Extended MILP Formulation to Solve Home Healthcare Scheduling and Routing Problem with Unpaid Caregiving

Ifeoma Ogbodo[1][a], Dario Landa-Silva[1][b]
[1]*School of Computer Science, University of Nottingham, Nottingham, United Kingdom*
{Ifeoma.ogbodo, Dario.landasilva}@nottingham.ac.uk

Keywords: Home Healthcare, Scheduling and Routing, Mixed-Integer Linear Programming, Unpaid Care, Family Member Participation, Informal Care, Collaborative Care, Multi-Resource Care.

Abstract: Traditional home healthcare scheduling and routing problems (HHCSRP) have primarily focused on paid caregivers, overlooking the significant contribution of unpaid caregivers (family members and friends) who provide approximately GBP 162 billion worth of care annually in England and Wales. This paper presents an extended mixed-integer linear programming (MILP) formulation that explicitly integrates unpaid care provision as decision variables within HHCSRP, incorporating medically informed eligibility constraints for service tasks. Computational experiments using 42 modified real-world instances demonstrate significant operational gains, with average cost savings of 59.45% at the highest level of unpaid care provision. Through systematic analysis across different provision scenarios (0%, 10%, 30%, 50%, 70%, 90%), we identify an optimal provision level of 30%, yielding the highest marginal benefit (20.92% additional improvement over the 10% provision level), while balancing solution quality and computational tractability. Interestingly, integrating unpaid care constraints enhances computational efficiency, with several complex instances reaching near optimality in seconds instead of hours. The findings demonstrate that explicitly modelling unpaid care constraints can improve the mathematical structure of HHCSRP as well as provide cost benefits.

1 INTRODUCTION

Healthcare systems globally face mounting challenges from demographic ageing, workforce shortages, and escalating costs. By 2050, approximately 2 billion people will be aged 60 and older, requiring sustained daily living support (United Nations, 2019), while a projected global shortfall of 17 million health workers by 2030 (Scheffler, et al., 2016). threatens sustainable health goals. These increasing demands and limited supply necessitate innovation in healthcare delivery optimisation.

Home healthcare (HHC) has emerged as a person-centred, cost-effective, and sustainable care (Chabouh et al., 2023). The home healthcare scheduling and routing problem (HHCSRP) addresses the operational challenge of optimally assigning constrained healthcare resources, primarily skilled caregivers, to geographically dispersed customers, while satisfying complex care requirements.

Despite extensive HHCSRP research, existing models exclusively focus on paid caregiving, assuming all customer care is provided by remunerated healthcare staff. This overlooks unpaid caregiving, a critical resource valued at £162 billion annually in England and Wales (Petrillo & Bennett, 2023), which provides essential support and a deeper understanding of clients' needs. Recent healthcare delivery trends emphasise collaborative care involving unpaid caregivers to enhance quality of life, service, and work (Džakula et al., 2023). While medical (Schulz & Sherwood, 2008), health economics (Bolin et al., 2008), and social care (Lemmon, 2020) fields have extensively studied unpaid caregiving in HHC, operations research (OR) has almost entirely neglected modelling unpaid care as explicit decisions or collaborative care arrangements in HHCSRP formulations. This gap represents a significant missed opportunity as integrating unpaid caregivers can enhance patient-centred care, alleviate burden on paid workers, and

[a] https://orcid.org/0009-0002-5406-4467
[b] https://orcid.org/0000-0002-9499-6827

reduce institutional care and costs (Džakula et al., 2023; Sattler et al., 2025).

This paper makes the following contributions. We present a MILP formulation for HHCSRP that explicitly incorporates unpaid care provision as decision variables, including medically informed task eligibility constraints to differentiate paid worker-only and unpaid care (family)-eligible tasks. Using 42 modified real-world instances across varying unpaid care provision levels or scenarios (0%, 10%, 30%, 50%, 70%, 90%), we determine trade-offs in efficiency, operational gains, quality, and risks. We demonstrate average cost savings of 59.45% at 90% provision and identify 30% as the optimal provision level, balancing benefits and computational complexity. We provide evidence that unpaid care constraints can enhance rather than complicate computational tractability for certain problem structures.

Section 2 reviews related work on HHCSRP, multi-resource and collaborative care, and unpaid care research. Section 3 presents our extended MILP formulation. Section 4 details the experimental study and the results analysis. Section 5 concludes with directions for future research.

2 RELATED WORKS

HHCSRP represents an optimisation problem integrating personnel scheduling and the vehicle routing problem with time windows (VRPTW) within healthcare contexts. Reviews by (Atta et al., 2025; Masmoudi et al., 2024) reported the evolution of HHCSRP research, which increasingly balances patient satisfaction, carers' workload, and organisational efficiency across multiple stakeholders. HHCSRP is predominantly formulated as MILP (Somar et al., 2023), with recent advancements incorporating stochastic aspects (Fathollahi-Fard et al., 2020), electric vehicles (Erdem et al., 2022), and telemedicine (Nasir et al., 2018).

Solution approaches span exact methods limited to small-medium instances (Tanoumand & Ünlüyurt, 2021), decomposition approaches (Laesanklang et al., 2016) and metaheuristics, including variable neighbourhood search (Kordi et al., 2023) and hybrid approaches (W. Liu et al., 2021). While real-world implementations have demonstrated cost reductions and service quality improvements (Eveborn et al., 2009), (Grieco et al., 2020) highlight that few studies address practical implementation challenges, revealing a persistent gap between theory and practice.

Unpaid care refers to non-professional, non-remunerated support provided to individuals with chronic diseases, frailty, disability, or long-term health conditions (Carers UK, 2025). (Pickard et al., 2016) demonstrate that such care complements paid HHC by addressing service gaps, promoting continuity, and reducing hospital admissions. Within scheduling and routing frameworks, unpaid caregivers represent additional resources, influencing professional visit assignment and scheduling in HHC.

OR literature has examined multiple resources and collaborative care, including multi-skill scheduling (M. Liu et al., 2024), subcontracting (Rekabi et al., 2024), and synergised home-based and centre-based care (Cappanera et al., 2025). However, these models typically involve resources controlled by HHC companies, are remunerated equivalently, or selected based on cost-efficiency trade-offs. In contrast, unpaid caregivers operate independently, provide non-remunerated services, and are chosen based on family relationships and suitability.

While unpaid caregiving is occasionally recognised in HHCSRP literature, noting its influence on temporal constraints (Yalçındağ et al., 2016), potential care demand adjustments (Rest & Hirsch, 2016), and benefits to HHC (Erdem & Bulkan, 2017), no prior work explicitly incorporates unpaid carers into mathematical formulations. Despite extensive research in clinical (Schulz & Sherwood, 2008), health economics (Bolin et al., 2008), and social care (Lemmon, 2020) fields, no HHCSRP models explicitly represent unpaid carer roles, distinguish task suitability between paid and unpaid carers, or optimise collaborative assignments jointly. This gap limits the translation of cost and service quality benefits in unpaid care into realistic optimisation approaches. Our work addresses this through explicit mathematical modelling and exact solution methods.

3 PROBLEM DEFINITION AND MATHEMATICAL FORMULATION

3.1 Problem Definition

We address the home healthcare scheduling and routing problem with family provision (HHCSRP-FP) by extending the existing HHCSRP to include clients, paid and unpaid caregivers. The problem involves assigning tasks to paid workers or unpaid caregivers (when eligible), determining paid workers' routes, and scheduling tasks to minimise costs and penalties whilst satisfying visit requirements and constraints.

Each client requires one or more care tasks with defined time windows, skill requirements, number of carers needed, and service durations. Paid caregivers are characterised by depot locations, work shifts, skills, working limits, and regional availability, whilst unpaid caregivers (family members) are assumed to be co-resident or readily available, incurring no travel costs.

The objective minimises unassigned visits, regional and availability penalties, client preference dissatisfaction, paid caregiver waiting time, and travel distance. The model assumes: tasks involving multiple caregivers suit family provision (Wagner et al., 2001), family carers are trained for specific tasks (Litwin & Attias-Donfut, 2009), unpaid carers operate only within clients' households, only one family member assists per task, paid and unpaid carers complement rather than substitute, and effective coordination exists between parties. The HHCSRP-FP is illustrated in Figure 1.

3.2 Mathematical Formulation

The problem is defined on a directed graph G=(V,E), where node V = D ∪ T ∪ D' partitions nodes into departure depots D, task locations T, and arrival depots D'. Arcs E denote travel routes. $V^d = D \cup T$ defines departure locations and $V^a = T \cup D'$ defines arrival locations.

Decision Variables: Binary $x_{i,j}^k$ equals 1 if paid carer $k \in K$ travels from i to j, 0 otherwise. Binary f_j equals 1 if task j receives family provision, 0 otherwise. Integer y_j captures unassigned visits. Continuous $wt_{k,j}$ represents waiting time, and a_j^k represents the arrival time at task j.

Key Parameters: r_j (visit requirements), fe_j (family eligibility), δ_j (service duration), H^k (work limit), W (waiting threshold), $[w_j^L, w_j^U]$ (lower and upper time windows), $[\alpha_L^k, \alpha_U^k]$ (worker availability windows), $t_{i,j}$ (travel time), γ_j^k (regional assignment), $\mu_{k,s}$ and $\eta_{s,j}$ (skill matching s ∈ S of worker and task, respectively, where S is the set of skills), $d_{i,j}$ (distance), and $\rho_{k,j}$ (preference cost).

Assignment and Flow Constraints: Constraint (1) ensures visit requirements through paid/unpaid assignments or unassigned visits. Constraint (2) limits family provision to eligible tasks only. Constraints (3)-(5) enforce flow conservation and unique depot usage:

$$\sum_{k \in K} \sum_{i \in V^d} x_{i,j}^k + y_j + f_j = r_j \qquad ,\forall j \in T \quad (1)$$

$$f_j \leq fe_j \qquad ,\forall j \in T \qquad (2)$$

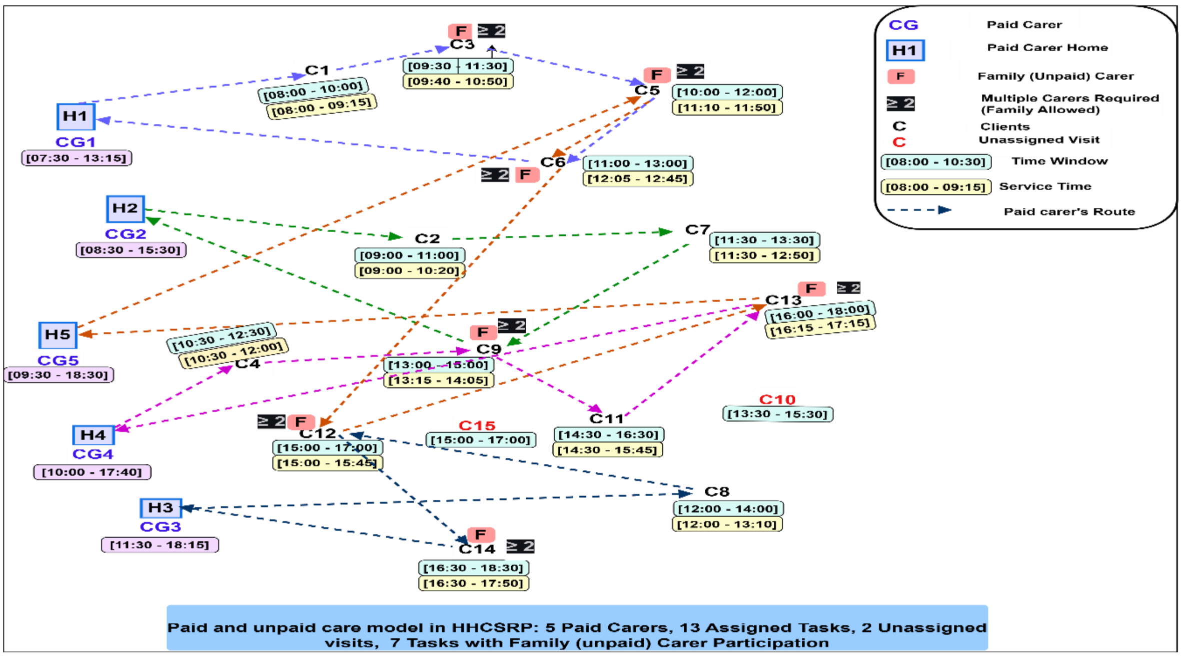

Figure 1: Illustrative example of HHCSRP-FP

$$\sum_{i\in V^d} x_{i,j}^k = \sum_{n\in V^a} x_{j,n}^k \quad ,\forall j \in T ,\forall k \in K \qquad (3)$$

$$\sum_{j\in V^a} x_{i,j}^k \le 1 \quad ,\forall i \in D, \forall k \in K \qquad (4)$$

$$\sum_{i\in V^d} x_{i,j}^k \le 1 \quad ,\forall j \in D', \forall k \in K \qquad (5)$$

Capacity, Time and Depot Assignment Constraints: Constraints (6)-(7) limit working and waiting times (typically 60 minutes). Constraints (8)-(10) ensure designated depot usage and prevent unproductive travel:

$$\sum_{i\in V^d}\sum_{j\in T} x_{i,j}^k \times \delta_j + \sum_{j\in T} wt_{k,j} \le H^k \quad ,\forall k \in K \quad (6)$$

$$wt_{k,j} \le W \qquad \forall k \in K\ \forall j \in T \qquad (7)$$

$$\sum_{i\in D\setminus D_k} \sum_{j\in T} x_{i,j}^k = 0 \quad ,\forall k \in K \qquad (8)$$

$$\sum_{i\in D'\setminus D'_k} \sum_{j\in T} x_{j,i}^k = 0 \quad ,\forall k \in K \qquad (9)$$

$$\sum_{i\in D} \sum_{j\in D'} x_{i,j}^k = 0 \quad ,\forall k \in K \qquad (10)$$

Scheduling Constraints: Constraint (11) enforces task sequencing (M is a sufficiently large constant). Constraints (12)-(13) enforce time windows:

$$a_j^k + M\left(1 - x_{i,j}^k\right) \ge a_i^k + \delta_i + t_{i,j} + wt_{k,i} \quad ,\forall k \in K, \forall i \in V^d ,\forall j \in T \quad (11)$$

$$a_j^k + wt_{k,j} \ge w_j^L \sum_{i\in V^s} x_{i,j}^k \quad ,\forall j \in T, \forall k \in K \quad (12)$$

$$a_j^k \le w_j^U \times \sum_{i\in V^s} x_{i,j}^k \quad ,\forall j \in T, \forall k \in K \quad (13)$$

Regional, Skill, and Availability Constraints: Constraint (14) assigns workers to regions (binary ψ_j equals 1 if assigned outside the region of j). Constraint (15) ensures skill matching. Constraints (16)-(17) enforce availability windows (binary ω_j equals 1 if outside availability):

$$\sum_{i\in V^d} x_{i,j}^k - \psi_j \le \gamma_j^k \quad ,\forall k \in K, \forall j \in T \quad (14)$$

$$x_{i,j}^k . \eta_{s,j} \le \mu_{k,s} \quad ,\forall k \in K, \forall i \in V^d ,\forall j \in T, \forall s \in S \quad (15)$$

$$\alpha_L^k - a_j^k \le M\left(1 - x_{i,j}^k + \omega_j\right) \quad \forall k \in K, \forall i \in V^s, \forall j \in T \quad (16)$$

$$a_j^k + \delta_j + wt_{k,j} - \alpha_U^k \le M\left(1 - x_{i,j}^k + \omega_j\right) \quad \forall k \in K, \forall i \in V^s ,\forall j \in T \quad (17)$$

Objective Function (18): Minimise weighted costs ($\lambda_5 > \lambda_4 > \lambda_3 > \lambda_2 > \lambda_1$) for unsatisfied visits, waiting time, penalties for time and regional violations, preferences, and travel:

Minimise:

$$\sum_{j\in T} \lambda_5\ y_j + \sum_{j\in T} \lambda_4 wt_{k,j} + \sum_{j\in T} \lambda_3\left(\omega_j + \psi_j\right) + \sum_{k\in K}\sum_{i\in V^d}\sum_{j\in V^a} \lambda_2(\rho_{k,j}) x_{i,j}^k + \sum_{k\in K}\sum_{i\in V^d}\sum_{j\in V^a} \lambda_1(d_{i,j}) x_{i,j}^k \qquad (18)$$

3.3 Differences Between HHCSRP-FP and Existing HHCSRP

HHCSRP-FP extends traditional models through: (1) explicit binary variable f_j enabling three task outcomes (paid service, family service, or unserved), ensuring continuity of care and enhancing realism for resource-constrained settings, (2) medically and socially informed eligibility criteria based on task complexity, reflecting integrated care principles where unpaid caregivers complement professional care (Džakula et al., 2023) and (3) cost structure where unpaid care incurs no direct costs, creating beneficial incentives for appropriate family use without requiring routing decisions.

While the binary variables f_j could theoretically be eliminated through pre-processing (reducing r_j for family-eligible tasks), our explicit formulation offers distinct advantages: (1) it provides transparency for healthcare practitioners in understanding unpaid care allocation decisions, (2) our computational experiments (see Section 4) reveal non-trivial interactions where family provision constraints enhance solver efficiency, suggesting they act as effective cutting planes rather than mere pre-processing steps, and (3) the explicit modelling enables systematic scenario analysis, leading to our key finding that 30% provision optimally balances operational benefits and computational tractability, an insight that would not have emerged from simple parameter reduction.

4 COMPUTATIONAL EXPERIMENTS AND RESULTS

4.1 Experimental Setup and Data Preparation

To evaluate the effectiveness of the proposed HHCSRP-FP model and examine the impact of varying degrees of family provision, we implemented the model in Python, solving it using Gurobi Optimiser 11.0.0 on a system with an AMD Ryzen 7 PRO 7730U processor and 16 GB RAM. Each execution was limited to a maximum of two hours of computation time (CPT).

Table 1: Characteristics of the test instances, with K and T representing caregivers and tasks, respectively, in the various 42 problem instances.

Instance	K	T	Instance	K	T
A01	23	31	D01	164	482
A02	22	31	D02	166	453
A03	22	38	D03	174	584
A04	19	28	D04	174	520
A05	19	13	D05	173	538
A06	21	28	D06	174	610
A07	21	13	D07	173	610
B01	25	36	E01	243	418
B02	25	12	E02	244	425
B03	34	69	E03	267	462
B04	34	30	E04	266	351
B05	32	61	E05	278	461
B06	32	57	E06	278	301
B07	32	61	E07	302	498
C01	1037	177	F01	805	1211
C02	618	7	F02	769	1243
C03	1077	150	F03	898	1479
C04	979	32	F04	789	1448
C05	821	29	F05	889	1599
C06	816	158	F06	783	1582
C07	349	6	F07	1011	1726

The 42 real-world instances (Table 1) were adapted to represent collaborative care scenarios. We modified task requirements so approximately 90% involved multiple caregivers (70% requiring two, 30% requiring three), making them family eligible. Five family provision scenarios were tested: 0% (baseline), 10% (low), 30% (moderate), 50% (high), and 90% (very high), generating 210 total problem instances across seven categories (A–F series).

The objective function weights were set to reflect operational priorities and maintain numerical stability. The weight for unassigned visits (λ_5) was set as the square of the weights for waiting time (λ_4) and availability/regional penalty violations (λ_3), which were equal. Preference dissatisfaction (λ_2) was set to 1, whilst travel distance (λ_1) was assigned values between 10^{-3} and 10^{-6}.

4.2 Result Analysis

Only 85 of 210 instances were solvable within time limits, with out-of-memory errors occurring in large instances (C01, C03, C04, C06, all D–F series). Small-scale instances solved in under 10 seconds, medium-scale required 15–110 seconds, whilst large-scale problems reached the 7,200-second limit.

Computational time did not follow monotonic patterns across provision scenarios. Higher provision levels occasionally improved solver convergence: instance B03 dropped from 7,200 seconds (0%) to 90 seconds (90%), with similar patterns in A03, B04, B07, and C07. This suggests that family provision constraints act as structural refinements, reducing search space. However, non-linear CPT variations (e.g., A01: 50.8s → 59.8s → 89.5s → 80.3s → 15.8s across scenarios) indicate complex constraint-solver interactions between provision levels, constraints, and solver behaviour. These findings highlight the dual nature of family provision: adding modelling complexity while occasionally improving computational tractability for certain problem instances.

In Figure 2, objective function values ranged from 33.0 (C07 at 50%, 90%) to 10,421.63 (B05 at 0%), reflecting differences in instance size, complexity, and difficulty. Increasing family provision generally reduced costs, confirming the positive effect of collaborative care on performance, though instance B02 showed an anomaly (98.8 to 123.6 between 10% and 30%), likely from the solver prioritising costly task combinations, resulting in a higher cost for unassigned visits. Additionally, limited family provision rates constrain the solution space, making it challenging to find solutions that lower the cost across the instances.

Of 85 solvable instances, 52 (61.2%) reached optimality, whilst 10 (11.8%) achieved near-optimality (<0.01 gap). Small-scale instances consistently solved optimally, whereas complex instances exhibited gaps up to 98.49% (B03).

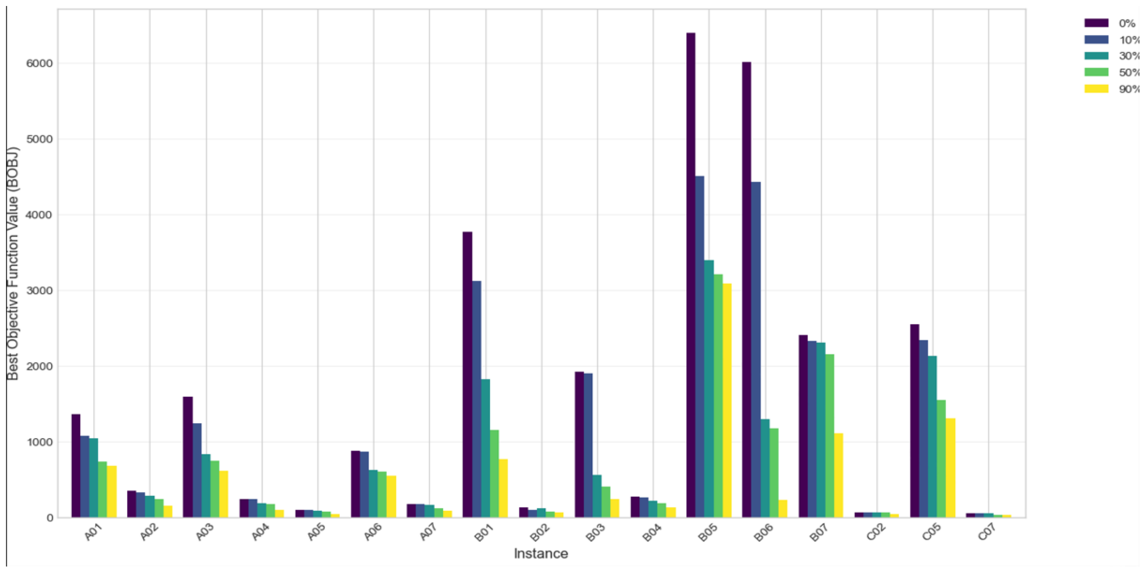

Figure 2: Objective function values across scenarios and solvable instances. The instance category B shows noticeably high values compared to other instance groups.

Table 2: Summary statistics across family provision scenario rates

Scenario	Average IOB (%)	STD IOB (%)	Min IOB (%)	Max IOB (%)	Marginal Improvement (%)
0%	0.00	0.00	0.00	0.00	0.00
10%	12.38	15.02	0.00	55.97	12.38
30%	33.30	25.50	4.57	78.34	20.92
50%	46.40	22.08	4.57	80.35	13.09
90%	59.85	18.81	29.76	96.06	13.45

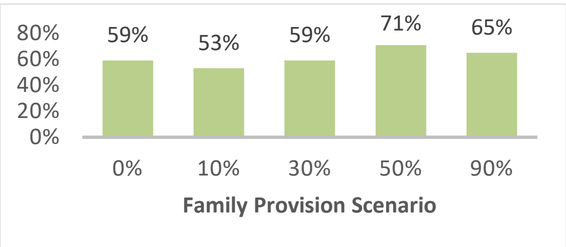

Figure 3: Percentage of instances reaching optimality across scenarios, which shows that solving the model at the 50% family participation scenario obtained the highest optimal solutions.

Optimality rates across scenarios (see Figure 3) are 59% (0%), 53% (10%), 59% (30%), 71% (50%), and 65% (90%), with 50% achieving the highest optimal solutions. Some complex instances (B03, B06) converged faster under high provision (seconds versus hours), suggesting family constraints may have acted as cutting planes.

The improvement over baseline (IOB) metric, calculated as IOB = (baseline cost − scenario cost) / baseline cost × 100, showed consistent benefits. Average IOB (see Table 2) increased monotonically: 12.38% (10%), 33.30% (30%), 46.40% (50%), 59.85% (90%), with individual improvements ranging from 0.25% to 96.06%. The largest marginal gain (20.92%) occurred between 10% and 30% scenarios, identifying 30% as the optimal provision level balancing benefits and computational complexity before diminishing returns. Higher provision levels (50–90%) continue to yield improvements, but at a slower rate.

Figure 4 shows the paid caregiver utilisation (PCU), calculated as (total available − used) / total available × 100, indicating a consistent reduction from nearly 100% at baseline to 24–29% at high provision, demonstrating efficient resource redistribution. However, this raises questions about whether unpaid carers complement or replace professionals. Most instances maintained or improved service quality (measured by unassigned

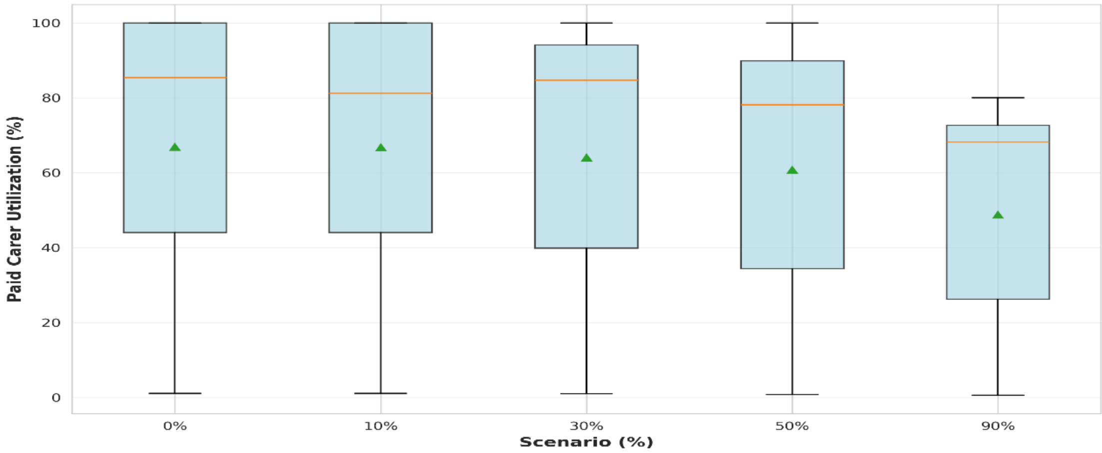

Figure 4: Paid caregiver utilisation across family provision scenarios.

tasks) as family involvement increased, confirming that collaborative care enhances delivery without compromising task coverage.

5 CONCLUSION AND FUTURE WORK

This paper developed an enhanced MILP formulation for home healthcare scheduling and routing with family provision (HHCSRP-FP), addressing a significant gap by explicitly incorporating unpaid caregivers into HHCSRP models. Through new decision variables and medically informed eligibility constraints, the formulation enables a realistic representation of collaborative care delivery.

Computational experiments using 42 real-world instances across five provision scenarios (0%, 10%, 30%, 50%, 90%) demonstrate substantial operational benefits. Results show average cost savings of 59.85% at the highest provision level, with 30% identified as optimal, yielding the greatest marginal benefit (20.92% additional improvement over 10%) whilst balancing solution quality and computational tractability. Interestingly, family provision constraints enhanced rather than hindered solver efficiency for certain problem structures, with several complex instances converging in seconds rather than hours. The study extends HHCSRP to explicitly model unpaid care, empirically validating collaborative care benefits, and identifying optimal integration strategies for healthcare providers. Future research will explore heuristic and hybrid solution methods for large-scale instances.

REFERENCES

Atta, S., Basto-Fernandes, V., & Emmerich, M. (2025). A Concise Review of the Home Health Care Routing and Scheduling Problem. *Operations Research Perspectives*, *15*, 100347. https://doi.org/10.1016/j.orp.2025.100347

Bolin, K., Lindgren, B., & Lundborg, P. (2008). Informal and formal care among single-living elderly in Europe. *Health Economics*, *17*(3), 393–409. https://doi.org/10.1002/hec.1275

Cappanera, P., Visintin, F., & Vannelli, S. (2025). Home-based care and center-based care: From being alternatives to being synergistic. Optimization models to support flexible care delivery. *Omega*, *131*, 103184. https://doi.org/10.1016/j.omega.2024.103184

Carers UK. (2025). *Facts About Carers*.

Chabouh, S., El-Amraoui, A., Hammami, S., & Bouchriha, H. (2023). A systematic review of the home health care planning literature: Emerging trends and future research directions. *Decision Analytics Journal*, *7*, 100215. https://doi.org/10.1016/j.dajour.2023.100215

Džakula, A., Banadinović, M., Lončarek, K., & Vočanec, D. (2023). Informal care: The indispensable pillar of care for complex patients. *Croatian Medical Journal*, *64*(6), 448–451. https://doi.org/10.3325/cmj.2023.64.448

Erdem, M., & Bulkan, S. (2017). A literature review on Home Healthcare Routing and Scheduling Problem. *Eurasian Journal of Health Technology Assessment*, *2*(1), Article 1.

Erdem, M., Koç, Ç., & Yücel, E. (2022). The electric home health care routing and scheduling problem with time windows and fast chargers. *Computers & Industrial Engineering*, *172*, 108580. https://doi.org/10.1016/j.cie.2022.108580

Eveborn, P., Rönnqvist, M., Einarsdóttir, H., Eklund, M., Lidén, K., & Almroth, M. (2009). Operations Research

Improves Quality and Efficiency in Home Care. *Interfaces*, *39*(1), 18–34.

Fathollahi-Fard, A. M., Ahmadi, A., & Karimi, B. (2020). A Robust Optimization for a Home Healthcare Routing and Scheduling Problem Considering Greenhouse Gas Emissions and Stochastic Travel and Service Times. In *Green Transportation and New Advances in Vehicle Routing Problems* (pp. 43–73). Scopus. https://doi.org/10.1007/978-3-030-45312-1_2

Grieco, L., Utley, M., & Crowe, S. (2020). Operational research applied to decisions in home health care: A systematic literature review. *Journal of the Operational Research Society*, *72*(9), 1960–1991. https://doi.org/10.1080/01605682.2020.1750311

Kordi, Gh., Divsalar, A., & Emami, S. (2023). Multi-objective home health care routing: A variable neighborhood search method. *Optimization Letters*, *17*(9), 2257–2298. https://doi.org/10.1007/s11590-023-01993-y

Laesanklang, W., Landa-Silva, D., & Castillo-Salazar, J. A. (2016). Mixed Integer Programming with Decomposition for Workforce Scheduling and Routing with Time-dependent Activities Constraints: *Proceedings of 5th the International Conference on Operations Research and Enterprise Systems*, 330–339. https://doi.org/10.5220/0005757503300339

Lemmon, E. (2020). Utilisation of personal care services in Scotland: The influence of unpaid carers. *Journal of Long-Term Care*, *2020*, 54–69.

Litwin, H., & Attias-Donfut, C. (2009). The inter-relationship between formal and informal care: A study in France and Israel. *Ageing and Society*, *29*(1), 71–91. https://doi.org/10.1017/S0144686X08007666

Liu, M., Zhao, Y., & Xie, X. (2024). Continuity-skill-restricted scheduling and routing problem: Formulation, optimization and implications. *IISE Transactions*, *56*(2), 201–220. https://doi.org/10.1080/24725854.2023.2215843

Liu, W., Dridi, M., Fei, H., & El Hassani, A. H. (2021). Hybrid metaheuristics for solving a home health care routing and scheduling problem with time windows, synchronized visits and lunch breaks. *Expert Systems with Applications*, *183*, 115307. https://doi.org/10.1016/j.eswa.2021.115307

Masmoudi, M., Euchi, J., & Siarry, P. (2024). Home healthcare routing and scheduling: Operations research approaches and contemporary challenges. *Annals of Operations Research*, *343*(2), 701–751. https://doi.org/10.1007/s10479-024-06244-6

Nasir, J. A., Hussain, S., & Dang, C. (2018). An Integrated Planning Approach Towards Home Health Care, Telehealth and Patients Group Based Care. *Journal of Network and Computer Applications*, *117*, 30–41. https://doi.org/10.1016/j.jnca.2018.05.009

Petrillo, M., & Bennett, M. R. (2023). *Valuing Carers 2021: England and Wales.*

Pickard, L., King, D., & Knapp, M. (2016). The 'visibility' of unpaid care in England. *Journal of Social Work (London, England)*, *16*(3), 263–282. https://doi.org/10.1177/1468017315569645

Rekabi, S., Moradi, B., Salamian, F., Fadavi, N., Zokaee, M., & Aghsami, A. (2024). A home healthcare routing-scheduling optimization model considering time-balancing and outsourcing. *Supply Chain Analytics*, *7*, 100077. https://doi.org/10.1016/j.sca.2024.100077

Rest, K.-D., & Hirsch, P. (2016). Daily scheduling of home health care services using time-dependent public transport. *Flexible Services and Manufacturing Journal*, *28*(3), 495–525. https://doi.org/10.1007/s10696-015-9227-1

Sattler, D., Howard, M., Nessim, D., McAlister, M., & Dolovich, L. (2025). Integrating informal and formal care: An innovative, scalable program blueprint. *Healthcare Management Forum*, *38*(3), 273–277. https://doi.org/10.1177/08404704241292329

Scheffler, R., Cometto, G., Tulenko, K., Bruckner, T., Liu, J., Keuffel, E. L., Preker, A., Stilwell, B., Brasileiro, J., & Campbell, J. (2016). Health workforce requirements for universal health coverage and the Sustainable Development Goals – Background paper N.1 to the WHO Global Strategy on Human Resources for Health: Workforce 2030. *Human Resources for Health*, *17*(1).

Schulz, R., & Sherwood, P. R. (2008). Physical and Mental Health Effects of Family Caregiving. *The American Journal of Nursing*, *108*(9 Suppl), 23–27. https://doi.org/10.1097/01.NAJ.0000336406.45248.4c

Somar, S., Urazel, B., & Buruk Sahin, Y. (2023). A modified metaheuristic algorithm for a home health care routing problem with health team skill levels. *Applied Soft Computing*, *148*, 110912. https://doi.org/10.1016/j.asoc.2023.110912

Tanoumand, N., & Ünlüyurt, T. (2021). An exact algorithm for the resource constrained home health care vehicle routing problem. *Annals of Operations Research*, *304*(1), 397–425. https://doi.org/10.1007/s10479-021-04061-9

United Nations. (2019). *World population ageing, 2019 highlights*. United Nations.

Wagner, E., Austin, B., Davis, C., Hindmarsh, M., Schaefer, J., & Bonomi, A. (2001). Improving Chronic Illness Care: Translating Evidence Into Action. *Health Affairs (Project Hope)*, *20*, 64–78. https://doi.org/10.1377/hlthaff.20.6.64

Yalçındağ, S., Matta, A., Şahin, E., & Shanthikumar, J. G. (2016). The patient assignment problem in home health care: Using a data-driven method to estimate the travel times of care givers. *Flexible Services and Manufacturing Journal*, *28*(1), 304–335. https://doi.org/10.1007/s10696-015-9222-6