

ORIGINAL RESEARCH

Open access

Artificial Intelligence-Based Home Health Scheduling System Using Patient Acuity, Geographic Routing, Clinician Skill Mix, Visit Duration Estimates, and Risk of Missed Follow-Up Care

Peter Novak^{1*}, Jana Svoboda¹

Abstract

Home health agencies must assign clinicians to patients across geographically dispersed service areas while balancing patient needs, workforce qualifications, and operational efficiency. Scheduling decisions must account for clinical urgency, visit complexity, travel burden, and continuity of care. Manual scheduling cannot reliably integrate real-time acuity changes, dynamic travel conditions, clinician availability, and the risk of patients refusing or missing care. As a result, agencies may experience avoidable inefficiencies, delayed visits, fragmented follow-up, and increased coordinator workload. This article proposes an AI-based home health scheduling system that integrates patient acuity, geographic routing, clinician skill profiles, visit duration estimates, and missed-care risk prediction. The system is designed to generate adaptive daily schedules that can be revised as clinical and operational conditions change. The framework includes a patient acuity classifier, visit duration estimator, geographic routing engine, skill-mix matcher, missed-care risk predictor, and real-time scheduling dashboard. These components operate together to support clinically appropriate, geographically efficient, and operationally feasible visit plans. The proposed system would be expected to improve scheduling responsiveness, reduce unnecessary travel, better align clinician competencies with patient needs, and support proactive follow-up for patients at risk of missed care. Its value depends on integration with electronic health records, mobile workflows, coordinator oversight, and transparent decision support. An AI-based home health scheduling system provides a pathway toward a more responsive and coordinated home health operations model. By combining clinical prioritization with routing, workforce matching, and follow-up risk mitigation, such a framework could support both care quality and workforce efficiency.

Keywords Artificial intelligence, Patient acuity, Home health care, Scheduling, Clinician routing, Skill mix

*Correspondence:

Peter Novak
peter.novak@gmail.com

¹ Department of Digital Health Systems, Faculty of Medicine, Charles University, Prague, Czech Republic

Introduction

Home health agencies face growing operational complexity as they coordinate skilled nursing, therapy, aide, and supportive services across dispersed patient homes. Unlike facility-based care, home health scheduling requires the daily allocation of a mobile workforce across changing addresses, service types, time windows, and patient preferences. Routing and scheduling reviews show that home health care differs from standard vehicle routing because clinical appropriateness, continuity, synchronization, and workforce constraints must be considered together [1, 2]. These pressures make scheduling a central operational function rather than a purely administrative task.

Poor scheduling can have direct clinical consequences when a high-acuity patient is visited too late, when a clinician without the appropriate competency is assigned, or when care continuity is disrupted. Predictive studies using home care observations and electronic health record data suggest that hospitalization risk, emergency department use, and care escalation can be anticipated from clinical, functional, and documented risk factors [3-5]. For home health agencies, these risks imply that visit sequencing and assignment should reflect patient acuity rather than only geography or staff availability. Scheduling systems that ignore risk stratification may therefore contribute to avoidable delays in follow-up care.

Current scheduling practices in many agencies remain manual or semi-automated, relying heavily on coordinator experience, static territories, and retrospective knowledge of clinician availability. Optimization studies show that routing, time windows, synchronization, stochastic service times, and uncertain travel conditions can be modeled more systematically than manual methods typically allow [6-8]. However, operational models alone are insufficient when they do not incorporate patient-level acuity, expected visit duration, missed-care risk, and clinician competency. This gap creates an opportunity for AI-supported decision systems that combine predictive modeling with constrained scheduling.

This article proposes an AI-based home health scheduling system that dynamically synthesizes patient acuity, geographic routing, clinician skill mix, visit duration estimates, and risk of missed follow-up care. The framework treats the daily schedule as a living operational plan that can be regenerated when visits cancel, clinicians are delayed, new needs emerge, or patient risk changes. Prior work on routing heuristics, stochastic home health planning, outpatient scheduling, decision support, and service length estimation provides the conceptual basis for such an integrated architecture. The proposed system is not presented as an experimental result but as a conceptual AI systems framework for future evaluation.

Background

Home health scheduling challenges

Home health scheduling is difficult because each visit carries clinical, spatial, temporal, and workforce constraints that interact throughout the day. A feasible schedule must respect time windows, service dependencies, clinician work rules, patient preferences, travel variability, and continuity requirements. Reviews and optimization studies describe this as a multi-dimensional routing and scheduling problem in which the objective is not merely travel minimization but coordinated care delivery under uncertainty [1, 2, 9]. These characteristics make home health an appropriate domain for AI-enabled operational decision support.

Patient acuity in home care

Patient acuity in home care reflects clinical severity, functional limitations, social barriers, resource intensity, and the urgency of follow-up after hospital discharge or clinical deterioration. EHR-based and home care observation studies show that hospitalization risk and emergency department use can be predicted from documented risk factors, clinician observations, and longitudinal care data [3-5]. In scheduling, acuity should influence visit timing, visit frequency, clinician skill requirements, and tolerance for delay. A scheduling framework that incorporates acuity can therefore prioritize clinically vulnerable patients while still respecting operational feasibility.

Geographic routing in home health

Geographic routing is central to home health operations because clinicians travel between patient homes rather than patients traveling to a clinic. Home care routing studies adapt vehicle routing, time-window, stochastic travel, and synchronization methods to account for mobile clinicians and uncertain travel or service times [7, 8, 10]. More recent models extend this logic to outpatient-linked services, electric vehicle constraints, multiple centers, complex community

behavior, and prioritized time windows [11-14]. These studies demonstrate that routing intelligence can support more efficient daily route construction while preserving clinical and temporal constraints.

Clinician skill mix and competency matching

Clinician assignment in home health must account for licensure, scope of practice, competency, continuity, workload balance, and patient-specific care requirements. Routing and scheduling models increasingly include multi-skilled workforces, synchronized services, caregiver allocation, and flexible visit sequences to reflect the operational reality of nursing, therapy, aide, and specialized care teams [15-17]. Skill matching is especially important when patients require wound care, infusion, rehabilitation, behavioral health support, or complex post-acute monitoring. A system that assigns purely by proximity may reduce travel but fail to produce clinically appropriate schedules.

Predictive models for missed follow-up care

Missed follow-up care in home health may result from patient refusal, unavailability, transportation instability, communication barriers, hospitalization, caregiver absence, or social risk. Predictive models for service demand, hospitalization risk, and home care outcomes show that machine learning can help identify patients whose care trajectories require closer monitoring or proactive outreach [5, 18, 19]. In a scheduling context, missed-care risk should be treated as an operational input rather than only a quality metric observed after the fact. If a patient is likely to miss or refuse a visit, the schedule can incorporate confirmation steps, earlier placement, coordinator review, or contingency planning.

System Overview

High-level architecture

The proposed architecture begins with data ingestion from the electronic health record, scheduling platform, mobile clinician application, GPS or routing interface, and agency workforce database. These inputs feed a modular AI engine that estimates acuity, visit duration, travel burden, clinician fit, and missed-care risk before constructing a daily schedule. Prior work on EHR-derived risk factors, home care observations, routing optimization, and decision support suggests that these data sources can support both predictive and operational decision-making when integrated carefully [3, 4, 20]. The resulting schedule is then updated continuously as new information enters the system.

Figure 1 illustrates the proposed end-to-end AI-enabled home health scheduling architecture, showing how patient acuity, geographic routing, clinician skill mix, visit duration estimation, and missed-care risk prediction are integrated into human-supervised operational scheduling.

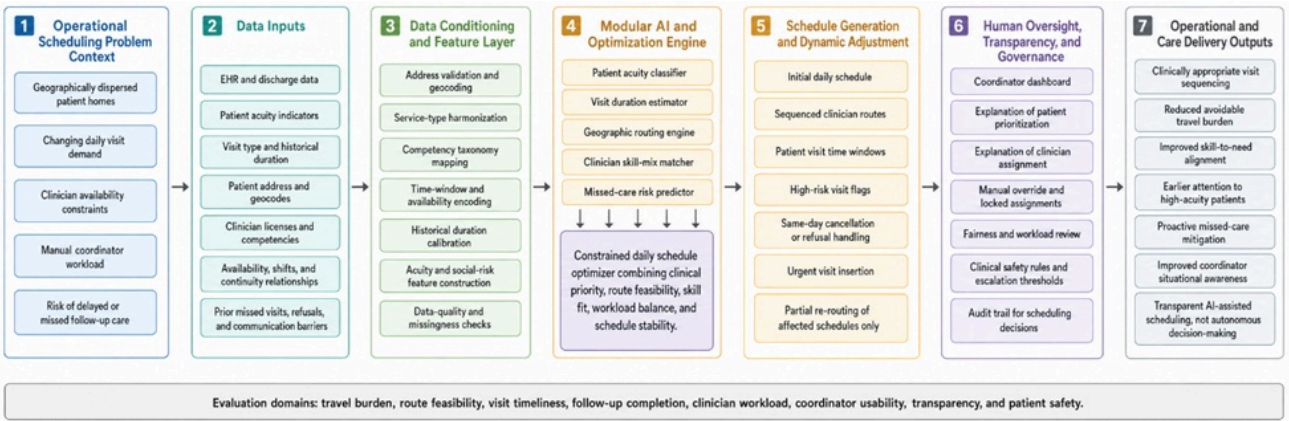


Figure 1. End-to-end AI-enabled home health scheduling architecture integrating acuity, routing, skill mix, visit duration, and missed-care risk.

Core inputs and outputs

The core inputs include patient acuity scores, patient address geocodes, clinician licenses and competencies, historical visit durations, service type, availability windows, continuity relationships, and missed-care risk scores. The outputs include daily clinician schedules, sequenced routes, patient visit time windows, alerts for high-risk visits, and suggested mitigation actions for coordinator review. Scheduling studies that incorporate priorities, time windows, synchronized services, caregiver allocation, and stochastic service assumptions provide the conceptual foundation for this input-output structure [15, 17, 21, 22]. The system is designed to recommend feasible schedules rather than replace clinical or managerial judgment.

Table 1 presents the operational input-output logic linking patient-level, clinician-level, geographic, and risk-related data to the AI scheduling functions proposed in this framework.

Table 1. Operational input-output logic of the proposed AI-based home health scheduling system

System domain	Core data elements	AI or optimization function	Scheduling decision supported	Practical operational value	Human oversight requirement
Patient acuity	Recent hospitalization, clinical deterioration, functional status, wound or infusion needs, medication complexity, caregiver support, social risk documentation	Dynamic acuity classification	Determines visit urgency, acceptable delay, and priority within the daily route	Helps prevent high-risk patients from being scheduled too late or displaced by geographically convenient visits	Coordinator and clinical supervisor review for unusually high-risk or ambiguous cases
Visit duration	Visit discipline, service type, prior visit length, patient complexity, acuity tier, documentation burden, travel context	Visit duration estimation	Estimates realistic service time for each scheduled encounter	Reduces overbooking, downstream delays, and unrealistic route compression	Coordinator review when estimates conflict with clinician experience
Geographic routing	Patient geocodes, travel distance, traffic conditions, parking constraints, route history, territory boundaries	Route sequencing and travel-time estimation	Determines efficient clinician route order and time windows	Reduces avoidable travel burden while preserving clinical feasibility	Human override for local knowledge, unsafe routes, or patient-specific access issues
Clinician skill mix	Discipline, license, certification, wound care competency, infusion competency, therapy specialization, continuity relationship, workload	Skill-mix matching and feasibility filtering	Assigns appropriate clinicians to patient needs	Prevents proximity-based assignments that are operationally efficient but clinically inappropriate	Mandatory review for specialized care, scope-of-practice constraints, and continuity exceptions

Missed-care risk	Prior missed visits, refusals, communication barriers, caregiver availability, hospitalization risk, social instability, confirmation history	Missed-care risk prediction	Flags visits requiring confirmation, earlier scheduling, backup routing, or coordinator outreach	Converts missed-care risk from a retrospective quality metric into a proactive scheduling input	Coordinator determines whether outreach, escalation, or route adjustment is appropriate
Dynamic schedule adjustment	Cancellations, urgent orders, clinician delays, failed confirmations, traffic disruption, same-day clinical changes	Partial re-routing and insertion logic	Revises affected portions of the schedule without rebuilding the entire day	Improves responsiveness while limiting disruption to stable assignments	Coordinator compares alternatives before dispatching changes
Coordinator dashboard	Route status, patient acuity, clinician availability, risk alerts, schedule feasibility, override history	Transparent decision-support interface	Supports review, modification, approval, and monitoring of AI-generated schedules	Positions AI as an assistive operational partner rather than an autonomous scheduler	Final scheduling authority remains with human coordinators and managers

Design principles

The framework is guided by four design principles: real-time adaptability, clinical prioritization, transparency for coordinators, and respect for workforce constraints. These principles reflect the need to balance route efficiency with patient safety, clinician workload, continuity, and acceptability to agency staff. Optimization and decision support models in home health and appointment scheduling show that operational efficiency must be paired with interpretability and constraint awareness to be usable in practice [23-25]. Accordingly, the system should explain why a patient was prioritized, why a clinician was assigned, and how a route was constructed.

Patient Acuity and Visit Duration Modelling

Acuity scoring from clinical and social data

The patient acuity module would integrate recent hospital discharge information, functional status, therapy needs, medication complexity, wound or infusion requirements, caregiver support, and social determinants into a dynamic acuity tier. EHR documentation and machine learning studies indicate that hospitalization risk and care escalation can be anticipated from structured and narrative clinical information, although documentation gaps must be recognized [4, 5, 26]. In this framework, acuity is not a static label but an operational signal that can change after a hospitalization, emergency department visit, missed visit, or clinician observation. The scheduling engine would use this tier to influence visit urgency, required skill level, and tolerance for reassignment.

Visit duration estimation

The visit duration estimator would use visit type, acuity tier, discipline, patient complexity, geographic context, historical service patterns, and travel-related context to estimate how long each visit is likely to require. Machine learning work on home health service length estimation supports the idea that visit duration can be modeled as a patient- and service-specific planning input rather than a fixed average [27]. Scheduling models that include stochastic service times also show why duration uncertainty can disrupt route feasibility when visits are packed too tightly [7, 22]. The system would

therefore generate duration estimates with sufficient caution to reduce over-scheduling and preserve flexibility for complex care.

Interplay of acuity and duration

Patient acuity and visit duration are closely linked because higher-acuity visits often require more assessment, documentation, coordination, education, and clinical intervention. The proposed system would model this relationship by allowing acuity to influence both clinician assignment and expected visit length, rather than treating visit duration as independent of clinical risk. Home health routing studies that consider priority, service time uncertainty, and complex care logistics support this integrated treatment of clinical and operational variables [8, 21, 28]. This design would help prevent schedules that appear efficient geographically but are unrealistic clinically.

Geographic Routing and Travel Optimization

Time-varying road network considerations

The routing engine would account for historical traffic patterns, real-time travel conditions, road closures, parking constraints, and location uncertainty when estimating travel times between patient homes. Robust and stochastic routing models show that uncertain travel and service times can materially affect home health route feasibility [7, 8]. In an AI-enabled implementation, travel time estimates would be continuously refreshed as clinicians move through their routes and as external conditions change. The system could then recommend schedule adjustments when predicted delays threaten downstream visits.

Territory clustering and daily route construction

Territory clustering would group nearby patients while preserving clinician skill requirements, patient time windows, continuity preferences, and workload balance. After clustering, the routing module would construct daily visit sequences that account for time windows, prioritized patients, synchronized services, and expected service duration. Set partitioning heuristics, memetic algorithms, multi-center evolutionary approaches, and prioritized time-window models provide relevant conceptual foundations for this two-stage construction process [6, 9, 14, 29]. The objective is not only the shortest route but a clinically feasible and resilient schedule.

Dynamic re-routing for emergencies and changes

Home health schedules often change after cancellations, patient refusals, clinician delays, emergency visits, or new same-day orders. The proposed system would use fast re-routing and insertion logic to revise only the affected portions of the schedule when possible, reducing disruption to the rest of the day. Research on adaptive routing, flexible sequencing, stochastic planning, and complex community-based scheduling supports the need for dynamic approaches that can respond to operational uncertainty [13, 17, 22, 30]. This capability would allow coordinators to compare alternative solutions rather than reconstructing the schedule manually.

Clinician Skill-Mix and Assignment Matching

Competency taxonomy and patient requirements

The skill-mix module would maintain a structured competency taxonomy that maps patient needs to clinician qualifications, certifications, discipline, scope of practice, and recent experience. Examples include wound care, IV infusion, post-surgical assessment, rehabilitation therapy, behavioral health support, medication reconciliation, and high-risk chronic disease monitoring. Models that address multiple synchronized services, caregiver allocation, and multi-objective home care logistics show that assignment decisions must incorporate workforce capability rather than proximity

alone [15, 16, 28]. This taxonomy would allow the scheduling engine to exclude infeasible assignments and rank feasible ones by clinical appropriateness.

Multi-objective assignment optimization

The assignment engine would optimize several objectives simultaneously, including skill alignment, continuity of care, workload balance, route efficiency, visit priority, and schedule stability. Because these objectives can conflict, the system would present trade-offs to coordinators rather than treating any single metric as dominant. Prior home health optimization models address patient prioritization, synchronization, ergonomic risk, flexible visit sequences, and multi-objective routing, illustrating how assignment logic can be expanded beyond simple travel minimization [17, 28, 31, 32]. In this framework, the best schedule is the one that remains clinically appropriate, operationally feasible, and understandable to human users.

Incorporating clinician preferences and availability

Clinician availability, shift length, requested time off, territory familiarity, continuity relationships, and reasonable preferences would be modeled as hard or soft constraints depending on agency policy. Soft constraints can improve acceptance and perceived fairness, while hard constraints preserve feasibility, licensure compliance, and patient safety. Home care planning studies that consider consistency, uncertain demand, workforce allocation, and ergonomic factors show that clinician-centered constraints are important for sustainable scheduling systems [23, 31, 33]. By incorporating these elements, the AI scheduler would be expected to support workforce stability while still prioritizing patient needs.

Risk of Missed Follow-Up Care and Mitigation

Predicting missed visit probability

The missed-care risk module would estimate the probability that a patient may refuse, miss, cancel, or be unavailable for a scheduled visit. It would use prior visit adherence, communication logs, clinical instability, caregiver availability, social risk indicators, recent hospitalization, and documented barriers to care as predictive inputs. Home care studies on emergency department use, hospitalization risk, and service demand demonstrate that patient-level risk can be inferred from observations, EHR data, and longitudinal home care information [3, 5, 18, 19]. In this framework, the risk score would not be used punitively but as a trigger for proactive scheduling support.

Scheduling adjustment for high-risk patients

Patients at higher risk of missed follow-up could be scheduled earlier in the day, assigned to a familiar or senior clinician, or given a narrower confirmation workflow before dispatch. The scheduling engine could also create contingency options so that if a high-risk visit fails, the clinician can be routed to another nearby patient without losing the remainder of the route. Prior work on home health routing with priorities, uncertain service times, and stochastic planning supports the idea that schedules should anticipate disruption rather than assume all visits will occur as planned [8, 21, 22, 34]. This approach would make missed-care risk an operational constraint within the scheduling process.

Proactive reminders and escalation workflows

The system would trigger reminders, confirmation requests, and coordinator alerts when a high-risk visit requires additional follow-up before the clinician arrives. If the patient does not confirm, the coordinator dashboard could recommend outreach, caregiver contact, telephonic triage, or route adjustment. Decision support and appointment scheduling frameworks show that predictive scheduling tools are most useful when they are connected to actionable workflows rather than isolated risk scores [20, 24, 25]. For home health agencies, this means the missed-care module should support same-day intervention and continuity planning

Real-Time Scheduling Engine and Exception Handling

Daily schedule generation and dispatch

The real-time scheduling engine would generate the initial daily plan overnight by combining acuity, duration estimates, clinician skill availability, geographic routing, and missed-care risk. The plan would then be released to clinicians through a mobile application that provides visit sequence, navigation, patient context, and updated time windows. During the day, the engine would recalculate affected routes when cancellations, delays, urgent orders, or risk alerts occur, drawing on dynamic routing and flexible sequencing concepts from home health optimization research [11, 13, 30]. The goal is to reduce manual coordinator workload while preserving human oversight over sensitive assignment decisions.

Handling unscheduled needs and emergency visits

Unscheduled needs and emergency visits would be handled through reserved capacity slots, rapid insertion heuristics, and coordinator review of trade-offs. The system could identify clinicians who are geographically near the new patient, clinically qualified, and least likely to disrupt high-acuity scheduled care. Home health routing models that incorporate synchronized services, multiple centers, lunch breaks, and complex constraints show that real-world schedules require flexibility beyond a fixed daily route [15, 29, 32]. In this framework, emergency insertion would be treated as controlled re-optimization rather than a complete schedule reset

Integration with Home Health Agency Operations

Mobile and EHR integration

Clinicians would receive schedules, navigation, patient context, risk alerts, and documentation prompts through a mobile interface connected to the EHR and scheduling platform. Completed visits, clinician observations, patient refusals, duration deviations, and care barriers would flow back into the scheduling model for ongoing learning and refinement. Research on EHR-based risk factors, home care observations, and clinical documentation highlights the importance of capturing both structured data and clinician-generated contextual information [3, 4, 26]. This feedback loop would allow the system to evolve from static scheduling support into an adaptive operational intelligence platform.

Coordinator dashboard and override capabilities

The coordinator dashboard would provide a holistic view of clinician routes, patient acuity, missed-care risk, visit status, travel disruption, and schedule feasibility. Coordinators could override recommendations, lock specific assignments, compare alternatives, and view explanations for why the system prioritized a patient or selected a clinician. Decision support systems for scheduling should remain transparent and interactive because operational feasibility depends on local knowledge, staff relationships, and exceptions that may not be fully captured in data [17, 20, 25]. The dashboard would therefore position AI as an assistive scheduling partner rather than an autonomous authority.

Evaluation strategy

Table 2 outlines the evaluation, governance, and implementation considerations required to assess whether AI-assisted home health scheduling is operationally useful, clinically safe, transparent, and fair.

Table 2. Evaluation, governance, and implementation framework for AI-assisted home health scheduling

Evaluation or governance domain	Key assessment question	Recommended indicators	Potential failure mode	Mitigation strategy	Decision-use implication

Operational efficiency	Does the system improve the feasibility and efficiency of daily scheduling?	Travel time, route distance, schedule stability, on-time visit rate, coordinator workload, clinician utilization	The system minimizes travel while ignoring clinical urgency or continuity	Use multi-objective optimization rather than travel-only optimization	Efficiency gains should be interpreted only alongside care-quality and workforce measures
Clinical prioritization	Does the schedule reflect patient acuity and urgency?	Time-to-visit for high-acuity patients, proportion of urgent visits completed within target windows, escalation frequency	Lower-acuity nearby patients may be favored over clinically urgent distant patients	Apply acuity-weighted scheduling rules and coordinator review	The system should support clinically informed routing, not only geographic clustering
Skill-to-need alignment	Are clinicians matched appropriately to patient requirements?	Match rate between required and assigned competencies, scope-of-practice exceptions, continuity preservation	A geographically efficient assignment may be clinically inappropriate	Use hard feasibility constraints for licensure and specialized competencies	Assignment recommendations must remain clinically auditable
Missed-care mitigation	Does the system reduce preventable missed or refused visits?	Missed-visit rate, confirmation success, outreach completion, backup route use, follow-up completion among high-risk patients	Risk scores may stigmatize socially complex patients or create inequitable scheduling	Use risk scores for supportive outreach only; monitor equity across patient groups	Missed-care prediction should trigger assistance, not penalization
Workforce fairness and sustainability	Does the schedule distribute workload reasonably?	Visit load, travel burden, overtime, complex-case concentration, clinician satisfaction, route acceptability	High-performing clinicians may receive disproportionate complex visits	Include workload balance and fairness constraints	AI scheduling must protect workforce sustainability
Transparency and usability	Can coordinators understand and modify recommendations?	Explanation availability, override frequency, user trust, perceived clarity, training burden	Users may reject opaque or rigid recommendations	Provide patient-priority, route, and skill-match explanations	Adoption depends on explainability at the operational decision level
Data quality and bias	Are scheduling recommendations	Address accuracy, missing acuity	Poor documentation may	Use local calibration,	Deployment should be agency-specific

	affected by incomplete or biased data?	fields, incomplete skill records, documentation variation, rural versus urban performance	misclassify acuity or missed-care risk	missingness checks, and periodic data audits	rather than assumed universally transferable
Safety and governance	Are AI recommendations monitored and accountable?	Override logs, adverse scheduling events, escalation reviews, audit trails, governance committee review	Automation bias may lead staff to accept unsafe assignments	Require human approval for high-risk changes and maintain audit trails	The system should be governed as clinical-operational decision support

Operational efficiency metrics

The proposed system should be evaluated using operational efficiency metrics such as travel burden, schedule feasibility, route stability, clinician utilization, and coordinator workload. These measures should be interpreted conceptually and prospectively rather than reported as assumed gains, because actual effects would depend on agency geography, workforce composition, patient density, and data quality. Routing and scheduling research provides relevant evaluation dimensions, including time-window feasibility, travel effort, synchronization quality, stochastic robustness, and workload balance [1, 2, 6, 9, 12]. A future pilot should compare AI-assisted scheduling decisions with existing agency scheduling processes under real operational constraints.

Clinical quality and follow-up completion

Clinical evaluation should examine whether the system supports timely skilled visits, appropriate clinician-patient matching, continuity of care, and reduced missed follow-up among high-risk patients. The evaluation should also consider whether acuity-driven prioritization helps agencies identify patients who require earlier visits, escalation, or closer monitoring. Studies of hospitalization prediction, emergency department use, service demand, and home care risk modeling suggest that clinical quality indicators should be connected to patient-level risk rather than treated only as aggregate outcomes [5, 18, 19]. The framework should therefore be assessed for its ability to align operational scheduling with clinical need.

User satisfaction and system usability

User satisfaction should be evaluated among clinicians, coordinators, managers, and possibly patients or caregivers affected by scheduling changes. Relevant usability domains include perceived fairness, clarity of recommendations, route reasonableness, workload balance, transparency, ease of override, and trust in AI-assisted scheduling. Research on appointment scheduling, decision support, caregiver allocation, and ergonomic risk suggests that system adoption depends on whether users experience the tool as supportive, explainable, and compatible with daily work [17, 20, 24, 31]. The evaluation should therefore include qualitative feedback alongside operational and clinical indicators.

Limitations

Data gaps and geographic bias

The proposed system depends on accurate patient addresses, reliable geocoding, timely clinical documentation, complete clinician skill records, and realistic estimates of travel and service duration. In practice, rural agencies, dense urban agencies, and agencies serving socially complex populations may face different data limitations and routing challenges. Prior studies on uncertainty, stochastic planning, geographic routing, and service duration estimation show

that schedules can become fragile when travel times, visit lengths, or patient availability are poorly estimated [7, 8, 22, 27]. Therefore, the framework should include uncertainty handling and local calibration before deployment.

Human factors and adoption

Clinicians and coordinators may resist algorithmically generated schedules if they perceive them as unfair, opaque, overly rigid, or misaligned with clinical judgment. Adoption would require transparent explanations, phased implementation, coordinator override authority, clinician feedback, and governance around how scheduling priorities are defined. Studies addressing consistency, flexible sequencing, workforce allocation, ergonomic risk, and decision support underscore that technically feasible schedules are not automatically acceptable to the people who must use them [17, 23, 31, 33]. Human factors should therefore be treated as a core design constraint rather than a post-implementation concern.

Conclusion

An AI-based home health scheduling system can provide a conceptual foundation for more coordinated, responsive, and clinically informed home health operations. By combining acuity assessment, visit duration estimation, geographic routing, clinician skill matching, and missed-care risk prediction, the system reframes scheduling as an integrated care logistics function.

The key strength of the proposed framework is its ability to connect clinical urgency with operational feasibility. Rather than optimizing travel alone, the system would consider which patient needs care, which clinician is appropriate, how long the visit may take, how the route should be sequenced, and whether follow-up is at risk.

Several challenges remain before such a system can be responsibly implemented across diverse home health settings. Data quality, rural and urban routing differences, patient behavior, clinician acceptance, EHR integration, and governance of AI recommendations would all require careful attention.

Future work should develop and prospectively evaluate pilot implementations in large home health agencies. Such studies should assess whether AI-assisted scheduling can support operational efficiency, workforce sustainability, care continuity, and timely follow-up without reducing transparency or clinical judgment.

Acknowledgements

None

Conflict of interest

None

Financial support

None

Ethics statement

None

Published online: 20 July 2024

Rights and permissions

Open Access The author(s) retain copyright. This article is licensed under the Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. It may be shared and adapted for non-commercial purposes with appropriate attribution, an indication of changes, and distribution of adaptations under the same license. Third-party material may be subject to separate terms identified in its credit line. View the license at <https://creativecommons.org/licenses/by-nc-sa/4.0/>.

References

- Fikar C, Hirsch P. Home health care routing and scheduling: a review. *Comput Oper Res.* 2017;77:86-95.
- Di Mascolo M, Martinez C, Espinouse ML. Routing and scheduling in home health care: a literature survey and bibliometric analysis. *Comput Ind Eng.* 2021;158:107255.
- Veyron JH, Friocourt P, Jeanjean O, Luquel L, Bonifas N, Denis F, et al. Home care aides' observations and machine learning algorithms for the prediction of visits to emergency departments by older community-dwelling individuals receiving home care assistance: a proof of concept study. *PLoS One.* 2019;14(8):e0220002.
- Hobensack M, Ojo M, Barrón Y, Bowles KH, Cato K, Chae S, et al. Documentation of hospitalization risk factors in electronic health records (EHRs): a qualitative study with home healthcare clinicians. *J Am Med Inform Assoc.* 2022;29(5):805-12.
- Jung D, Pollack HA, Konetzka RT. Predicting hospitalization among Medicaid home- and community-based services users using machine learning methods. *J Appl Gerontol.* 2023;42(2):241-51.
- Decerle J, Grunder O, El Hassani AH, Barakat O. A memetic algorithm for a home health care routing and scheduling problem. *Oper Res Health Care.* 2018;16:59-71.
- Shi Y, Boudouh T, Grunder O, Wang D. Modeling and solving simultaneous delivery and pick-up problem with stochastic travel and service times in home health care. *Expert Syst Appl.* 2018;102:218-33.
- Shi Y, Boudouh T, Grunder O. A robust optimization for a home health care routing and scheduling problem with consideration of uncertain travel and service times. *Transp Res Part E Logist Transp Rev.* 2019;128:52-95.
- Grenouilleau F, Legrain A, Lahrichi N, Rousseau LM. A set partitioning heuristic for the home health care routing and scheduling problem. *Eur J Oper Res.* 2019;275(1):295-303.
- Shi Y, Boudouh T, Grunder O. A hybrid genetic algorithm for a home health care routing problem with time window and fuzzy demand. *Expert Syst Appl.* 2017;72:160-76.
- Li Y, Xiang T, Szeto WY. Home health care routing and scheduling problem with the consideration of outpatient services. *Transp Res Part E Logist Transp Rev.* 2021;152:102420.
- Erdem M, Koç Ç, Yücel E. The electric home health care routing and scheduling problem with time windows and fast chargers. *Comput Ind Eng.* 2022;172:108580.
- Zhang T, Liu Y, Yang X, Chen J, Huang J. Home health care routing and scheduling in densely populated communities considering complex human behaviours. *Comput Ind Eng.* 2023;182:109332.

Du J, Wang X. A branch-and-price-and-cut algorithm for the home health care routing and scheduling problem with multiple prioritized time windows. *Comput Oper Res.* 2024;170:106749.

Bazirha M, Kadrani A, Benmansour R. Stochastic home health care routing and scheduling problem with multiple synchronized services. *Ann Oper Res.* 2023;320(2):573-601.

de Aguiar AR, Ramos TR, Gomes MI. Home care routing and scheduling problem with teams' synchronization. *Socioecon Plann Sci.* 2023;86:101503.

Sharifnia SM, Bagheri F, Kobza JE, Sawhney R, Macias De Anda E, Hajiaghahi-Keshteli M, et al. Decision support framework for home healthcaregiver allocation: a case study of HHC agency in Tennessee, USA. 2024;5(2):100339.

Huang Y, Xu T, Yang Q, Pan C, Zhan L, Chen H, et al. Demand prediction of medical services in home and community-based services for older adults in China using machine learning. *Front Public Health.* 2023;11:1142794.

Windle N, Alam A, Patel H, Street JM, Lathwood M, Farrington T, et al. Predicting hospitalization risk among home care residents in the United Kingdom: development and validation of a machine learning-based predictive model. *Home Health Care Manag Pract.* 2024;36(4):253-61.

Feng H, Jia Y, Huang T, Zhou S, Chen H. An adaptive decision support system for outpatient appointment scheduling with heterogeneous service times. *Sci Rep.* 2024;14(1):27731.

Du G, Liang X, Sun C. Scheduling optimization of home health care service considering patients' priorities and time windows. *Sustainability.* 2017;9(2):253.

Nikzad E, Bashiri M, Abbasi B. A matheuristic algorithm for stochastic home health care planning. *Eur J Oper Res.* 2021;288(3):753-74.

Cappanera P, Scutellà MG. Addressing consistency and demand uncertainty in the home care planning problem. *Flex Serv Manuf J.* 2022;34(1):1-39.

Ala A, Chen F. Appointment scheduling problem in complexity systems of the healthcare services: a comprehensive review. *J Healthc Eng.* 2022;2022:5819813.

Han Y, Johnson ME, Shan X, Khasawneh M. A multi-appointment patient scheduling system with machine learning and optimization. *Decis Anal J.* 2024;10:100392.

Xiao C, Choi E, Sun J. Opportunities and challenges in developing deep learning models using electronic health records data: a systematic review. *J Am Med Inform Assoc.* 2018;25(10):1419-28.

Menteş N, Çakmak MA, Kurt ME. Estimation of service length with the machine learning algorithms and neural networks for patients who receiving home health care. *Eval Program Plann.* 2023;100:102324.

Rekabi S, Moradi B, Salamian F, Fadavi N, Zokaee M, Aghsami A. A home healthcare routing-scheduling optimization model considering time-balancing and outsourcing. *Supply Chain Anal.* 2024;7:100077.

Ma X, Fu Y, Gao K, Zhang H, Mou J. A knowledge-based multi-objective evolutionary algorithm for solving home health care routing and scheduling problems with multiple centers. *Appl Soft Comput.* 2023;144:110491.

Bazirha M, Benmansour R, Kadrani A. An efficient two-phase heuristic for the home care routing and scheduling problem. *Comput Ind Eng.* 2023;181:109329.

Durak Z, Mutlu O. Home health care nurse routing and scheduling problem considering ergonomic risk factors. *Heliyon.* 2024;10(1):e23864.

Bazirha M, Kadrani A, Benmansour R. Pareto and decomposition based approaches for the multi-objective home health care routing and scheduling problem with lunch breaks. *Eng Appl Artif Intell.* 2024;128:107502.

Zhao J, Wang T, Monteiro T. A bi-objective home health care routing and scheduling problem under uncertainty. *Int J Environ Res Public Health.* 2024;21(3):377.

Liu W, Dridi M, Fei H, El Hassani AH. Solving a multi-period home health care routing and scheduling problem using an efficient matheuristic. *Comput Ind Eng.* 2021;162:107721.