden (PHHCRSP-E). Given the lack of access to real patient data, a synthetic dataset was generated to reflect the operational realities of mobile palliative care services in Türkiye. The study emphasizes a novel multi-objective optimization model aimed at balancing operational efficiency with emotional and relational care goals.

MATHEMATICAL FORMULATION OF PHHCRSP-E

Sets

P: Set of patients indexed by p

N: Set of nurses indexed by n

L: Set of all locations (patients and depot), indexed by i, j

Parameters

s_p: Service time required by patient p (in minutes)

e_p, l_p: Earliest and latest visit times for patient p (in minutes, e.g., 0 to 480)

b_p: Emotional burden score of patient p (ranging from 1 to 5)

τ_{ij}: Travel time in minutes from location i to location j

W_n: Maximum working time (in minutes) allowed per nurse per day

M: A large positive constant used in time and routing constraints

V_i: Maximum number of patients a nurse can visit per day

a_{pn}: Start time (in minutes) of service for patient p by nurse n

u_{in}: Auxiliary variable used to eliminate sub tours (continuous, only needed for patients i ∈ P)

α, β: Weighting coefficients for travel time, emotional imbalance

Decision variables

$x_p^n \in \{0,1\}$: 1 if nurse n visits patient p

$y_{ij}^n \in \{0,1\}$: 1 if nurse n travels from location i to j

$a_p^n \geq 0$: Start time of service for patient p by nurse n

$EB_{nt} \geq 0$: Emotional imbalance indicator for nurse n

Objective function (multi-objective weighted sum)

As shown in Equation (1), the objective function minimizes a weighted sum of travel distance and emotional imbalance.

$$Z_{min} = \alpha . \sum_{n \in N} \sum_{i \in L} \sum_{j \in L, j \neq i} \tau_{ij} . y_{ij}^{n} + \beta . \sum_{n \in N} EB_n \tag{1}$$

Constraints

- Patient visit constraint: As shown in Equation (2), each patient must be visited by one nurse on each period.

$$\sum_{n \in N} x_p^n = 1 \qquad \forall\, p \in P \tag{2}$$

- Nurse daily workload constraint: As shown in Equation (3), total service and travel time for each nurse per day must not exceed the working time limit.

$$\sum_{p \in P} s_p . x_p^n + \sum_{i \in L} \sum_{j \in L} \tau_{ij} . y_{ij}^n \leq W_n \qquad \forall\, n \in N \tag{3}$$

- Time window constraint: As shown in Equation (4), each visit must occur within the patient's allowable time window.

$$e_p . x_p^n \leq a_p^n + s_p \leq l_p . x_p^n \qquad \forall\, p \in P, n \in N \tag{4}$$

- Sub tour elimination constraint: As shown in Equation (5), to ensure proper routing, the MTZ (Miller–Tucker–Zemlin) formulation is applied.

$$u_i^n - u_j^n + |P| . y_{ij}^n \leq |P| - 1 \qquad \forall\, i, j \in P, i \neq j, n \in N \tag{5}$$

- Routing implies visiting constraint: As shown in Equation (6), a nurse can only travel between two nodes if both are visited

$$y_{ij}^n \leq x_i^n, y_{ij}^n \leq x_j^n \qquad \forall\, i,j \in L, n \in N \tag{6}$$

- Maximum Number of Visits per Nurse: As shown in Equation (7), a nurse cannot be assigned to more patients than the maximum allowed number of visits per day.

$$\sum_{p \in P} x_p^n \leq V_n \qquad \forall\, n \in N \tag{7}$$

- Emotional imbalance constraint: As shown in Equation (8), emotional imbalance for each nurse-day is defined as the deviation from average emotional burden.

$$EB_n \geq \left| b_p . x_p^n - \frac{1}{|P|} \sum_{p \in P} b_p . x_p^n \right| \qquad \forall\, n \in N \tag{8}$$

- Domain constraints shown in Equation (9):

$$x_p^n, y_{ij}^n \in \{0,1\};\ a_p^n \geq 0;\ EB_n \geq 0 \qquad \forall\, p,n,i,j \tag{9}$$

EXPERIMENTAL DESIGN

To evaluate the PHHCRSP-E model under realistic yet controllable conditions, a synthetic dataset was created, consisting of 5 patients and 2 nurses. Each patient record includes spatial coordinates, a preferred time window for visits, service duration, and an emotional burden score (1 = low burden, 5 = high burden). These values reflect the multi-dimensional nature of home-based palliative care, balancing logistical constraints with psychosocial sensitivity.

Table 1 provides the patient-level attributes, including randomly distributed locations on a 100×100 grid, service times ranging from 30 to 60 minutes, and time preferences within a standard working day (08:00–17:00). Emotional burden levels were included to simulate the psychosocial component of the model.

Table 1. Synthetic patient dataset

Patient ID	Service Time (min)	Earliest Visit Time (Hour)	Latest Visit Time (Hour)	Earliest (min)	Latest (min)	Emotional Burden (1-5)	Location X	Location Y
P1	45	08:00	11:00	0	180	3	81	14
P2	30	09:00	12:00	60	240	2	3	94
P3	60	10:00	14:00	120	360	5	35	31
P4	30	13:00	17:00	300	540	4	28	17
P5	45	14:00	17:00	360	540	1	94	13

To model nurse constraints, each caregiver was limited to a maximum of 480 minutes of work per day (8 hours) and allowed up to 4 patient visits.

Table 2. Synthetic nurse parameters

Nurse ID	Max Working Time (min)	Max Visits per Day
N1	480	4
N2	480	4

To model the travel time between all relevant locations (including depot and patients), generated a symmetric travel time matrix based on Euclidean distances. All locations—including patients and the depot—were assigned spatial coordinates within a 100×100 Cartesian grid. The coordinates were randomly distributed to simulate geographic dispersion in an urban or semi-urban area.

Let (x_i, y_i) and (x_j, y_j) be the coordinates of locations i and j, respectively. The Euclidean distance d_{ij} between any two locations is calculated using Equation (10):

$$d_{ij} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{10}$$

To convert this spatial distance into travel time in minutes, it assumed a constant average speed, consistent with urban driving conditions. In this study, it adopted an average speed of 30 km/h, which is equivalent to 0.5 km/minute. Given that each grid unit corresponds to 1 km, the conversion from distance to time is done as using Equation (11):

$$\tau_{ij} = \left\lceil \frac{d_{ij}}{0.5} \right\rceil = \left\lceil 2.\, d_{ij} \right\rceil \tag{11}$$

Where τ_{ij} is the estimated travel time in minutes between locations i and j, and the ceiling operator ensures that time values are in whole minutes to align with scheduling requirements.

According to defined calculations table 3 provides travel time matrix between locations in minutes.

Table 3. Travel time matrix (in minutes)

	Depot	P1	P2	P3	P4	P5
Depot	0	17	81	63	65	78
P1	17	0	66	47	53	66
P2	81	66	0	21	80	88
P3	63	47	21	0	61	70
P4	65	53	80	61	0	13
P5	78	66	88	70	13	0

MODEL IMPLEMENTATION AND SOLUTION

To validate the proposed PHHCRSP-E model, the formulation was implemented in Python using the PuLP library, and solved via the CBC MILP solver on a personal computer running Microsoft Windows 10 (Intel Core i5, 8GB RAM, Python 3.13). The synthetic dataset includes five patients and two nurses, with input parameters reflecting realistic constraints such as time windows, service durations, emotional burden scores, and travel times between locations.

Upon execution, the solver identified an optimal solution within milliseconds. The objective function, defined as the weighted sum of total travel time and emotional imbalance, yielded a final value of 225. The optimal nurse-to-patient assignment is detailed below:

- Nurse N2 is assigned to patients P1, P2, P3 and P4.
- Nurse N1 is assigned to patient P5.

All constraints were satisfied, including individual patient time windows, nurse working hour limits (480 minutes), and the maximum number of daily visits (4 per nurse).

A visual representation of the nurse routes is provided in Figure 1, showing that both nurses begin and end their routes at the depot (0,0), which corresponds to the hospital or care center. Nurse N2 covers patients located in the upper and central zones, whereas Nurse N1 is assigned to a single patient in the lower region, respecting the constraint of patient clustering and travel efficiency.

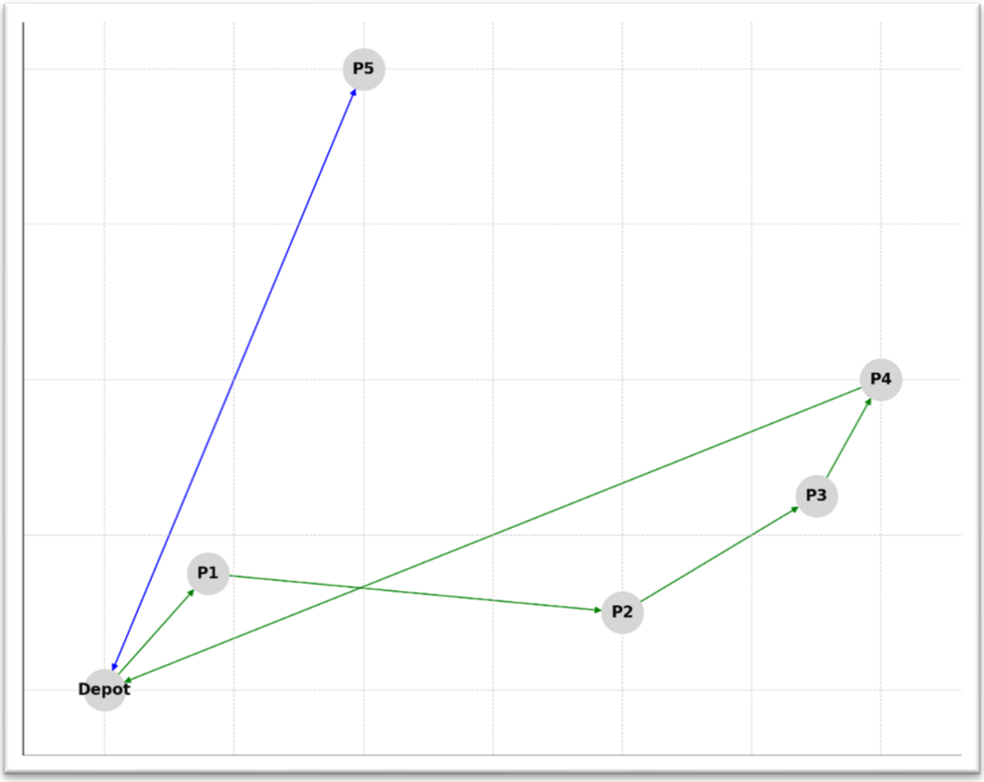

Figure 1. Optimized nurse routes

DISCUSSION AND CONCLUSION

This study introduces a novel optimization-based model, PHHCRSP-E, for addressing the complex routing and scheduling needs of home-based palliative care services. By integrating operational constraints such as time windows, travel durations, and caregiver capacity with psychosocial indicators like emotional burden, the model offers a multidimensional solution framework that balances efficiency with human-centric values.

The implementation of the model on a synthetic dataset representing five patients and two nurses demonstrates its practical feasibility and computational tractability. The results show that optimal assignments can be generated that minimize total travel time while maintaining emotional balance among caregivers. Specifically, all patients were visited within their respective time windows, nurses did not exceed their working hour or patient limit constraints, and emotional burden was equitably distributed. The visualized routes further underscore the efficiency and practicality of the resulting solution.

The findings are consistent with recent optimization-based studies in home-based palliative care and home health care routing. Parreño-Torres et al. (2024) demonstrated that integer linear programming approaches can significantly reduce logistical inefficiencies, and the present results confirm that a similar modeling framework can produce feasible, optimal solutions under realistic constraints. Atta et al. (2025) emphasized the importance of balancing service quality with resource limitations, which is reflected in this model's ability to satisfy patient time windows while minimizing caregiver overload. Furthermore, the integration of emotional burden represents a distinctive contribution, extending beyond prior works that mainly focused on travel time minimization or cost reduction. This aspect directly addresses the observation by Crape et al. (2024) that the frequency and timing of nurse visits strongly influence the quality of end-of-life experiences as measured by the Good Death Inventory. Incorporating psychosocial factors into a mathematical optimization model therefore strengthens the ethical dimension of care planning.

Beyond methodological contributions, the model can be used as a decision-support tool for daily planning and resource allocation. In urban settings, it may help balance workload distribution and reduce caregiver burnout, while in rural settings it can optimize scarce resources and promote continuity of care—an aspect previously emphasized by Sítima et al. (2024) and Huu & Gandhi (2025). By systematically including emotional burden, this approach advances the literature on compassionate logistics, offering a framework that operationalizes human-centered design principles.

Recommendations

Based on these findings, healthcare organizations that provide home-based palliative care services are encouraged to adopt optimization-based planning tools, such as the PHHCRSP-E model, to ensure equitable workload distribution among caregivers and to reduce unnecessary travel time. Implementing such models may contribute to lower caregiver burnout, improved patient satisfaction, and more efficient resource utilization.

For policymakers, supporting the development of data infrastructure and interoperability standards could facilitate the use of such decision-support systems at a national level. Future research should focus on validating the model using real-world data and exploring hybrid methods to handle uncertainties in demand and travel time.

Limitations and strengths

This study has several limitations. It is based on a synthetic dataset of five patients and two nurses, which, while useful for proof-of-concept validation, may not fully capture the complexity of real-world palliative care operations. Subjective parameters such as emotional burden scores were assumed rather than measured from real patient-caregiver interactions, which may affect the generalizability of results. The model assumes constant travel speed and does not incorporate real-time disruptions such as traffic delays.

Despite these limitations, the study has several strengths. It is one of the first attempts to explicitly integrate emotional burden balancing into a formal routing and scheduling optimization framework for home-based palliative care. The use of a multi-objective MILP model allows simultaneous consideration of logistical efficiency and psychosocial well-being.

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Tasarım *Design*	Yöntem ve araştırma desenini tasarlamak *To design the method and research design.*	Pınar GÜROL
Literatür Tarama *Literature Review*	Çalışma için gerekli literatürü taramak *Review the literature required for the study*	Pınar GÜROL
Veri Toplama ve İşleme *Data Collecting and Processing*	Verileri toplamak, düzenlemek ve raporlaştırmak *Collecting, organizing and reporting data*	Pınar GÜROL
Tartışma ve Yorum *Discussion and Commentary*	Elde edilen bulguların değerlendirilmesi *Evaluation of the obtained finding*	Pınar GÜROL

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