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SURVEY

Optimization Techniques for Physician Scheduling Problem: A Systematic Review of Recent Advancements and Future Directions

NORIZAL ABDULLAH[1], MASRI AYOB[1], MENG CHUN LAM[2], NASSER R. SABAR[3], GRAHAM KENDALL[4,5], AND MOHAMAD KHAIRULAMIRIN MD RAZALI[6]

[1]Data Mining and Optimization Laboratory, Center for Artificial Intelligence Technology (CAIT), Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia (UKM), Bangi, Selangor 43600, Malaysia
[2]Mixed Reality and Pervasive Computing Laboratory, Center for Artificial Intelligence Technology (CAIT), Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia (UKM), Bangi, Selangor 43600, Malaysia
[3]Department of Computer Science and Information Technology, La Trobe University, Melbourne, VIC 3086, Australia
[4]School of Engineering and Computing, MILA University, Nilai, Negeri Sembilan 71800, Malaysia
[5]School of Computer Science, University of Nottingham, University Park, NG7 2RD Nottingham, U.K.
[6]Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia (UKM), Bangi, Selangor 43600, Malaysia

Corresponding author: Masri Ayob (masri@ukm.edu.my)

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ABSTRACT The Physician Scheduling Problem (PSP) has emerged as a critical challenge in healthcare management, directly relevant to Sustainable Development Goal 3 (SDG 3) - Good Health and Well-being. Driven by physician shortages, rising operational costs, and the need for efficient workforce planning, PSP affects the quality of patient care, staff satisfaction, and the overall efficiency of the healthcare system. While previous reviews have addressed PSP, they are lacking in a comprehensive analysis of recent optimization methodologies and their effectiveness. This work aims to bridge this gap by analyzing 60 research studies which addressed PSP, published between January 2014 and June 2024. Our study also extends the problem definition, constraints, evaluation functions, and the variants of PSP. We examine a wide range of optimization methodologies, including mathematical programming, heuristics, matheuristics, and machine learning, highlighting their strengths and limitations in addressing the multifaceted nature of PSP. This review also analyzes the datasets used in PSP research, noting the lack of standardized benchmarks. Key findings reveal the prevalence of mathematical optimization methods, the growing importance of multi-objective optimization and robustness, as well as the potential of machine learning and data-driven approaches. Future research directions are outlined, emphasizing the need for more scalable algorithms, real-time scheduling capabilities, improved user interfaces, and comprehensive validation studies. This review contributes to the advancement of PSP optimization, aiming to enhance healthcare workforce management, improve patient care, and ultimately address the pressing challenges faced by healthcare systems worldwide, thus supporting the achievement of SDG 3 and promoting universal health coverage.

INDEX TERMS Physician scheduling, personnel scheduling, systematic literature review, combinatorial optimization, operational research, sustainable development goals.

I. INTRODUCTION

The achievement of Sustainable Development Goal 3 (SDG 3) requires substantial additional healthcare investment by 2030, estimated between $274 billion and $371 billion annually [1]. The Physician Scheduling Problem (PSP) has emerged as an important element in healthcare management, significantly impacting patient care quality, staff satisfaction, and operational efficiency [2], [3], [4], [5]. Efficient physician scheduling is crucial in helping achieve the goals of SDG 3 by 2030.

The PSP has gained increasing attention from researchers and practitioners due to its vital role in healthcare operations [6], [7]. The latest review on the PSP by

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Erhard et al. [8] provides valuable insights into related studies up to 2016, covering problem characteristics, modelling approaches, and solution methods. However, rapid developments in healthcare systems, technological advancements, and emerging challenges necessitate an updated and expanded review of the field.

The complexity and multifaceted nature of the PSP necessitates optimization methodologies to produce high-quality solutions in reasonable computational times. These methodologies can consider multiple objectives and constraints, potentially leading to more balanced and efficient schedules [9], [10], [11]. Methodologies such as linear programming, integer programming, and metaheuristics, have shown promise in tackling complex scheduling problems across various domains [12], [13], [14]. Applied to healthcare, these approaches could help hospitals achieve better staff utilization, improve work-life balance for physicians, and ultimately enhance patient care quality [15], [16]. However, despite their potential, the application of these methodologies to PSP remains underexplored compared to other healthcare scheduling problems, such as the Nurse Scheduling Problem (NSP) [17].

Our study extends the work of Erhard et al. [8] to present an up-to-date analysis of PSP methodologies. Unlike previous reviews, which have primarily focused on other personnel scheduling problems in healthcare, this study specifically examines PSP. We expand upon earlier work by analyzing a wide range of methodologies, including mathematical programming, heuristics, matheuristics, and machine learning. Additionally, we provide new insights into:

i. The evolution of PSP definitions and variants since 2016.
ii. The current state of datasets used in PSP research, highlighting the lack of standardized benchmarks.
iii. Recent advancements in multi-objective optimization and robustness considerations for PSP.
iv. The emerging role of machine learning and data-driven approaches in PSP.

This review extends the problem definition, constraints, evaluation functions, and variants of PSP. By focusing on these elements, this review aims to bridge the gap between theoretical advancements and practical implementation, ultimately contributing to the enhancement of healthcare workforce management and thus contributing to SDG 3.

This is the first comprehensive systematic literature review focusing on optimization methodologies for PSP, analyzing 60 research studies from January 2014 to June 2024. It differs from the work of Ngoo et al. [17] on NSP and builds upon the foundation laid by Erhard et al. [8] for PSP. The key distinctions lie in our specific focus on PSP, the extended time frame considered, and the analysis of recent optimization methodologies.

The primary research question we address is: What are the current trends, effectiveness, and gaps in optimization methodologies applied to the PSP from 2014 to 2024, and how can these insights guide future research to address challenges in healthcare workforce management?

TABLE 1. The search terms and Boolean operators for paper selection in this review.

No	Searching terms
1	“Physician scheduling” OR “Physician rostering”
2	“Doctor scheduling” OR “Doctor rostering”
3	“Medical staff scheduling” OR “Medical staff rostering”
4	“Anaesthetist scheduling” OR “Anaesthetist rostering”
5	“Anesthetist scheduling” OR “Anesthetist rostering”
6	“Optimization” OR “Optimisation”
7	“Algorithm” OR “Heuristic”
8	“Metaheuristic” OR “Hyper-heuristics”
9	“Exact” OR “Matheuristics”
10	“Mathematical programming” or “Mathematical model”
11	(1 OR 2 OR 3 OR 4 OR 5) AND 6
12	(1 OR 2 OR 3 OR 4 OR 5) AND 7
13	(1 OR 2 OR 3 OR 4 OR 5) AND 8
14	(1 OR 2 OR 3 OR 4 OR 5) AND 9
15	(1 OR 2 OR 3 OR 4 OR 5) AND 10

This main research question encapsulates the essence of the following seven sub-questions (RQs):
RQ1: How is PSP defined in the literature?
RQ2: What datasets have been used for the PSP?
RQ3: What are the problem constraints and evaluation functions of the PSP?
RQ4: What are the problem variants of the PSP?
RQ5: What optimization methodologies have been applied to the PSP?
RQ6: What are the strengths and weaknesses of current optimization methodologies that have been applied to the PSP?
RQ7: What are the challenges and potential future work of the PSP?

This paper is structured as follows: Section II outlines the research scope and methodology. Section III presents the findings from our systematic literature review. Finally, Section IV concludes the paper with a comprehensive summary.

II. SCOPE AND METHODOLOGY

This systematic literature review follows the guidelines provided by [18], [19], and [20], which offer a basis for identifying the relevant scientific literature. The inclusion and exclusion criteria were established based on [21] and [22], ensuring that only high-quality, pertinent studies were included in our review.

We searched for studies related to the PSP from nine bibliographic databases: i) Scopus, ii) Web of Science, iii) ACM Digital Library, iv) Wiley, v) IEEE Xplore, vi) Springer Link, vii) ScienceDirect, viii) SAGE, and ix) Taylor & Francis. We employed a two-stage process for identifying and evaluating relevant studies.

A. SEARCH TERMS AND BOOLEAN OPERATORS

The search terms applied to each database are presented in Table 1.

TABLE 2. The inclusion and exclusion criteria of this review.

Inclusion	Exclusion
Published between 1st Jan 2014 to 30th Jun 2024	Articles not meeting the inclusion criteria
Written in English	Written in non-English
Available and accessible online	Duplicate articles or inaccessible works
Related to the research questions	Does not relate to the research questions
Is an academic publication	Is an incomplete article
Focused on Physician Scheduling/Rostering Problems in the context of the optimization techniques	Focused on unrelated topics that deviate from the optimization technique in Physician Scheduling/Rostering Problems.
Included empirical results based on a specified research methodology	

We include studies that use the term "rostering", as it is often used interchangeably with scheduling in the literature. We account for both British and American English spellings, such as "anaesthetist" and "anesthetist", as well as "optimisation" and "optimization". To address the intricacy of search queries, we employ a combined approach utilizing problem domain terminology alongside optimization technique keywords.

B. INCLUSION AND EXCLUSION CRITERIA

We refined our initial search results using specific inclusion and exclusion criteria, as detailed in Table 2.

Our primary search, covering the period from January 1, 2014, to June 30, 2024, was strategically chosen for several reasons. First, this timeframe ensures a comprehensive coverage of developments since the last major PSP review by Erhard et al. [8], while providing sufficient overlap to track the evolution of the field. Secondly, our preliminary analysis showed that a shorter period of five years would have yielded only 28 relevant papers, whereas the ten-year span provided 60 papers, allowing for a more robust trend analysis. Additionally, this period encompasses significant technological advances in optimization techniques and computing capabilities, particularly in machine learning and hybrid methodologies, as well as major changes in healthcare delivery models. The search yielded 310 papers across various databases: Scopus (35), Web of Science (32), ACM Digital Library (11), Wiley (20), IEEE Xplore (8), Springer Link (56), ScienceDirect (109), SAGE (9), and Taylor & Francis (30). After removing duplicates and applying our criteria, we selected 60 papers for review, as depicted in Fig. 1.

Figure 2 shows the publication trends from 2014 to 2024. It illustrates fluctuations in research interest and advancements in optimization methodologies for the PSP. Initial interest in 2014 saw three articles, which doubled to six in 2015. However, this interest was not sustained, as evidenced in 2016 and 2017. The peak of ten articles in 2021 could be attributed to the increased focus on healthcare optimization driven by the global pandemic. The overall trend shows a changing research landscape, with peaks and troughs in the number of publications, with no significant upward or downward trend.

TABLE 3. List of publication sources considered for this review.

Publisher	Publication source	Paper Count
Pergamon-Elsevier Science LTD	Omega	5
Taylor & Francis LTD	Journal of the Operational Research Society	4
Elsevier	Operations Research for Health Care	3
Springer	Flexible Services and Manufacturing Journal	3
IEEE-Inst Electrical Electronics Engineers INC	IEEE Transactions journals	2
Taylor & Francis LTD	Health Systems	2
Springer	Annals of Operations Research	2
Pergamon-Elsevier Science LTD	Computers & Industrial Engineering	2
Elsevier	Applied Soft Computing Journal	2
-	Proceedings publications	6
-	Others	29

Table 3 presents the publication sources, encompassing peer-reviewed journals and conference proceedings. This table highlights the diverse array of journals publishing PSP research, reflecting the interdisciplinary nature of the field.

C. ANALYSIS PROCESS

After selecting the relevant papers, we conducted a thorough analysis of each study. This process involved:

i. Extracting key information related to each research question.
ii. Identifying common themes, methodologies, and trends across the studies.
iii. Synthesizing the findings to provide comprehensive answers to each research question.
iv. Critically evaluating the strengths and limitations of various approaches.

The analysis was conducted independently by multiple researchers to ensure objectivity and comprehensiveness. Any discrepancies were resolved through discussion and consensus.

III. FINDINGS AND DISCUSSION

This section presents a synthesis of the data extracted from the selected studies, providing answers to the research questions posed in this study. Figure 3 presents a comprehensive

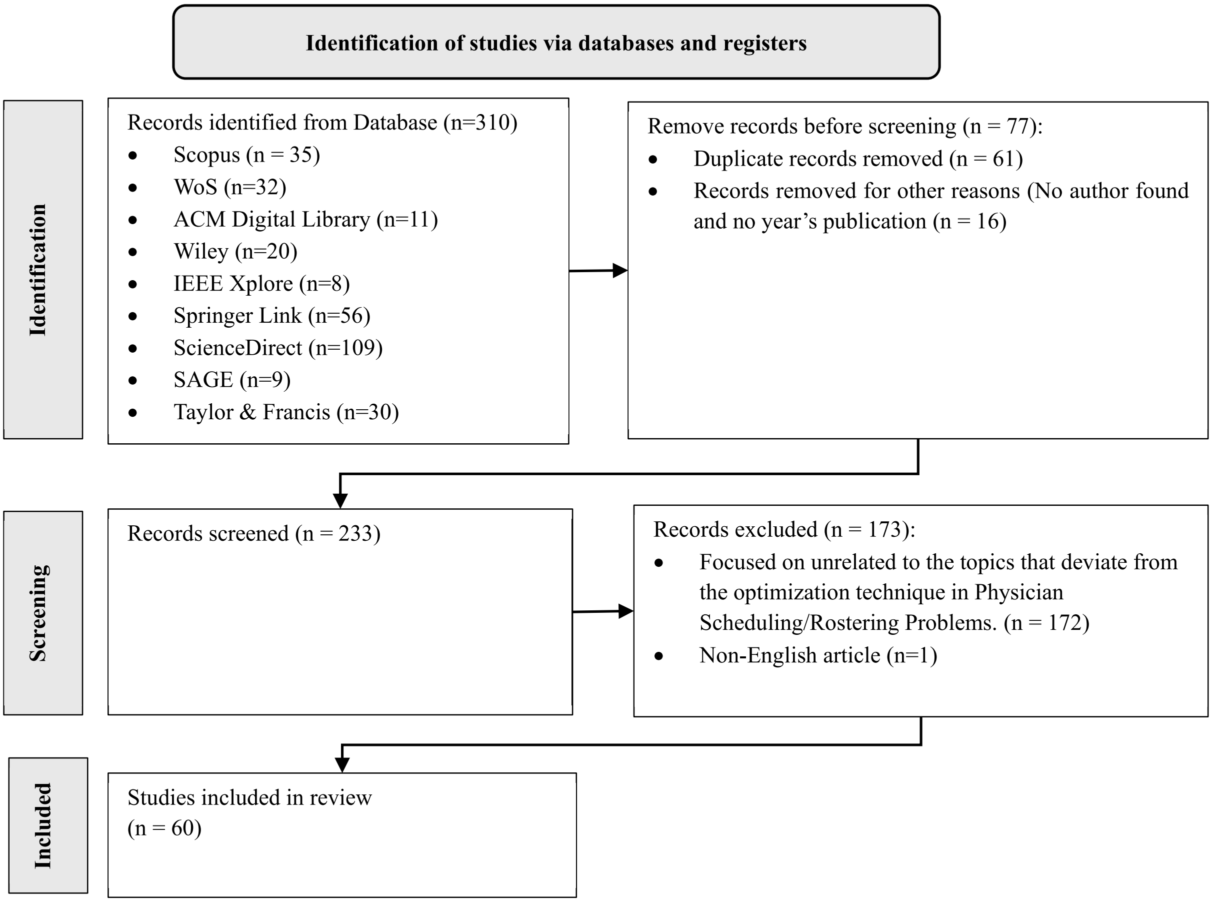

FIGURE 1. Paper selection process.

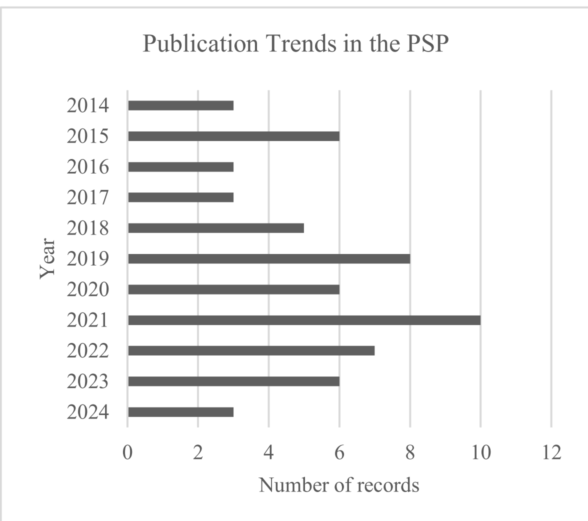

FIGURE 2. Publication trends in the PSP from 2014 to 2024.

taxonomy of the PSP, providing a framework for understanding the subsequent analysis.

A. RQ1: HOW IS PSP DEFINED IN THE LITERATURE?

In the rapidly evolving landscape of healthcare management, efficient resource allocation and workforce scheduling have become critical factors in ensuring high-quality patient care and operational effectiveness. Among the many challenges faced by healthcare institutions, the task of scheduling physicians stands out as particularly complex. This complexity arises from the need to balance multiple, often conflicting, objectives while adhering to a wide array of constraints.

In the scientific literature, the PSP is generally described as a multifaceted optimization problem involving the assignment of physicians to shifts or duties while adhering to diverse constraints and objectives [23], [24], [25], [26], [27]. This complex task incorporates numerous factors, including personnel qualifications, shift types, contractual variations, learning curves, continuous operational hours, uneven workload distribution, and stochastic elements in emergencies and surgeries [8].

Given its combinatorial nature and the multitude of variables involved, the PSP is typically classified as NP-hard (nondeterministic polynomial-time hard), meaning that there are no known efficient algorithms to solve any given instance to optimality [28], [29], [30]. The primary objectives are to create schedules that fulfil service requirements, comply with legal and contractual obligations, and account for physicians' preferences and work-life balance [31], [32], [33].

Since the seminal review by Erhard et al. [8], PSP definitions have evolved to incorporate uncertainty and dynamic

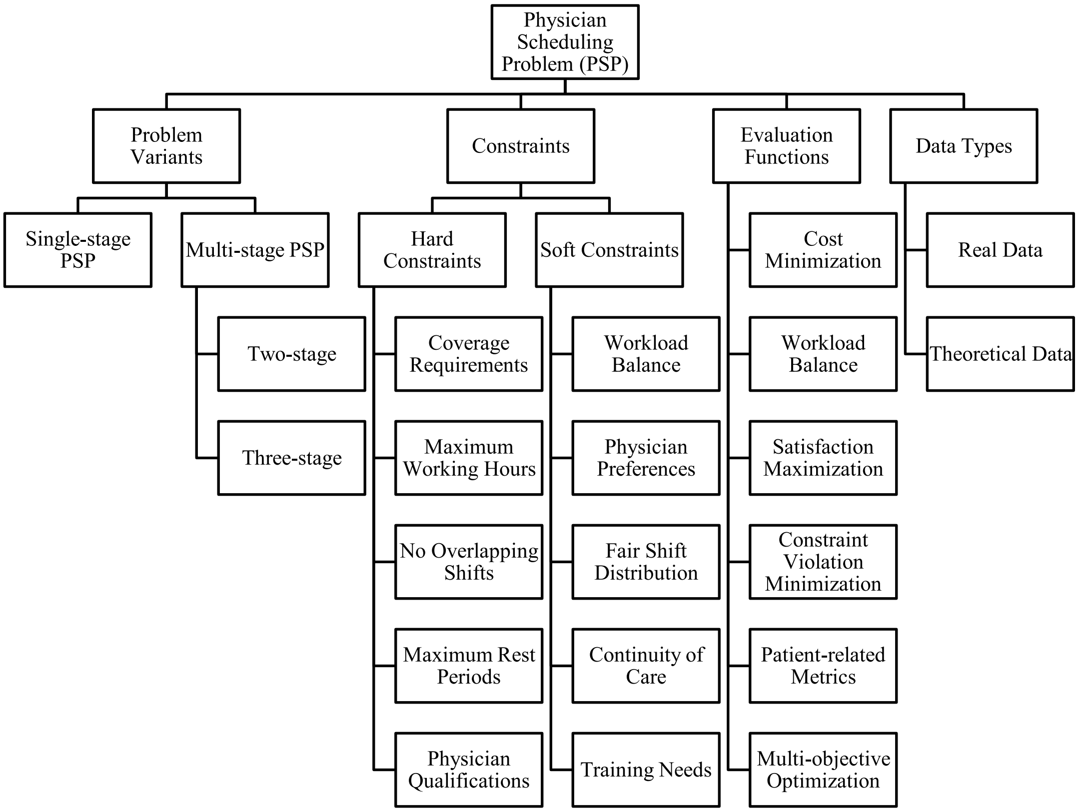

FIGURE 3. Overall taxonomy of PSP.

elements into PSP models, reflecting the increasing complexity of healthcare environments. There is also a growing trend towards integrating PSP with other healthcare scheduling problems, such as operating room scheduling or patient appointment scheduling, to create more holistic optimization models.

B. RQ2: WHAT DATASETS HAVE BEEN USED FOR THE PSP?

Our analysis reveals a predominant use of real-world data in PSP research. However, there is a notable lack of standardized benchmark datasets. Table 4 shows the types of benchmark datasets among the selected studies.

The majority of studies use real data from specific healthcare institutions. However, these datasets are rarely made publicly available, hindering the ability to conduct comparative studies across different optimization approaches. Recent advancements in PSP optimization have increasingly relied on real-world data for benchmarking purposes. Many studies utilize data collected from actual hospital operations, emergency departments, and specialized units. For instance, research has incorporated data from partner hospitals' emergency departments [23], [25], pediatric intensive care units [27], and specialized departments such as endocrinology [34] and anesthesiology [32], [35].

While real-world data is prevalent, some studies employ theoretical or synthesized datasets for benchmarking purposes. These datasets are often created to test specific aspects of scheduling algorithms or to provide a standardized reference point. For example, one study used a theoretical dataset to evaluate an early-stage prototype of an anesthesiologist scheduling framework [29].

TABLE 4. Categorization of benchmark datasets.

Category	Research
Theoretical data	[28, 29, 36, 37]
Real data	[23-25, 27, 30, 32-35, 38-59]

The benchmark datasets used in PSP vary in their characteristics and sources. Many studies collect data over extended periods, ranging from several weeks to multiple years [23], [27], [34], [48]. The datasets often include a wide range of information, such as patient arrivals, physician shifts, workload distribution, and specific constraints related to different medical specialities [38], [44], [45].

This finding highlights a significant gap in PSP research, including the need for standardized and publicly available benchmark datasets that reflect the complexity of real-world scheduling scenarios. The availability of this dataset will allow for reproducible research and fair comparisons of different methodologies.

C. RQ3: WHAT ARE THE PROBLEM CONSTRAINTS AND EVALUATION FUNCTIONS OF THE PSP?

Table 5 lists the common constraints and evaluation functions from the literature, organized in a descending order

TABLE 5. List of hard constraints, soft constraints, and evaluation functions exist in selected studies.

Category	Description	Frequency	References
Hard constraints			
Maximum working hours/shifts.	• No more than 48 hours per week. • Maximum 12-hour shift duration. • At most one shift per 24-hour period. • Weekly quota restrictions	42	[23-26, 28, 30, 33-35, 37-42, 45-52, 54-56, 58-73]
No overlapping shifts.	• Single shift assignment per day. • Clear separation between consecutive shifts. • No concurrent duty assignments.	30	[23-25, 28, 33, 35, 38, 39, 41, 42, 45, 47, 49-52, 55, 56, 60-69, 71, 72]
Minimum rest periods.	• 16 hours minimum between shifts. • 24 hours after night shifts. • Extended rest after consecutive night shifts	28	[23, 24, 28, 30, 33, 35, 39-41, 45, 47-49, 51, 52, 55, 56, 59-67, 69, 71]
Physician qualifications.	• Specialty-specific assignments. • Experience level requirements. • Training/certification matching.	18	[25, 32, 33, 35, 37-39, 42, 44, 45, 50-52, 57, 60, 62, 64, 67]
Labour law compliance.	• National working time directives. • Local healthcare regulations. • Hospital policy requirements.	11	[39, 45, 46, 60, 61, 63, 67, 74-77]
Soft constraints			
Workload balance.	• Equal distribution of shifts. • Fair allocation of night/weekend duties. • Balanced overtime assignments.	28	[33, 35, 36, 39, 40, 45, 47-52, 55, 59-62, 64, 65, 67, 69-71, 73, 74, 78-80]
Physician preferences.	• Preferred shifts/days off. • Location preferences. • Vacation requests.	25	[32, 33, 35, 36, 39, 40, 45, 48, 49, 51, 52, 57, 59-62, 64, 65, 67-69, 73, 74, 76, 77]
Fair shift distribution.	• Equitable weekend assignments. • Balanced holiday coverage. • Even distribution of unpopular shifts.	24	[32, 33, 35, 36, 39, 40, 45, 47-49, 51, 52, 55, 59-62, 64, 65, 67, 69-71, 78]
Continuity of care.	• Minimized patient handoffs. • Consistent physician assignments. • Care team stability.	6	[39, 44, 47, 50, 51, 63]
Physician training needs.	• Educational requirements. • Skill development opportunities. • Training rotation coverage.	6	[32, 50, 51, 70, 72, 78]
Evaluation functions			
Minimize total costs.	• Direct labour costs. • Overtime expenses. • Operational efficiency.	26	[23, 30, 31, 33-35, 37-42, 44-49, 51, 52, 56, 61, 62, 64, 66, 69]
Balance workload.	• Equitable shift distribution. • Fair workload allocation. • Balanced duty assignments.	25	[33, 35, 36, 39, 40, 45, 47-52, 55, 59-62, 64, 65, 67, 69-71, 74, 78]

TABLE 5. ***(Continued.)*** **List of hard constraints, soft constraints, and evaluation functions exist in selected studies.**

Maximize satisfaction and preferences.	• Schedule preference fulfilment. • Work-life balance optimization. • Personal request accommodation.	22	[32, 33, 35, 36, 39, 40, 45, 48, 49, 51, 52, 57, 60-62, 65, 67-69, 71, 74, 77]
Minimize constraint violation.	• Weighted penalty minimization. • Constraint satisfaction optimization. • Quality metric achievement.	20	[32, 35, 36, 39, 40, 45, 47-49, 51, 52, 60-62, 65, 67, 69, 73, 74, 77]
Optimize patient-related metrics.	• Wait time reduction. • Patient flow optimization. • Care quality maximization.	12	[23, 24, 33, 37-41, 53, 54, 66, 81]
Multi-objective optimization.	• Cost-quality trade-offs. • Multiple stakeholder objectives. • Competing priority balancing.	10	[29, 38, 40, 47, 50, 56, 58, 76, 81, 82]

of frequency. Constraints in the PSP can be categorized into two types: hard constraints, which are non-negotiable and must always be adhered to, and soft constraints, which can be violated but incur penalties according to predefined evaluation functions.

PSP involves complex constraints and evaluation functions to create fair and efficient schedules while ensuring high-quality patient care. Hard constraints in the PSP primarily focus on regulatory compliance and operational feasibility. Working hours and shift assignments must adhere to labour laws and hospital policies [23], [24], [25], [26], [28], [30], with clear specifications for rest periods between shifts [33], [38], [39], [40]. Coverage requirements ensure adequate staffing across all periods while matching physician qualifications to specific tasks [25], [32], [33], [35].

Soft constraints reflect institutional preferences and workforce considerations, with workload balance emerging as a critical factor [33], [34], [38], [39]. Modern PSP models increasingly incorporate sophisticated fairness metrics [44], [46], [47], [48], [49], [50], [51], [52] and comprehensive preference systems that consider not just shift preferences but also location and team composition preferences [32], [33], [34], [38], [39].

Quality of care constraints have gained prominence, particularly in specialized units. These include continuity of care requirements [38], [43], [46], patient handoff minimization [49], [50], and specific training requirements for teaching hospitals [32], [49], [50]. Such constraints demonstrate the evolution of PSP beyond simple workforce allocation to comprehensive care delivery optimization.

Evaluation functions have evolved to address multiple competing objectives simultaneously. While traditional cost minimization remains important [23], [30], [31], modern approaches increasingly incorporate service quality metrics [23], [24], [33] and stakeholder satisfaction measures [32], [33], [34], [38]. Multi-objective optimization frameworks [29], [37], [39] enable balanced consideration of institutional efficiency, physician preferences, and patient care quality.

Building upon the foundation established by Erhard et al. [8], we identify several key advancements in PSP optimization. First, the integration of machine learning and data-driven approaches [23], [58] represents a new direction in PSP optimization. Second, the consideration of uncertainty and robustness [29], [56] has become more sophisticated. Third, there is greater emphasis on quality-of-care metrics and patient-centred outcomes [37], [38], [39], [40]. Finally, the emergence of real-time rescheduling capabilities [39], [44], [50] addresses the dynamic nature of modern healthcare environments.

D. RQ4: WHAT ARE THE PROBLEM VARIANTS OF THE PSP?

Our review identified two main variants of PSP: single-stage and multi-stage approaches.

1) SINGLE-STAGE PSP

Single-stage PSP approaches aim to generate complete schedules in one optimization step. These models often use complex mathematical formulations to simultaneously handle multiple constraints and objectives. Key advantages of single-stage PSP include:

i. Ability to consider all constraints and objectives simultaneously [17].
ii. Potential for finding globally optimal solutions [83].
iii. Simpler implementation in terms of workflow [84].

Notable works in single-stage PSP include Cappanera et al. [36] developed a network flow optimization model for emergency department physician rostering, focusing on equity considerations. Gross et al. [51] proposed a mixed-integer linear programming (MILP) model for physician duty and workstation scheduling, incorporating work regulations, qualifications, and preferences. Tohidi et al. [52] addressed the Integrated Physician and Clinic Scheduling

Problem in ambulatory cancer treatment polyclinics using a single-stage multi-objective optimization approach.

2) MULTI-STAGE PSP

Multi-stage approaches decompose the PSP into distinct phases, such as demand forecasting, shift design, and physician assignment. This decomposition offers several advantages:

i. It allows for the use of specialized optimization techniques at each stage [17].
ii. It can reduce computational complexity by breaking down large problems into smaller, more manageable sub-problems [85].
iii. It provides flexibility to adapt different stages to changing circumstances or preferences [86].
iv. It may be more intuitive for healthcare administrators to understand and implement [87].

Examples of multi-stage PSP approaches include Liu et al. [23] showed how their two-stage approach separates the complex emergency department scheduling into more manageable demand prediction and shift assignment phases. Zaerpour et al. [46] demonstrated how breaking down the scheduling process improved computational efficiency in emergency departments. Liu et al. [30] validated the benefits of multi-stage decomposition in their branch-and-price algorithm for fever clinic scheduling.

Compared to the findings of Erhard et al. [8], our review shows an increasing trend towards multi-stage approaches. This shift is likely driven by:

i. The growing complexity of healthcare scheduling environments
ii. The need for more flexible and adaptable solutions
iii. Advancements in optimization techniques that allow for efficient solving of decomposed problems

Additionally, we observed an emerging trend of integrating PSP with other healthcare scheduling problems, such as operating room scheduling or patient appointment scheduling [25], [52], [53], [54], [66], to create more holistic optimization models. This integration often leads to multi-stage formulations that can better capture the interdependencies between different scheduling decisions in healthcare settings.

The choice between single-stage and multi-stage approaches often depends on the specific context of the scheduling problem, the size of the healthcare facility, and the computational resources available. While single-stage models may provide more globally optimal solutions, multi-stage approaches offer greater flexibility and may be more practical for implementation in dynamic healthcare environments.

E. RQ5: WHAT OPTIMIZATION METHODOLOGIES HAVE BEEN APPLIED TO THE PSP?

Our review reveals a diverse range of optimization methodologies applied to the PSP. Figure 4 shows the distribution of optimization methodologies across different categories, whereas Figure 5 presents comprehensive taxonomies of the optimization methodologies. The optimization methodologies are organized into various taxonomies based on different criteria, including the problem type, solution approach, and computational resources.

Based on taxonomies from the literature [5], [17], we categorize PSP optimization approaches into four main groups (Fig. 5): mathematical optimization, heuristics, matheuristics, and machine learning. This classification highlights the relationships between different solution approaches and their variants, providing a framework for understanding the evolution and current state of PSP optimization techniques.

1) MATHEMATICAL OPTIMIZATION METHODS

Mathematical optimization methods have been extensively applied to address PSP in healthcare settings. Mathematical optimization methods in PSP refer to techniques that use formal mathematical programming formulations to find optimal or near-optimal solutions for physician scheduling problems [88]. Mixed-integer programming (MIP) and mixed-integer linear programming (MILP) models are commonly employed to generate optimal schedules while considering various constraints and objectives [17], [88], [89]. These models aim to balance multiple factors such as workload distribution, physician preferences, patient demand, and organizational requirements. For example, a two-stage stochastic program using the L-shaped method was proposed to account for physician preferences in shift scheduling [39], while another study developed a MILP model to minimize the combined cost of patient wait times, handoffs, and physician shifts [38].

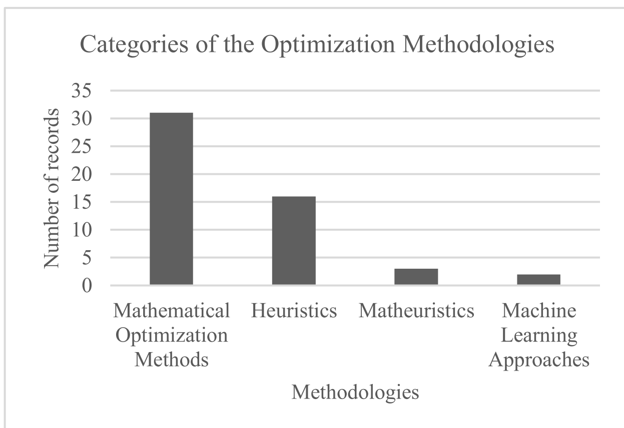

FIGURE 4. Categories of the optimization techniques.

Several studies have focused on improving the computational efficiency of these models. A branch-and-price algorithm was developed to solve a complex staffing model efficiently [30], whereas other research utilized a branch-and-cut solution framework with new valid inequalities to enhance the quality of schedules concerning soft constraints [62]. To address the computational challenges associated with

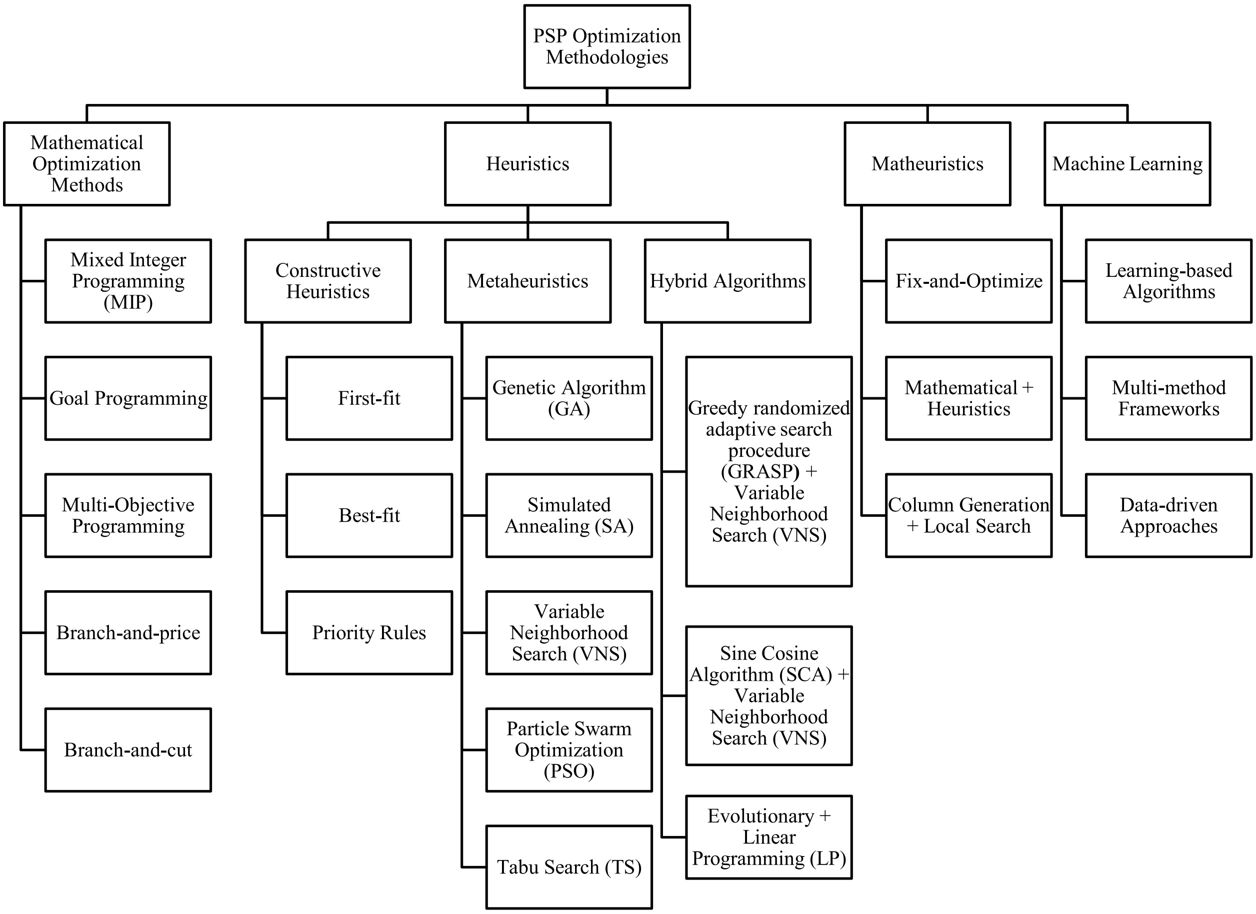

FIGURE 5. The optimization methodologies taxonomy.

larger problem instances, some researchers have proposed decomposition approaches. For example, a Dantzig-Wolfe decomposition and column generation heuristic were employed to solve the PSP more efficiently [45], [72].

The application of goal programming and multi-objective optimization approaches has been observed in several studies. A goal programming model was used to minimize deviations from soft constraints in PSP [69], whereas other research proposed a MIP model to address the PSP [29], [32]. Fairness and equity in PSP have been addressed through various mathematical optimization approaches. A mixed-integer quadratic programming formulation was developed to provide balanced schedules in terms of fairness [28], whereas another study proposed a MIP model to maximize continuity and familiarity in physician schedules [63]. These models aim to ensure equitable distribution of workload and desirable shifts among physicians.

To enhance the practical applicability of mathematical optimization methods, several studies have focused on developing user-friendly interfaces and incorporating real-world constraints. A MIP model with a spreadsheet-based user interface was developed to improve usability for practitioners [60], while another study proposed a comprehensive two-level physician planning framework for polyclinics under uncertainty [56]. These approaches aim to bridge the gap between theoretical models and practical implementation in healthcare settings.

Mathematical optimization methods have significantly advanced PSP in healthcare. The strengths of these methods include their ability to find optimal solutions and handle complex constraints. However, they often face scalability issues for large problem instances.

2) HEURISTICS

a: CONSTRUCTIVE HEURISTICS

Constructive heuristics, which iteratively build solutions using problem-specific data [88], [90], [91], [92], offer a means to rapidly generate complete solutions within reasonable timeframes [93], [94]. These heuristics have been applied to address the complexity of PSP in healthcare settings. Van Huele and Vanhoucke [76] explored constructive heuristics for operating theatre scheduling, investigating priority rules (e.g., First-fit, Best-fit), generation schemes, feasibility checks, and decomposition-based heuristics by integrating the PSP. While these approaches enabled direct computation of complex instances and could inform metaheuristic solutions, they produced lower-quality solutions for larger instances compared to metaheuristics.

Constructive heuristics have also been integrated into more complex optimization frameworks. Bard et al. [70] integrated constructive heuristics into a more complex optimization framework for PSP in academic medical settings. Their approach, which aimed to balance workload and ensure equitable training experiences, improved upon current practices. However, due to the complexity of the initial model, they developed a three-step heuristic that generated high-quality solutions within minutes. Saadouli et al. [64] incorporated constructive heuristics into their Integrated Physician and Surgery Scheduling Problem. While this integrated approach provided a general representation of the problem at the mixed tactical-operational level, the computational complexity and limited scalability for larger problem instances were noted as significant challenges.

Constructive heuristics have proven valuable for addressing the PSP. These methods offer rapid solution generation [93], [94], showing promise in various settings [70], [76]. While effective for complex instances, they may struggle with larger problems compared to metaheuristics. Integration into advanced frameworks [64] shows potential but faces computational challenges. Despite limitations, constructive heuristics remain crucial for generating initial solutions and handling time-sensitive scheduling scenarios in healthcare operations.

b: METAHEURISTICS

Metaheuristic algorithms have demonstrated significant potential in addressing complex optimization problems, particularly in healthcare workforce management [95], [96], [97]. Metaheuristics are formally defined as iterative generation processes that direct subordinate heuristics through the intelligent integration of diverse exploration and exploitation strategies, utilizing learning techniques to systematically structure information and enhance the search for efficient, near-optimal solutions [90], [98].The PSP has been extensively studied using various metaheuristic approaches. Several studies have explored the application of Particle Swarm Optimization (PSO) [73], Genetic Algorithms (GA) [71] and Variable Neighborhood Search (VNS) [42], [67] to PSP. For example, improved PSO algorithms have been employed to optimize inter-hospital staff allocation and scheduling [73], while GA has been utilized to balance human resources and service quality in primary care clinics [71]. VNS, often combined with other techniques such as Dynamic Programming or the Sine Cosine Algorithm, has shown promise in effectively generating high-quality solutions [42], [67].

Simulated Annealing (SA) has been applied to iteratively explore diverse PSP, addressing the challenge of local optima entrapment [53], [65]. While SA-based approaches can evaluate numerous possibilities and generate schedules faster than standard methods, they may be computationally expensive and do not guarantee global optimality [53], [65]. Other metaheuristic techniques, such as modified Bat Algorithms and TS, have also been investigated [57], [74]. These approaches have demonstrated improved performance compared to some traditional methods.

Metaheuristic algorithms have proven effective in addressing the complex PSP in healthcare [95], [96]. Techniques like PSO [73], 82], GA [71], and VNS [42], [67] offer promising solutions for staff allocation and resource balancing. While these approaches outperform traditional methods, they face challenges in computational cost and guaranteeing (near) optimality. Nevertheless, metaheuristics remain valuable tools, providing flexible solutions for diverse healthcare scheduling scenarios.

c: HYBRID ALGORITHMS

Hybrid algorithms integrate various optimization techniques and have shown significant potential in addressing the complexities inherent in PSP. Unlike matheuristics, which specifically combines mathematical programming with heuristic methods, hybrid algorithms can combine any optimization technique [99]. Matheuristics and hybrid heuristics both involve combining methods, but their foundations, goals, and applications differ significantly. While matheuristics could conceptually be seen as a hybrid approach, calling them hybrid heuristics would overlook the essential role that exact methods play in matheuristics. Therefore, it is more accurate to maintain a distinction between the two, as each addresses different aspects of the optimization process.

For example, Lan et al. combined the Sine Cosine Algorithm with VNS to tackle physician and medical staff assignment problems [67]. This combination aims to improve both computational efficiency and solution quality, addressing the dynamic and multifaceted nature of medical staff scheduling.

Some researchers have focused on the synergy between metaheuristics and mathematical programming strategies. A greedy randomized adaptive search procedure or GRASP-based algorithm, incorporating Variable Neighborhood Descent Search, Network Flow Optimization, and Linear Programming, provides near-optimal solutions for large PSP instances within minutes [55]. This approach exemplifies the power of combining different optimization techniques to handle large-scale and complex scheduling problems effectively.

Addressing uncertainty in PSP is another critical area of research. A comprehensive two-level physician planning framework for polyclinics under uncertainty has been proposed, which combines robust optimization and stochastic programming techniques [56]. This methodology has demonstrated superior performance in terms of total cost compared to single-level deterministic models, although it may require complex computational resources for implementation. Such approaches are crucial for dealing with real-world uncertainties and variability in healthcare settings. Furthermore, hybrid multi-method modelling and simulation approaches have been explored to tackle the PSP. One study combined data analytics, machine learning, and optimization to understand complex hospital systems and optimize staffing patterns and shift schedules [58]. This innovative approach has actively contributed to solving emergency department overcrowding problems, significantly reducing average patient waiting times.

The state-of-the-art hybrid optimization techniques for PSP highlight the promising potential of combining methodologies to enhance solution quality and computational efficiency. This is because heuristics approaches offer improved scalability and flexibility compared to exact methods but may not guarantee optimal solutions.

3) MATHEURISTICS

The application of matheuristics to the PSP represents a significant advancement in healthcare workforce management. Matheuristics, which specifically combines mathematical programming and heuristic techniques. A notable example is the Fix-and-Optimize matheuristic proposed by Bruni and Detti [45], which generates high-quality rosters within acceptable time limits. This approach's flexibility in accommodating input data changes and allowing roster re-computation makes it particularly suitable for dynamic healthcare environments where schedule updates frequently occur.

Similarly, Fugener et al. [47] demonstrated the potential of matheuristics to improve roster stability in a surgical clinic setting. Their method effectively reduced unwanted consecutive shifts, emergency day shift congestion, and consecutive weekend work, addressing key concerns in physician scheduling. The integration of matheuristics into more complex scheduling scenarios, such as the Integrated Physician and Surgery Scheduling Problem studied by Saadouli et al. [64], further illustrates the versatility of these approaches. By simultaneously addressing surgery planning and physician scheduling, this method provides a more holistic approach to healthcare resource management.

However, while these studies showcase the potential of matheuristics, they also highlight areas for further research. The scalability of these approaches to larger, more complex healthcare systems remains a challenge. Additionally, the integration of real-time data and the ability to adapt to unforeseen circumstances (such as sudden staff shortages or emergencies) are areas that warrant further investigation.

Matheuristics offer a promising direction for addressing the complexities of PSP, combining the strengths of mathematical programming and metaheuristics. These approaches aim to leverage the strengths of both mathematical programming and heuristics, particularly for complex or large-scale PSP instances.

4) MACHINE LEARNING APPROACH

Machine learning (ML) is a field of computer science that allows computers to learn without being explicitly programmed [100]. ML approaches have emerged as a promising avenue for addressing the PSP in healthcare settings. A study by Liu et al. [23] proposed a learning-based algorithm for PSP in the emergency department. This approach leveraged ML models trained on real-world data from a partner hospital to accelerate the solution process of the algorithm's initial stage. The integration of learning-based strategies enhanced the performance of a two-stage algorithm, demonstrating ML's potential to improve scheduling efficiency.

In a related study, Rashwan et al. [58] developed a multi-method framework incorporating ML to optimize PSP in hospital emergency departments. This comprehensive approach combines data analytics, statistical analysis, and ML techniques to address and model patient demand patterns. By integrating ML with other optimization methods, the researchers created a holistic solution that considered patient, staff, and hospital factors in the decision-making process. Recent studies [23], [58] demonstrated the potential of machine learning in addressing the PSP. These approaches show potential in handling complex, dynamic scheduling environments and improving solution quality over time through learning mechanisms.

A notable trend in ML approaches is the increasing shift toward hybrid and multi-method approaches that combine different optimization techniques. Besides, ML approaches, while promising, are still underexplored in PSP research. There is a need for more comparative studies to evaluate the effectiveness of different methodologies across various PSP contexts.

This review highlights the diversity of optimization methodologies applied to PSP, reflecting the complex and multifaceted nature of the problem. While mathematical optimization methods remain prevalent, there is an increasing interest in heuristic, matheuristic, and machine learning approaches to address the challenges of large-scale, dynamic scheduling environments in healthcare.

F. RQ6: WHAT ARE THE STRENGTHS AND WEAKNESSES OF CURRENT OPTIMIZATION METHODOLOGIES THAT HAVE BEEN APPLIED TO THE PSP?

Table 6 summarizes the strengths, weaknesses, and recent developments of the main optimization methodologies applied to the PSP. This comprehensive overview highlights the trade-offs between solution quality, computational efficiency, and practical applicability for each approach.

Despite these advancements, several challenges persist in the practical application of optimization techniques to PSP. Integration of sophisticated models with user-friendly interfaces and decision support systems remains crucial for widespread adoption in healthcare settings [35], [60]. There is a growing need for scalable algorithms capable of handling large-scale problems and incorporating real-time scheduling capabilities [40], [45], [50], [51]. The lack of standardized benchmark datasets hinders comprehensive validation and comparison of different optimization approaches [58], [61], [101].

Future research directions should focus on developing more efficient solution methods, exploring data-driven approaches to enhance model accuracy and adaptability [23], [58], and conducting comprehensive validation studies across diverse healthcare environments [58], [61], [101]. Addressing these challenges will be essential for bridging the gap between theoretical advancements and practical implementation, ultimately leading to more effective and efficient physician scheduling practices in healthcare systems.

G. RQ7: WHAT ARE THE CHALLENGES AND FUTURE WORK OF THE PSP?

Current methodologies often struggle with the complexity and dynamic nature of real-world healthcare environments. By identifying challenges and future directions, this research can drive the development of more sophisticated, adaptable, and practical scheduling solutions. These advancements have the potential to significantly improve healthcare delivery, resource utilization, and work-life balance for medical professionals, ultimately contributing to better patient outcomes and system performance in an increasingly demanding healthcare landscape.

The optimization of PSP has seen significant advancements in recent years, with researchers employing a variety of methodologies to address the complex challenges inherent in healthcare workforce management. From mathematical optimization methods to metaheuristics, and from hybrid algorithms to machine learning approaches, each methodology has demonstrated unique strengths in tackling different aspects of the PSP. These methods have shown promise in improving resource allocation, reducing patient waiting times, and enhancing overall operational efficiency in healthcare settings.

However, as healthcare systems continue to evolve and face new challenges, there is a pressing need for further innovation and refinement in optimization methodologies. The increasing complexity of healthcare operations, coupled with growing demands for personalized care and work-life balance for medical professionals, necessitates the development of more sophisticated, adaptable, and practical scheduling solutions.

In light of these ongoing challenges and the potential for further improvement, this section outlines key areas for future research in the PSP. These directions aim to address current limitations, leverage emerging technologies, and pave the way for more effective and implementable scheduling systems in diverse healthcare contexts. By pursuing these avenues of research, we can work towards creating scheduling solutions that not only optimize resources but also contribute to improved patient care, physician satisfaction, and overall healthcare system performance. We addressed seven key areas for future work:

1) Computational Efficiency and Scalability: Developing more efficient algorithms capable of handling large-scale, complex PSP instances remains a primary challenge. Future work should focus on advanced decomposition techniques and parallel computing strategies to improve solution times for extensive planning horizons [102], [103].

TABLE 6. Strengths and weaknesses of optimization methodologies for the PSP.

Methodology	Strengths	Weaknesses
Mathematical optimization methods	• Generate optimal or near-optimal solutions while considering multiple objectives and constraints [32, 38, 46]. • Provide a systematic framework for staffing and scheduling, often resulting in improved resource allocation and reduced patient waiting times [38, 48, 66]. • Capable of handling complex constraints and integrating various aspects of healthcare operations [33, 51].	• High computational complexity, particularly for large-scale problems or extended planning horizons [33, 39, 46, 51, 63, 66]. • May be impractical for real-time decision-making in dynamic healthcare environments [40, 50]. • Often requires simplification of real-world constraints, potentially reducing solution applicability [35, 60].
Heuristics	• Improved efficiency and scalability for large-scale PSP instances [26, 42, 61, 65, 71, 73, 74]. • Flexibility in handling complex constraints and objectives, making them suitable for diverse healthcare settings [41, 49, 57]. • Ability to generate good quality solutions in reasonable computational times [53, 62].	• Do not guarantee optimal solutions [26, 61, 74]. • Performance can be sensitive to problem-specific parameters and initial conditions [49, 53]. • May require extensive tuning to achieve good performance across different problem instances [57, 65].
Matheuristics	• Balance the strengths of exact methods with the efficiency of heuristics [37, 47, 52, 55, 67]. • Often achieve a favourable compromise between solution quality and computational time [45, 101]. • Particularly suitable for large-scale PSP instances where exact methods become computationally intractable [47, 101].	• Effectiveness can vary depending on the specific problem characteristics [67, 101]. • May require careful design and tuning of both the mathematical and heuristic components [45, 101]. • Potentially increased complexity in implementation and parameter setting [55].
Machine Learning	• Ability to handle stochastic elements, such as patient arrivals and service times [23, 53, 81]. • Can provide valuable insights into system performance under various scenarios [58]. • Potential to improve algorithm performance over time through learning [23].	• Often requires significant computational resources and high-quality historical data [23, 58, 81]. • May lacks interpretability compared to traditional optimization methods [58]. • Effectiveness is heavily dependent on the quality and representativeness of training data [23].

2) Standardized Datasets and Benchmarks: A significant gap in PSP research is the lack of publicly available, standardized datasets. Future efforts should prioritize the creation and sharing of comprehensive benchmark datasets that reflect various healthcare settings and scheduling scenarios. This will facilitate reproducible research, enable fair comparisons between different optimization approaches, and accelerate progress in the field [104].
3) Integration of Machine Learning and Data-Driven Approaches: Exploring the potential of machine learning techniques to enhance prediction accuracy, improve algorithm performance, and adapt to changing healthcare environments represents a promising direction for future research [23], [58].
4) Multi-Objective Optimization and Robustness: Refining techniques to balance multiple, often conflicting objectives while accounting for uncertainties in healthcare settings remains an ongoing challenge. Future work should focus on developing more sophisticated multi-objective optimization models and robust optimization approaches [105].
5) Real-Time Scheduling and Rescheduling: Developing methods that can quickly adapt to unexpected changes and efficiently update existing schedules with minimal disruption is crucial for practical implementation in dynamic healthcare environments [40], [45], [51].
6) User Interfaces and Decision Support Systems: Bridging the gap between theoretical models and practical implementation requires the development of intuitive tools for schedule creation, modification, and visualization. Future research should focus on creating user-friendly interfaces and comprehensive decision support systems that can be easily integrated into existing hospital information systems [35], [60].
7) Validation and Comparative Studies: Conducting large-scale studies to compare different algorithms across various healthcare settings is essential for advancing the field. This includes developing standardized evaluation metrics and conducting comprehensive validation studies in real-world healthcare environments [58], [61].

By addressing these challenges, future research can contribute to the development of more effective, efficient, and implementable PSP solutions, ultimately improving healthcare workforce management and patient care outcomes.

IV. CONCLUSION

This systematic review highlights the PSP as a complex optimization challenge that extends beyond simple shift assignments, involving constraints such as coverage requirements, working hours, and physician preferences. Both single-stage and multi-stage PSP models offer unique advantages, with recent research focusing on multi-stage approaches that incorporate uncertainty and dynamic factors to reflect real healthcare environments.

A variety of optimization techniques have been applied to PSP, including mathematical models, metaheuristics, and emerging machine-learning approaches, each offering distinct insights. Despite these advancements, PSP still faces challenges, particularly in computational efficiency and scalability for large-scale, real-world applications. The need for real-time scheduling and rescheduling highlights the gap between theoretical models and practical applications, emphasizing the need for user-friendly interfaces and robust decision support systems.

Future research should prioritize advancing computational methods to handle complex scenarios, integrating data-driven adaptability, and refining multi-objective optimization to balance competing priorities. Comprehensive validation studies and standardized benchmarks are also essential for effective comparative analysis. In conclusion, while significant progress has been made, there is still substantial potential for innovation in developing scalable, adaptable, and practical scheduling solutions that address the dynamic demands of modern healthcare environments.

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NORIZAL ABDULLAH is currently pursuing the Ph.D. degree with the Center Artificial Intelligence Technology (CAIT), Faculty of Information Science and Technology, Universiti Kebangsaan Malaysia. He is also with the Data Mining and Optimization Laboratory. His research interests include optimization, scheduling, and artificial intelligence.

MASRI AYOB received the Ph.D. degree in computer science from the University of Nottingham, in 2005. Since 1997, she has been a Lecturer at the Faculty of Information Science and Technology (FTSM), Universiti Kebangsaan Malaysia (UKM). She is currently a Professor and a Principal Researcher with the Data Mining and Optimization Research Group (DMO), Centre for Artificial Intelligence (CAIT), Universiti Kebangsaan Malaysia. She is also the Chairperson of CAIT and a Principal Researcher at DMO, FTSM, UKM, CAIT. She has served on a program committee for more than 50 international conferences and a reviewer for high-impact journals. She has published more than 150 papers in international journals and peer-reviewed international conferences. Her main research interests include meta-heuristics, hyper-heuristics, scheduling, and timetabling, particularly educational timetabling, healthcare scheduling, and routing problems.

MENG CHUN LAM received the bachelor's degree in information technology and the Ph.D. degree in industrial computing from Universiti Kebangsaan Malaysia (UKM), Bangi, Malaysia. He is currently a Lecturer at UKM and the Head of the Mixed Reality and Pervasive Computing Laboratory (MyXLab). MyXLab focuses the study on mixed reality and mobile application technology which aligns with his research interests include human–computer interaction, extended reality, and mobile application. He has published several research papers in reputable journals and conferences. He was a recipient of numerous awards, including the Gold Award KNOVASI 2020, the Outstanding Paper Award, the Best Paper Award, the NASA Space App Challenge–First Prize Winner, and the IEEE Gold Malaysia Best Paper Award.

NASSER R. SABAR is currently a Lecturer with the Computer Science and IT Department, La Trobe University, Australia. He has published more than 85 papers in international journals and peer-reviewed conferences. His current research interests include designing and developing hyper-heuristic frameworks, deep learning, machine learning, evolutionary computation, and hybrid algorithms with a specific interest in big data optimization problems, cloud computing, dynamic optimization, and data-mining problems.

GRAHAM KENDALL received the degree in computation from the University of Manchester Institute of Science and Technology (UMIST), U.K., and the Ph.D. degree in computer science from the University of Nottingham. He is one of the Deputy Vice-Chancellors at MILA University, Malaysia. In his more than 40-year career, he has worked in almost equal amounts in both industry and academia. His research interests include solving real-world problems through the use of operations research and utilizing artificial intelligence methods, which are based on Charles Darwin's principles of natural evolution. He has written over 250 peer-reviewed papers and has served on several editorial boards, including being the Editor-in-Chief for IEEE TRANSACTIONS OF COMPUTATIONAL INTELLIGENCE AND AI IN GAMES and an Associate Editor for *Journal of the Operational Research Society*.

MOHAMAD KHAIRULAMIRIN MD RAZALI received the bachelor's (Hons.) and Ph.D. degrees in computer science from Universiti Kebangsaan Malaysia (UKM), in 2021 and 2024, respectively. His main research interests include combinatorial optimization problems, healthcare scheduling, artificial intelligence, and optimization algorithms.