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Dynamic ergonomic workload modeling to support workforce-aware scheduling in home health care services

Zehra Durak
pamukkale university
Elif Danisman
elif.danisman@idu.edu.tr

Izmir Democracy University
Ozcan Mutlu
pamukkale university

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Abstract

Background

Home health care (HHC) services are expanding rapidly as health systems respond to population ageing, increasing prevalence of chronic conditions, and efforts to shift care delivery from hospitals to community settings. While these services improve accessibility and patient satisfaction, they also introduce significant workforce planning challenges. In particular, nurses providing home-based care often work in highly variable environments that can influence both physical and psychosocial workload. Despite these realities, most existing scheduling approaches in home health care focus primarily on operational efficiency indicators such as travel time, service duration, or cost. As a result, ergonomic and contextual factors that shape nurses' workload are rarely considered in planning decisions, potentially leading to schedules that are operationally efficient but uneven in terms of staff workload and well-being.

Methods

This study develops a decision-support framework designed to incorporate ergonomic workload considerations into home health care scheduling. First, nurses' perceived workload following patient visits is captured through a structured post-task assessment that evaluates multiple categories of stressors encountered during care delivery. These assessments are converted into quantitative workload scores using a fuzzy inference system that accommodates the subjective and linguistic nature of workload perceptions. To account for temporal variability in workload exposure, a multi-state Markov modeling approach is then used to estimate transitions between different workload states across consecutive visits. The resulting workload estimates are incorporated into a goal programming–based scheduling model that simultaneously considers patient demand satisfaction and equitable distribution of workload among nurses.

Results

Computational experiments were conducted using simulated home care scenarios of varying sizes to explore how the integration of dynamic workload information influences scheduling decisions. The results indicate that incorporating ergonomic workload estimates enables more balanced allocation of tasks across nurses while maintaining acceptable levels of service coverage. By adjusting workload limits and objective weights, decision makers can explicitly manage trade-offs between maximizing the number of completed visits and limiting excessive workload exposure for individual staff members.

Conclusions

Integrating dynamic ergonomic workload information into scheduling decisions provides a more comprehensive approach to workforce planning in home health care services. The proposed framework demonstrates how operational planning models can incorporate contextual and human-centered workload factors alongside traditional efficiency objectives. Such approaches may help health care organizations design more sustainable service delivery systems that protect workforce well-being while continuing to meet growing patient demand.

1. Introduction

The rapid expansion of home health care (HHC) services, driven by population aging, increasing prevalence of chronic conditions, and health system cost-containment pressures, has intensified the challenge of balancing growing patient demand with the sustainability of the nursing workforce. As an alternative to traditional hospitalization, HHC improves patient satisfaction and reduces costs by delivering care within patients' homes (Rodriguez-Verjan et al., 2018; Moscato et al., 2021). However, the decentralized and heterogeneous nature of home-based care creates operational and workforce-related complexities that differ substantially from institutional settings and therefore require adaptation of planning approaches and workforce management strategies.

HHC systems involve interrelated decision problems concerning service design, allocation, and daily routing (Grieco et al., 2021). A substantial body of research has focused on the Home Health Care Routing and Scheduling Problem (HHCRSP), primarily aiming to minimize travel time, distance, or operational cost while satisfying patient demand (Gutiérrez and Vidal, 2013; Sahin and Matta, 2015;

Fikar and Hirsch, 2017; Di Mascolo et al., 2021). Although these models have significantly improved operational efficiency, workload is predominantly conceptualized as a function of service duration and travel time. Consequently, ergonomic and psychosocial conditions that shape nurses' perceived workload remain insufficiently integrated into scheduling decisions. Recent contributions continue to expand the scope of HHCRSP formulations by incorporating increasingly diverse operational constraints and multi-objective considerations, reflecting the growing complexity of home care planning environments (Masmoudi et al., 2024).

Beyond these operational considerations, HHC nurses operate in diverse and unpredictable home settings that introduce additional sources of variability. Physical constraints, lack of assistive equipment, transportation demands, and challenging social interactions may increase both physical and mental strain. Moreover, these stressors vary not only across patients but also over time. Changes in patient acuity, household conditions, or nurse–patient familiarity can alter perceived task difficulty from one visit to another. Therefore, workload in HHC cannot be adequately represented through time-based metrics alone. Qualitative evidence has documented that home care professionals are exposed to a wide range of environmental and psychosocial stressors influencing their working conditions (Rydenfält et al., 2023).

From a broader system perspective, sustaining a stable nursing workforce has been identified as a global priority in health system strengthening efforts (World Health Organization, 2020), particularly in the context of persistent workforce shortages and retention challenges. Empirical evidence has consistently shown that high nursing workloads are associated with burnout and job dissatisfaction (Aiken et al., 2002), factors that threaten workforce stability and service continuity. When ergonomic variability is not considered in planning processes, uneven workload distribution may contribute to retention risks and undermine the long-term sustainability of HHC services. While stakeholder perspectives in HHC have been widely discussed (Burgess, 2012), nurses' subjective workload perceptions remain underrepresented in operational planning models. Recent health services research further emphasizes that workload regulation and supportive work conditions play a central role in nurse retention and long-term workforce sustainability (Yamamoto et al., 2024).

Recent research has begun to acknowledge the relevance of ergonomic risk factors in HHC routing and scheduling contexts (Durak & Mutlu, 2024). However, existing approaches largely treat workload as a static measure and do not explicitly model how perceived strain may evolve across consecutive visits. The temporal dynamics of ergonomically induced workload—and their integration into daily scheduling decisions—remain insufficiently explored within current modeling frameworks.

To address this gap, this study proposes an integrated decision-support framework that models ergonomically derived workload as a dynamic and state-dependent process within HHC scheduling. A structured post-task assessment model is introduced to capture nurses' perceived ergonomic strain, which is translated into quantitative workload scores through a fuzzy inference approach. To represent temporal changes in workload conditions, a multi-state Markov model is employed to estimate probabilistic transitions between workload states. These predicted workload states are subsequently embedded within a goal programming–based scheduling model to generate balanced care plans that simultaneously address patient demand and anticipated workload exposure.

By modeling ergonomically induced workload as a dynamic and temporally evolving variable within operational decision-making, the proposed framework advances HHC planning beyond static workload balancing. By integrating ergonomic variability and temporal workload dynamics into scheduling decisions, the proposed framework extends existing approaches to workforce-aware planning in home health care systems.

2. Methods

This study develops an integrated decision-support framework to incorporate ergonomically grounded and temporally evolving workload representations into home health care (HHC) nurse scheduling decisions. Although the Home Health Care Routing and Scheduling Problem (HHCRSP) has been extensively investigated in the operations research literature (Fikar & Hirsch, 2017; Cissé et al., 2017; Di Mascolo et al., 2021), most existing models prioritize operational efficiency measures such as travel time, service duration, overtime, or cost minimization. Workload balancing, when considered, is generally operationalized through simplified proxies such as number of visits, total working time, or travel distance (Alves et al., 2022; Bahadori-Chinibelagh et al., 2019), and rarely reflects the multidimensional ergonomic exposure experienced by home care nurses.

Empirical evidence from occupational health and ergonomics studies indicates that home healthcare professionals are exposed to heterogeneous physical, environmental, postural, and psychosocial stressors that vary across patients and over time (Bien et al., 2020; Suarez et al., 2017; Rydenfält et al., 2023). Unlike institutional healthcare settings, home environments are inherently uncontrolled and

context-specific, leading to workload patterns that are perception-dependent and temporally dynamic. However, this temporal variability and subjectivity are largely absent from existing HHCRSP formulations.

To address this gap, we conceptualize nurse workload not as a static or deterministic parameter but as a multidimensional and state-dependent process that evolves across consecutive visits. The proposed framework integrates four interrelated components:

1. a structured post-task ergonomic assessment instrument capturing nurse-specific perceptions of predefined stressor categories,
2. a Fuzzy Inference System (FIS) that transforms subjective and heterogeneous exposure indicators into a continuous workload score,
3. a multi-state modeling approach to represent temporal transitions between workload states, and
4. a goal programming–based scheduling model that embeds dynamic workload constraints into daily routing and assignment decisions.

The contribution of this study lies in explicitly linking ergonomic perception, temporal workload dynamics, and operational scheduling within a unified modeling structure. By treating workload as an evolving probabilistic process rather than a static constraint, the proposed approach enables scheduling decisions to anticipate cumulative strain and support workforce sustainability alongside patient demand satisfaction. The overall structure of the proposed framework is illustrated in Fig. 1.

The methodological components of the framework are detailed in the following subsections.

2.1. Ergonomic Workload Conceptualization in Home Health Care

Workload balancing has increasingly been recognized as an important objective within the Home Health Care Routing and Scheduling Problem (HHCRSP). According to the comprehensive classification proposed by Di Mascolo et al. (2021), objectives in HHCRSP can broadly be grouped into cost-related criteria and preference-related criteria, where balanced workload is considered a staff-oriented preference. However, despite its acknowledged importance, workload balancing remains relatively underrepresented in the literature and is frequently operationalized through simplified quantitative proxies such as total working time, number of visits, travel duration, or overtime (Alves et al., 2022; Bahadori-Chinibelagh et al., 2019).

Some studies attempt to combine multiple operational components when balancing workload. For instance, Hertz and Lahrichi (2009) simultaneously consider visit load, transaction load, and travel load. Nevertheless, these approaches remain primarily operational in nature and do not explicitly incorporate ergonomic exposure or perception-based strain factors into the workload construct.

Empirical research in occupational health indicates that home healthcare nurses are exposed to a diverse set of physical, environmental, postural, and psychosocial stressors (Bien et al., 2020; Suarez et al., 2017). Unlike hospital environments, home care settings are highly heterogeneous and largely uncontrollable. Nurses may encounter variations in space constraints, temperature, ventilation, lighting conditions, aggressive pets, unsafe hygiene environments, and challenging interactions with patients or relatives. Furthermore, workload perception may vary not only across different patients but also across repeated visits to the same patient due to changes in environmental conditions, patient acuity, or relational dynamics (Rydenfält et al., 2023).

Despite this multidimensional and perception-dependent structure, existing HHCRSP models largely treat workload as static, deterministic, and nurse-independent. Such simplifications limit the ability of scheduling models to reflect the true ergonomic burden experienced in practice.

In this study, workload is conceptualized as a multidimensional construct arising from four categories of stressors: (i) physical job demand, (ii) environmental stressors, (iii) body motion and postural strain, and (iv) mental job demand. These categories are derived from ergonomic literature and adapted to the home care context. The specific ergonomic stressors considered under each category are presented in Table 1.

Table 1
The ergonomic stressors

Physical job demand stressors (S1)	**P1: activities such as lifting or turning the patient**
	P2: carrying service-specific equipment/materials
Environmental stressors (S2)	E1: humidity and temperature
	E2: noise
	E3: lighting conditions
	E4: pet behavior
	E5: chemical risks
	E6: poor air quality (insufficient ventilation, bad smells, cigarette smoke, etc.)
	E7: unhygienic conditions
Body motion and postural stressors (S3)	B1: activities such as walking for a long time, using stairs, etc.
	B2: activities such as bending, squatting, standing, etc.
Mental job demand stressors (S4)	M1: making critical decisions
	M2: activities such as thinking, remembering, and searching
	M3: informing the patient and/or the patient's relatives
	M4: difficult patient behaviors
	M5: negative behaviors of the patient's relatives
	M6: adverse traffic conditions

Rather than relying on physiological measurements—which are impractical in mobile care settings—we adopt a structured post-task subjective assessment approach to capture nurse-specific workload perception following each visit. This conceptualization forms the foundation for the quantitative modeling components described in the subsequent sections.

Durak and Mutlu (2024) proposed an ergonomic workload quantification framework in which post-task assessments were transformed into analytical workload scores and directly incorporated into a mathematical scheduling model. In that study, the most recently observed workload value was assumed to represent the expected workload in subsequent planning periods. While this approach enabled workload-aware scheduling, it did not explicitly model stochastic transitions between workload states over time. The present study advances this framework by introducing a multi-state modeling approach to capture temporal workload evolution and by embedding predicted workload states within a goal programming–based scheduling structure.

2.2. Fuzzy-Based Workload Quantification

The multidimensional and perception-dependent structure of ergonomic workload in home healthcare requires a modeling approach capable of handling linguistic evaluations and subjective judgments. Since nurses evaluate stressors in qualitative terms such as “low,” “moderate,” or “high,” deterministic aggregation methods are insufficient to capture the inherent ambiguity of perception-based assessments. Fuzzy set theory, introduced by Zadeh (1965), provides a suitable mathematical framework for modeling imprecise and linguistically expressed information in complex human-centered systems.

Fuzzy-based workload assessment has been applied in various ergonomic contexts. (Chen et al., 1994; Liou and Wang, 1994; Jung, 1998; Jung, 2000) developed fuzzy approaches to integrate multiple stress factors into composite workload indices. Jung and Jung (2001) further proposed an overall workload assessment technique incorporating multiple ergonomic dimensions. While fuzzy logic has also been used in HHCRSP studies to model uncertainties related to demand, travel time, or service duration (Shi et al., 2017; Tohidifard et al., 2018; Fathollahi-Fard et al., 2020), its application for modeling ergonomic workload perception within scheduling decisions remains limited.

In this study, a Fuzzy Inference System (FIS) is developed to transform post-task questionnaire responses into a continuous workload score ranging between 0 and 100. Following each patient visit, nurses evaluate predefined ergonomic stressors using a structured

questionnaire. Each stressor is rated using linguistic levels, which are converted into numerical scores and aggregated within four stressor categories defined in Section 2.1.

During the fuzzification stage, aggregated stressor scores are mapped onto linguistic terms using triangular membership functions. The inference mechanism is based on the Mamdani approach (Mamdani and Assilian, 1975), where a set of expert-defined IF–THEN rules capture the combined effects of physical, environmental, postural, and mental stressors on overall workload. The complete rule base, developed in consultation with domain experts in home health care operations, is provided in Appendix A. In the final stage, the defuzzification process employs the center-of-gravity method to generate a crisp workload score.

The overall structure of the developed FIS is presented in Fig. 2.

The resulting output represents the observed workload level associated with a specific nurse–patient visit. These observed workload scores serve as the quantitative basis for modeling temporal workload transitions in the subsequent subsection.

2.3. Multi-State Modeling of Temporal Workload Dynamics

While the FIS provides a quantified workload score for each completed nurse–patient visit, operational scheduling decisions require an estimation of workload levels expected in future visits. In home healthcare settings, workload perception is inherently dynamic. Environmental conditions, patient acuity, relational factors, and contextual stressors may evolve over time, leading to variability in perceived strain across consecutive visits to the same patient.

To represent this temporal variability, a multi-state modeling approach based on the Markov assumption is adopted. Multi-state models describe systems that evolve through a finite number of discrete states, where the probability of transitioning to a future state depends on the current state (Jackson, 2011). Such models have been widely applied in healthcare research to represent progressive or fluctuating processes under uncertainty (Sato and Zouain, 2010; Uhry et al., 2010; Xiong et al., 2021). In contrast to deterministic forecasting methods, multi-state models provide a probabilistic structure for capturing transitions between levels of a variable over time.

In the proposed framework, continuous workload scores obtained from the FIS are categorized into five discrete workload states: very low (0–19), low (20–39), normal (40–59), high (60–79), and very high (80–100). For each nurse–patient pair, historical workload observations are used to estimate transition probabilities between these states. The resulting transition probability matrix defines the likelihood of moving from one workload state to another in the subsequent visit.

Based on the estimated transition probabilities, the most probable next workload state is identified, and the midpoint of the corresponding workload interval is used as the expected workload value for the next planning period. In this manner, future workload is treated as a probabilistic state-dependent variable rather than a fixed continuation of the most recent observation.

Durak and Mutlu (2024) incorporated observed workload values directly into a scheduling model by assuming that the most recently observed workload level represents the expected workload in subsequent planning periods. While this assumption enabled workload-aware scheduling, it did not explicitly model probabilistic transitions between workload states. The present study extends this approach by explicitly incorporating state-transition dynamics, thereby allowing the scheduling model to account for potential workload escalation or reduction across consecutive visits.

By modeling workload evolution as a probabilistic state-transition process, the proposed framework captures temporal uncertainty and cumulative strain patterns that are otherwise neglected in static formulations. The estimated workload values derived from the multi-state model are subsequently embedded within the goal programming scheduling structure described in the next subsection.

2.4. Goal Programming Scheduling Model

Home Health Care Routing and Scheduling Problems involve multiple and often competing objectives, including service efficiency and equitable workload distribution. In addition to standard operational constraints such as time windows, skill compatibility, and working time limits, the proposed model incorporates dynamically estimated ergonomic workload into daily assignment and routing decisions.

To balance these objectives, a weighted goal programming (GP) formulation is employed. This approach enables the simultaneous regulation of daily workload exposure and fulfillment of patient demand through adjustable priority weights.

The scheduling problem is defined for a set of nurses with heterogeneous skill levels who depart from the HHC center, perform their assigned visits within an eight-hour shift, and return to the center without overtime. Each nurse is required to take a one-hour lunch break within a predefined time interval, and this break may include travel time.

Time windows are treated as strict constraints: early arrivals result in waiting, whereas late arrivals are not permitted. Each patient can be visited at most once, and nurse–patient skill compatibility must be satisfied. Service times are deterministic and known in advance, and travel times are assumed to be proportional to distances. The number of nurses is fixed, and no explicit patient or nurse preference structures are considered. Workload values may vary across nurse–patient pairs, reflecting the ergonomic variability captured through the proposed assessment and dynamic workload modeling framework.

Let $x_{i,j,s}$ denote the routing decision variable indicating whether nurse *s* travels from node *i* to node *j*. Arrival time and waiting time variables are defined to ensure time feasibility. The workload parameter $wl_{i,s}$ represents the dynamically estimated workload associated with nurse

s serving patient *i*, as derived from the multi-state modeling framework described in Section 2.3.

The weighted goal programming objective function minimizes the normalized deviations associated with workload regulation and patient coverage:

$$Minw_1\left(\frac{\sum_{s=1}^{m} dwl_s^+}{f_1}\right)+w_2\left(\frac{drv^-}{f_2}\right)$$

Workload regulation is enforced through a goal constraint linking the total assigned workload of each nurse with the predetermined maximum daily workload threshold *Max_load.* Additional constraints ensure routing flow conservation, departure and return to the HHC center, lunch break allocation within the specified interval, time window compliance through Big-M propagation logic, maximum daily working time (540 minutes), and appropriate binary and non-negativity conditions.

The complete mathematical formulation, including all sets, indices, parameters, decision variables, and constraints, is presented in Appendix B. The routing structure remains consistent with standard HHCRSP formulations; the contribution of the proposed model lies in embedding dynamically estimated workload parameters within the goal programming framework to enable workload-aware scheduling decisions without altering the fundamental routing architecture.

3. Computational results and discussion

This section evaluates the operational implications of integrating dynamically estimated ergonomic workload into home health care scheduling. The computational experiments are designed to analyze how the proposed framework manages trade-offs between workload regulation and patient demand satisfaction under varying workload limits and policy weight configurations. The results illustrate how dynamic workload modeling influences assignment decisions compared to purely time-based planning approaches.

3.1. Experimental Design

Due to the absence of standardized benchmark datasets in the HHCRSP literature, stemming from variations in modeling assumptions and objectives, problem-specific test instances were generated following established practices in the field (Di Mascolo et al., 2021).

Three problem sizes were considered: 20 patients with 3 nurses (20×3), 25 patients with 4 nurses (25×4), and 30 patients with 5 nurses (30×5). The smallest instance is presented in Table 2 to illustrate the structure of the data.

Patient coordinates were randomly generated within the range [0,100], and the HHC center was positioned at (50,50). Distances were computed using Euclidean metrics, assuming proportionality between travel distance and travel time. Service times were generated between 1 and 30 minutes. The planning horizon spans 540 minutes (8:00 AM–5:00 PM), and patient time windows were defined within this interval. A mandatory one-hour lunch break was scheduled within [180,360] minutes.

Skill compatibility between nurses and patients was represented using binary parameters. Estimated workload values for the next visit were obtained by processing simulated post-task questionnaire data through the FIS and subsequently applying the developed multi-state modeling framework.

All instances were solved using CPLEX 12.2.0.0 within the GAMS 23.5.1 environment.

3.2. Results and Policy Trade-Off Analysis

Table 3 presents computational results under different maximum workload thresholds (100, 150, and 200 units) and varying objective weight combinations. For each problem size, multiple configurations of workload weight w_1 and demand weight w_2 were examined to analyze trade-offs between ergonomic workload regulation and service coverage.

The final two columns of Table 3 report deviations from the workload and demand targets. These deviations quantify the compromise between limiting nurse workload exposure and maximizing the number of completed visits.

For example, in the 20×3 instance with a maximum workload limit of 100 units and weights w_1 = 0.3 and w_2 = 0.7, the model results in a positive workload deviation of 20 units and 6 unmet patient visits. As the allowable workload threshold increases (e.g., to 150 or 200 units), workload deviations decrease and demand satisfaction improves.

Across all tested scenarios, larger instances (e.g., 30×5) exhibit greater flexibility in balancing objectives. Increased staffing capacity allows the system to better absorb workload variability while maintaining higher service coverage levels. These results highlight the sensitivity of scheduling outcomes to both workload thresholds and objective weight configurations.

3.3. Managerial Implications for Workforce Sustainability

The computational findings demonstrate that incorporating dynamic ergonomic workload into scheduling decisions provides a structured mechanism for managing workforce-related trade-offs. Rather than implicitly prioritizing full demand coverage at the expense of nurse exposure, the proposed framework allows decision makers to explicitly regulate acceptable workload levels.

By adjusting the workload threshold (Max_load) and objective weights, managers can determine whether short-term service maximization or long-term workforce protection should be prioritized. Under stricter workload limits, some reduction in service coverage may occur; however, this reduction prevents systematic overexposure of specific nurses to excessive strain.

From a sustainability perspective, this flexibility is critical. Integrating dynamically estimated workload values enables more balanced task allocation over time and may support staff retention while mitigating burnout risks in home health care systems. The proposed framework thus functions not only as a routing optimization tool but also as a workforce-aware decision-support mechanism that aligns operational efficiency with long-term workforce stability.

Table 2
The details of the instance with 3 nurses and 20 patients

Patient No	Coordinates of patient homes		Service time (min.)	Time window (min.)		Possession of the necessary skills			Estimated workload value for the next visit		
	X coordinate	Y coordinate		Earliest	Latest	Nurse 1	Nurse 2	Nurse 3	Nurse 1	Nurse 2	Nurse 3
1	21	19	20	0	540	1	1	1	10	10	30
2	83	30	21	0	540	1	1	1	70	50	70
3	19	45	23	0	360	1	1	1	30	50	50
4	43	20	22	120	540	1	1	1	50	90	50
5	27	71	30	0	540	1	0	1	30	-	30
6	21	82	28	0	540	1	1	1	70	90	50
7	53	39	23	0	540	1	1	1	10	50	30
8	89	71	28	0	540	1	1	1	90	90	50
9	77	32	24	0	540	1	1	1	90	50	90
10	94	30	29	0	540	1	1	1	90	10	50
11	84	19	23	0	540	1	1	1	50	30	30
12	89	21	15	0	540	1	1	1	70	70	50
13	9	83	24	0	540	1	1	1	30	70	10
14	98	37	26	0	540	1	1	0	50	50	-
15	21	20	24	0	540	1	1	1	90	10	50
16	19	11	16	0	540	1	1	1	90	50	70
17	37	89	30	0	540	0	1	1	-	90	30
18	23	41	25	0	540	1	1	1	30	70	50
19	24	86	19	0	540	1	1	1	90	50	10
20	88	38	20	0	540	1	1	1	90	10	10

Table 3
Computational results

Problem size	*Max_load*	w_1	w_2	*Z*	f_1	f_2	$\sum_{s=1}^{m} dwl_s^+$	drv^- :
20x3	100	0.3	0.7	0.23	300	20	20	6
		0.4	0.6	0.207	300	20	20	6
		0.5	0.5	0.175	300	20	0	7
		0.6	0.4	0.14	300	20	0	7
		0.7	0.3	0.105	300	20	0	7
	150	0.3	0.7	0.113	450	20	170	0
		0.4	0.6	0.108	450	20	20	3
		0.5	0.5	0.097	450	20	20	3
		0.6	0.4	0.08	450	20	0	4
		0.7	0.3	0.06	450	20	0	4
	200	0.3	0.7	0.01	600	20	20	0
		0.4	0.6	0.013	600	20	20	0
		0.5	0.5	0.017	600	20	20	0
		0.6	0.4	0.02	600	20	20	0
		0.7	0.3	0.015	600	20	0	1
25x4	100	0.3	0.7	0.091	400	25	10	3
		0.4	0.6	0.082	400	25	10	3
		0.5	0.5	0.072	400	25	10	3
		0.6	0.4	0.063	400	25	10	3
		0.7	0.3	0.048	400	25	0	4
	150	0.3	0.7	0.005	600	25	10	0
		0.4	0.6	0.007	600	25	10	0
		0.5	0.5	0.008	600	25	10	0
		0.6	0.4	0.01	600	25	10	0
		0.7	0.3	0.012	600	25	10	0
	200	0.3	0.7	0.004	800	25	10	0
		0.4	0.6	0	800	25	0	0
		0.5	0.5	0	800	25	0	0
		0.6	0.4	0	800	25	0	0
		0.7	0.3	0	800	25	0	0
30x5	100	0.3	0.7	0.071	500	30	40	2
		0.4	0.6	0.068	500	30	10	3
		0.5	0.5	0.060	500	30	10	3
		0.6	0.4	0.052	500	30	10	3

Problem size	*Max_load*	w_1	w_2	Z	f_1	f_2	$\sum_{s=1}^{m} dwl_s^+$	drv^- :
		0.7	0.3	0.040	500	30	0	4
	150	0.3	0.7	0.004	750	30	10	0
		0.4	0.6	0.01	750	30	20	0
		0.5	0.5	0.013	750	30	20	0
		0.6	0.4	0.013	750	30	0	1
		0.7	0.3	0.01	750	30	0	1
	200	0.3	0.7	0	1000	30	0	0
		0.4	0.6	0.02	1000	30	0	1
		0.5	0.5	0	1000	30	0	0
		0.6	0.4	0	1000	30	0	0
		0.7	0.3	0.01	1000	30	0	1

4. Conclusion

Home health care (HHC) has emerged as a rapidly expanding alternative to conventional hospitalization, increasing the operational complexity of workforce planning in decentralized care environments. Given the physically and psychosocially demanding conditions faced by HHC nurses, incorporating ergonomic considerations into scheduling decisions is essential for sustaining workforce stability and service quality.

This study proposed an integrated decision-support framework that models and embeds dynamic ergonomic workload into home health care routing and scheduling. Unlike conventional HHCRSP formulations that approximate workload using time-based proxies, the proposed approach quantifies perceived ergonomic strain through a structured post-task assessment and a fuzzy inference system. Temporal variability in workload is subsequently modeled through a multi-state framework, enabling the estimation of future workload exposure for each nurse–patient pair. These dynamically estimated workload values are then incorporated into a goal programming–based scheduling model to generate balanced and policy-sensitive work plans.

The computational results demonstrate that integrating dynamic workload estimates alters scheduling trade-offs between service coverage and workload regulation. By adjusting workload thresholds and objective weights, decision makers can explicitly manage the balance between short-term demand satisfaction and long-term workforce protection. This structured flexibility supports more sustainable allocation policies and reduces the risk of systematic nurse overexposure.

From a managerial perspective, the proposed framework extends traditional efficiency-driven routing models toward workforce-aware planning. Overall, the study illustrates how ergonomic workload dynamics can be incorporated into home health care scheduling to support more workforce-aware planning approaches.

Future research may explore validation using real-world datasets, integration of travel time uncertainty, and longitudinal assessment of cumulative workload exposure.

Declarations

Ethics Statement

This study is based on simulated data and does not involve human participants or real patient information. Therefore, ethical approval was not required.

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Conflict of Interest

The authors declare no conflict of interest.

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Figures

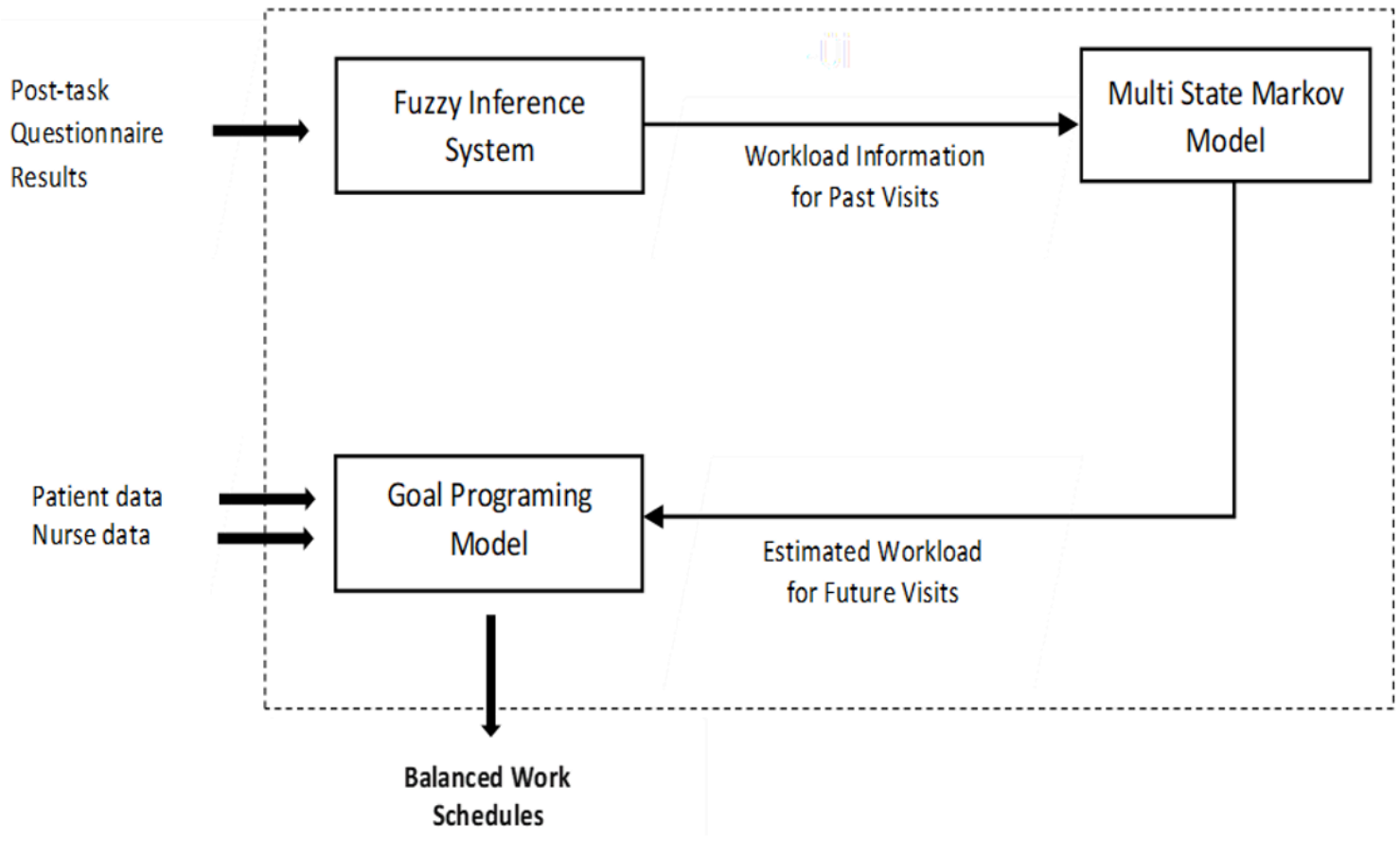


Figure 1

Conceptual architecture of the proposed workload-aware scheduling framework

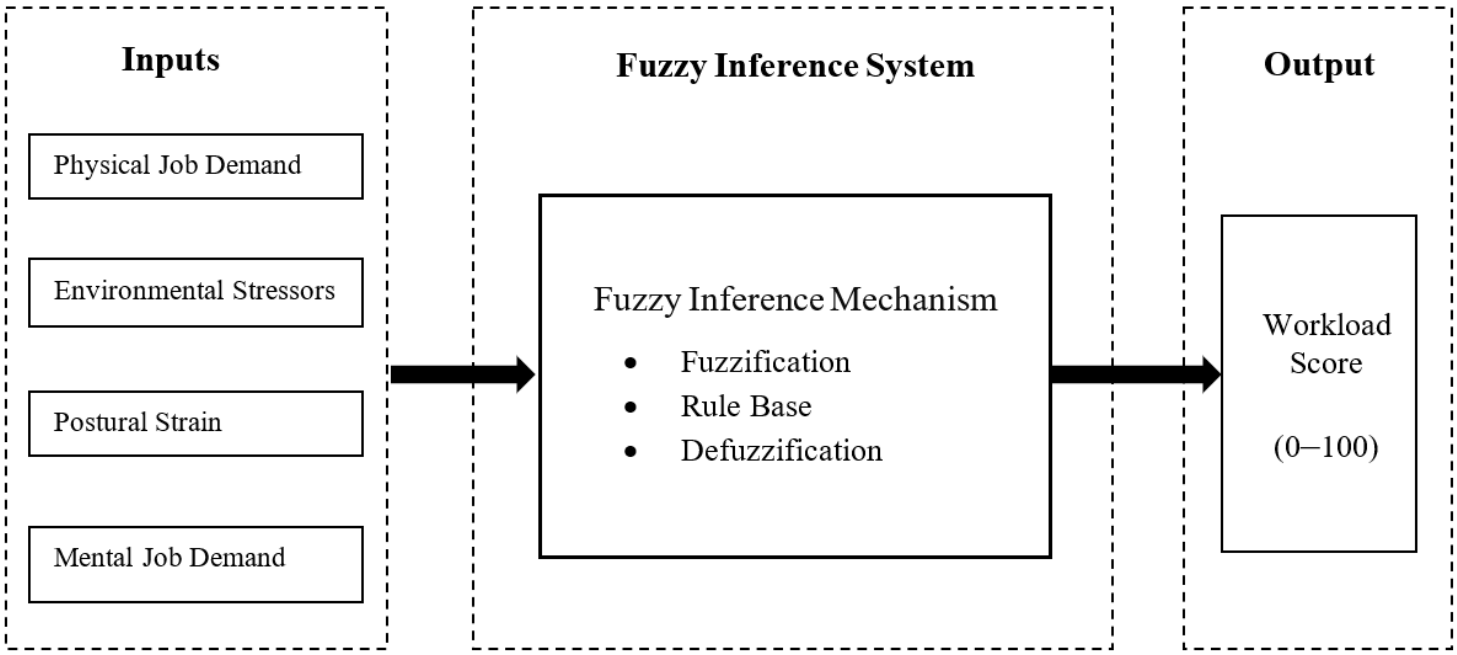


Figure 2

Structure of the proposed fuzzy inference system

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