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A Collaborative Control Protocol with Artificial Intelligence for Medical Student Work Scheduling

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Abstract

Effective work scheduling for clinical training is essential for medical education, yet it remains challenging. Creating a clinical training schedule is a difficult task, due to the complexity of curriculum requirements, hospital demands, and student well-being. This study proposes the Collaborative Control Protocol with Artificial Intelligence for Medical Student Work Scheduling (CCP-AI-MWS) to optimize clinical training schedules. The CCP-AI-MWS integrates the Collaborative Requirement Planning principle with Artificial Intelligence (AI). Two experiments have been conducted comparing CCP-AI-MWS with current practice. Results show that the newly developed protocol outperforms the current method. CCP-AI-MWS achieves a more equitable distribution of assignments, better accommodates student preferences, and reduces unnecessary workload, thus mitigating student burnout and improving satisfaction. Moreover, the CCP-AI-MWS exhibits adaptability to unexpected situations and minimizes disruptions to the current schedule. The findings present the potential of CCP-AI-MWS to transform scheduling practices in medical education, offering an efficient solution that could benefit medical schools worldwide.

Keywords: Healthcare, Rostering, Multi-objective Optimization, Collaboration, Ward Rotation.

1 Introduction

Clinical training is an important part of the medical student curriculum because it bridges theory and practice, allowing students to gain hands-on experience with patients under the supervision of senior physicians [8]. The structure and demands of clinical training schedules, however, often pose the challenges. The workload can be overwhelming, as evidenced by unsatisfactory self-reports by students [19]. In addition, the students may also face unbalanced workloads, long working hours, and a lack of control over their schedules due to unexpected circumstances [18, 21, 24]. High patient demands and limited medical resources also add pressure on students. These challenges contribute to chronic fatigue, sleep deprivation, and limited personal time, which affect both the physical and mental health of the students [13, 20, 26, 28].

Moreover, current research indicates that more than 40% of medical students experience stress from work overload, especially during their clinical years [9, 19]. The high levels of stress and anxiety during medical education can negatively impact medical students' learning outcomes and their clinical-year success [25], leading to students dropping out of school [5], which consequently results in a shortage of skilled healthcare professionals in the healthcare sector of the country.

To address this issue, a well-developed scheduling system is essential. Research indicates that a high-quality work schedule, distinguished by increased control and flexibility, could improve the work performance of medical personnel [30]. The improvement aims to support the health and well-being of medical personnel and, at the same time, minimize overall system costs.

A common approach for creating medical personnel work schedules is mathematical modeling, i.e., mixed integer programming. For example, Beaulieu *et al.* [3] implemented a mathematical model to optimize the schedules of physicians in an emergency department. The model considers working hours, days off, and personal experiences. Moreover, mixed integer programming has shown its application in reducing surgeons' operation completion time, operation room overtime, and makespan [35]. In addition, Gür *et al.* [11] utilized mathematical programming to optimize equipment and resource utilization in hospital operating rooms. For nurse scheduling, mathematical modeling has also been extensively utilized (see [4] for more details). It is noteworthy that, despite the extensive exploration of work schedules for medical personnel, such as physicians and nurses, the investigation into the scheduling of medical students remains scarce in the literature.

Another important aspect of the work scheduling system for medical students is the ability to respond to real-time issues, e.g., absence of students or fluctuation of demand. To enhance system ability as well as improve system efficiency, the Collaborative Control Protocol (CCP) is a critical tool. Because CCP leverages cyber technology to optimize communication processes and enhance collaboration among multiple agents, systems developed using CCP tend to exhibit superior performance and have minimal system conflicts and errors [2]. CCP has been investigated in various domains. For example, CCP is applied to complex agriculture systems, integrating a human operator, a mobile robot, and sensors to develop Agricultural Robotics System [27]. The implementation can reduce system cost and improve system performance compared to alternative approaches [6]. In addition, CCP not only optimizes resource utilization but also succeeds in addressing real-time problems with minimal information delay [7]. Therefore, the implementation of CCP allows for the fast resolution of unforeseen issues in the system that might happen in real-time and, consequently, minimizes impact on the original plan, which will benefit the healthcare scheduling system.

Therefore, the combination of mathematical modeling and CCP is employed in this research to solve the medical student scheduling problem. The newly developed CCP, called Collaborative Control Protocol with Artificial Intelligence for Medical Student Work Scheduling (CCP-AI-MWS), consists of two modules, that follow the Collaborative Requirement Planning principle in Collaborative Control Theory [22, 23]: Planning module (M_1) and Execution and AI-Control module (M_2). M_1 utilized the mathematical model to solve the medical student scheduling problems. The M_1 is performed by the given assumed parameters to deliver the optimal schedule that satisfies all significant constraints of the situation in clinical training and ward rotation. Constraints include 1) Hospital requirements (i.e., a specific number of students for each ward to ensure smooth operation); 2) Student requirements (i.e., the attendance of students at each ward to fulfill medical curriculum); and 3) Regulatory requirements (i.e., limitations on work days for students). In addition, the M_1 is executed before the real situation, assuming a reasonable amount of time to solve and/or create the initial schedule.

When the initial schedule from M_1 is implemented; however, in real execution, unexpected situations can happen. For example, students may be absent without advanced notice due to personal reasons such as illness, family emergencies, or other commitments requiring them to request work schedule changes. Hence, M_2, which is a module for managing such real-time changes, is necessary.

M_2 utilizes AI and algorithms to deal with unexpected situations with the objective of minimizing the impact on the overall initial schedule (from M_1).

In this research, we selected Thailand's medical curriculum for our case study. Moreover, we focus on the first clinical year. This transition period (from pre-clinical to clinical years) is critical for students as they need to adapt to a new environment. A smooth transition is essential for students to succeed in their studies and become competent healthcare professionals in the future.

This research differs from general healthcare personnel scheduling by specifically considering the academic workload, necessary rest periods, equitable workload assignments, and, importantly, communication and control procedures for unexpected circumstances. The objective is to both balance academic fulfillment and ensure health and well-being of students.

By implementing the proposed protocol at the case study medical school, we aim to demonstrate an efficient solution to the scheduling challenges that can be applied to other medical schools.

The remaining parts of the article are structured as follows. Section 2 presents detailed explanation of the problem and methodology utilized. Then, two experiments and results are presented in Section 3. Lastly, Section 4 provides the conclusion, discussion, and future research directions.

2 Problem Description and Methodology

2.1 Problem Description

Consider a medical school with a set of medical students, denoted by I. Each medical student $i \in I$ has his/her preferred working date, denoted by p_{idw}, where $d \in D$ represents the operating day, and $w \in W$ is a week of the planning horizon. The hospital has a set of wards, denoted by J, and each ward $j \in J$ has its own requirement, namely the minimum number of medical students needed (R_{jdw}) to operate smoothly and effectively. In this regard, R_{jdw} may vary, depending on the expected number of patients each day. Another influencing factor that may affect the value of R_{jdw} is the difficulty of tasks performed at ward $j \in J$. Particularly, wards with more complex tasks typically require more medical students.

To fulfill the curriculum requirements, medical student $i \in I$ needs at least C_j working days at ward $j \in J$ to guarantee the minimum number of practicing times. Considering the regulatory restrictions, each week, medical student $i \in I$ cannot work more than α days to avoid burnout. In addition, working consecutively for more than β days is also prohibited.

Furthermore, in real-world scenarios, there is possibility of unexpected situations. For example, students may be absent without advanced notice due to illness or personal emergencies. Moreover, although the number of students needed in each ward daily is determined based on historical data and patient appointments, unexpected walk-in patients can arise, requiring more students to ensure smooth ward operations [33]. In such situations, wards experiencing a shortage will request additional students (called an urgent request) to maintain or enhance operational efficiency. Figure 1 presents the system architecture of the problem.

2.2 Collaborative Control Protocol with Artificial Intelligence for Medical Student Work Scheduling (CCP-AI-MWS)

Figure 2 presents the CCP-AI-MWS. The protocol has two main modules: Planning module (M_1) and Execution and AI-Control module (M_2). M_1 utilized historical data and constraints to develop an initial schedule, while M_2 is needed for dealing with real-time unexpected situations.

2.2.1 Planning module (M_1) of CCP-AI-MWS

In this section, the mathematical model utilized in M_1 is presented. Note that, because of the complexity of the model, it may require a sufficient amount of time to solve. M_1, however, will run on a monthly basis (based on the planning horizon), so that computational time is assumed to be sufficient and is not a primary concern of this module.

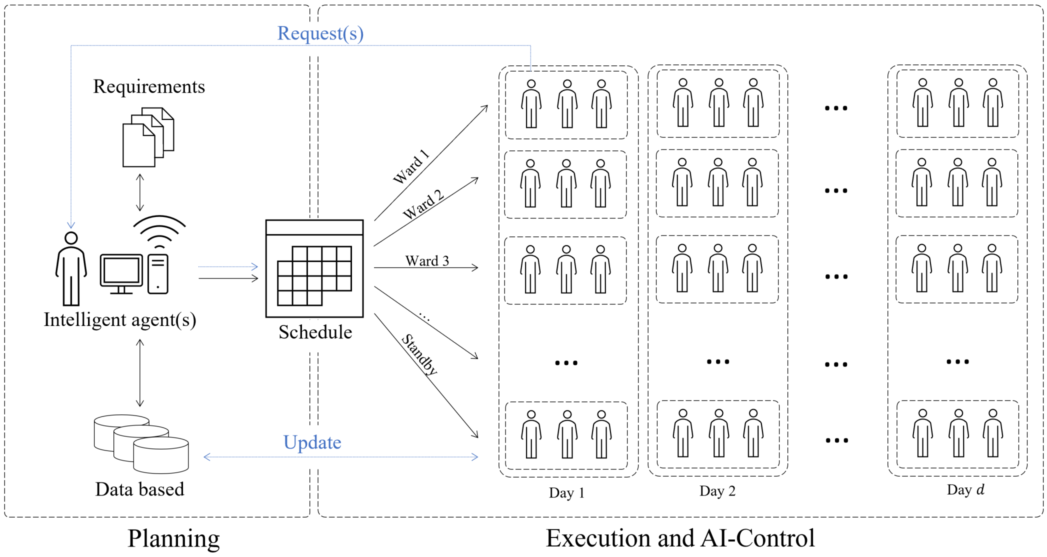

Figure 1: System architecture

The main decision of M_1 to be made in this problem is which medical student $i \in I$ will be assigned to ward $j \in J$ on day $d \in D$ and week $w \in W$. To improve the quality of the work schedule, three objectives are optimized simultaneously.

- **Workload fairness:** Each medical student $i \in I$ should receive comparable assignments, as the perception of workload fairness significantly influences job satisfaction [14]. To this end, we can represent this objective as the minimization of the sum of absolute differences between the number of assignments (workloads) that each medical student receives and the average number of assignments per medical student.
- **Preference of students:** Each medical student $i \in I$ may have a different preference in the working day. Therefore, the schedule must take into account the preferences of the students by maximizing the minimum number of preferred assignments for each student.
- **Overall system workload:** Finally, we want to avoid unnecessary assignments, as long working hours reduce work satisfaction [10]. Therefore, the total workload in the system must also be minimized.

Mathematical Modeling

Sets and Parameters

I	Set of medical students; $i \in I$
J	Set of wards; $j \in J$
W	Set of weeks; $w \in W$
D	Set of days; $d \in D$
p_{idw}	$\begin{cases} 1 & \text{if student } i \in I \text{ preferred to work at day } d \in D, \text{week } w \in W \\ 0 & \text{otherwise} \end{cases}$
R_{jdw}	Minimum number of medical students needed at ward $j \in J$ for day $d \in D$, week $w \in W$
C_j	Minimum number of days each student needs to be assigned to ward $j \in J$ to complete the curriculum requirement
α	Maximum number of days a student can work each week
β	Maximum number of consecutive working days

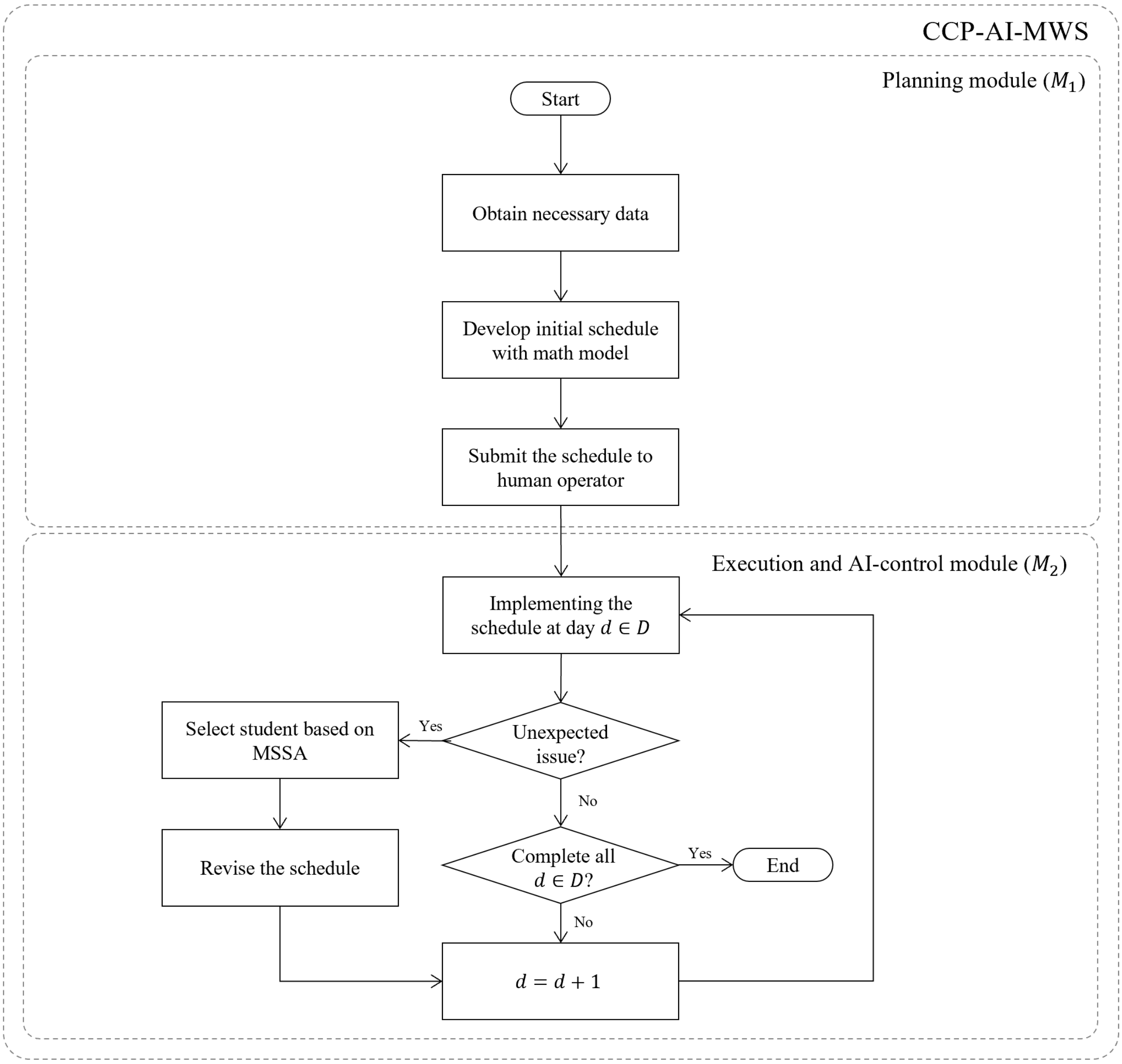

Figure 2: CCP-AI-MWS

Decision Variables

$$x_{ijdw} \quad \begin{cases} 1 & \text{if student } \ i \in I \text{ is assigned to ward } j \in J, \text{ day } d \in D, \text{ week } w \in W \\ 0 & \text{otherwise} \end{cases}$$

Objective Functions

$$\min \sum_{i \in I} f_{1i} \tag{1}$$

$$\max \quad f_2 \tag{2}$$

$$\min \quad f_3 \tag{3}$$

Constraints

$$\left(\sum_{j\in J}\sum_{d\in D}\sum_{w\in W} x_{ijdw}\right) - \bar{x} \leq f_{1i} \qquad \forall i \in I \tag{4}$$

$$\bar{x} - \left(\sum_{j\in J}\sum_{d\in D}\sum_{w\in W} x_{ijdw}\right) \leq f_{1i} \qquad \forall i \in I \tag{5}$$

$$\sum_{j\in J}\sum_{d\in D}\sum_{w\in W} p_{idw} x_{ijdw} \geq f_2 \qquad \forall i \in I \tag{6}$$

$$\sum_{i\in I}\sum_{j\in J}\sum_{d\in D}\sum_{w\in W} x_{ijdw} = f_3 \tag{7}$$

$$\frac{1}{|I|}\sum_{i\in I}\sum_{j\in J}\sum_{d\in D}\sum_{w\in W} x_{ijdw} = \bar{x} \tag{8}$$

$$\sum_{j\in J} x_{ijdw} \leq 1 \qquad \forall j \in J, d \in D, w \in W \tag{9}$$

$$\sum_{j\in J}\sum_{d\in D} x_{ijdw} \leq \alpha \qquad \forall i \in I, w \in W \tag{10}$$

$$\sum_{j\in J}\sum_{d=\varepsilon}^{\varepsilon+H} x_{ijdw} \leq \beta \qquad \forall i \in I, w \in W, \varepsilon \in \{1, 2, \ldots, |D| - H + 1\} \tag{11}$$

$$\sum_{j\in J}\sum_{d=|D|-H+\varepsilon}^{|D|} x_{ijdw} + \sum_{j\in J}\sum_{d=1}^{\varepsilon} x_{i(jd)(w+1)} \leq \beta \qquad \forall i \in I, w \in W \setminus \{|W|\}, \varepsilon \in \{1, 2, \ldots, H\} \tag{12}$$

$$\sum_{i\in I} x_{ijdw} \geq R_{jdw} \qquad \forall j \in J, d \in D, w \in W \tag{13}$$

$$\sum_{i\in I}\sum_{d\in D}\sum_{w\in W} x_{ijdw} \geq C_j \qquad \forall j \in J \tag{14}$$

$$x_{ijdw} \in \{0, 1\} \qquad \forall i \in I, j \in J, d \in D, w \in W \tag{15}$$

$$f_{1i} \geq 0 \qquad \forall i \in I \tag{16}$$

$$f_2, f_3 \geq 0 \tag{17}$$

The model has three objectives: 1) Minimize the difference between total assignments for each student and the average assignment from all students (Equation 1), 2) Maximize the minimum number of assignments with student preferences (Equation 2), and 3) Minimize total number of assignments across all students (Equation 3).

Equations 4 and 5 are the linearization of the first objective. Equation 6 calculates the number of assignments that align with student preferences and Equation 7 computes the total number of assignments in the schedule. Equation 8 calculates the average number of assignments per student. Equation 9 ensures that a student is not assigned to more than one ward a day. The weekly working limit is calculated by Equation 10. Equations 11 and 12 restrict the number of consecutive working days. Equation 13 ensures that each ward receives at least the minimum number of students required per day. Equation 14 guarantees that each student meets the minimum day requirement for each ward to meet the curriculum requirement. Equations 15 – 17 are variable constraints.

The result from M_1 is the assignments for each student, indicating the days and weeks of work allocated for each ward. In addition, M_1 identifies any unassigned dates for the students. Students with unassigned dates will be placed in a standby position, potentially called upon to address urgent requests as they arise (by the suggestion from M_2).

2.2.2 Execution and AI-Control module (M_2) of CCP-AI-MWS

In this section, the M_2 is presented. Because M_2 deals with the real-time urgent requests discussed earlier, the AI and algorithms that can deliver fast solutions are preferred [7].

Medical Students Substitute Algorithm (MSSA)

The MSSA is activated when there is an urgent request. With an AI-supported algorithm, MSSA identifies a standby student best suited to address the urgent request, to minimize the impact on the initial schedule from M_1. MSSA is presented below.

Algorithm 1 Medical Student Substitute Algorithm (MSSA)

```
Require: Absent Student, Day, Week, Ward
Ensure: Best Candidate
  Initialize Available Students on a specific Day, Week
  Initialize Candidate Pool as Empty
  Initialize Best Candidate as None
  for each student in Available Students do
      if student exceeds assignment limits OR impacts curriculum requirements then
          Eliminate student
      else
          Candidate Pool = Candidate Pool + student
      end if
  end for
  Sort students in Candidate Pool in ascending order by total number of assignments
  for each candidate in the sorted Candidate Pool do
      if candidate preference is 1 then
          Best Candidate = candidate
          break
      end if
  end for
  if Best Candidate is not Empty then
      return Best Candidate
  else
      return None
  end if
```

3 Experiments and Results

The developed protocol is validated and compared with the alternative in this section. Two computer simulation experiments have been conducted to test the protocol in different perspectives and situations. The number of students, number of wards, and other parameters were randomly generated. The first experiment presents the operation in an ideal situation, i.e., no urgent request. The second experiment illustrates a case where there are urgent requests from unexpected situations, such as student's absence.

3.1 Experiment Design

Two protocols are applied in the experiments: 1) CCP-AI-MWS and 2) Current practice. CCP-AI-MWS is a newly developed protocol. The current practice is the greedy-based algorithm, representing current scheduling practice that applied simple rules to develop the schedule.

In addition, a total of 30 randomly generated sets of parameters are loaded to each protocol with the distribution shown in Table 1. Python programming was utilized for the experiments. CPLEX Studio Optimization with Goal Programming procedure is also employed for solving the multi-objective mathematical model. Note that, for the multi-objective problem, the priority of each objective function is pre-set by an intelligent agent such as a scheduling manager [15, 32] to deal with non-dominated solutions and effectively solve the model [29]. In actual practice, the scheduling manager can also utilize AI to analyze the current situation and policy to suggest the priorities of the objectives.

Four metrics are used for determining the performance of each protocol: 1) Difference between total assignments for each student and the average assignment from all students (z_1), 2) Minimum number of assignments with student preferences for each student (z_2), 3) Total number of assignments in the system (z_3), 4) Number of unsolved urgent requests (z_4).

As mentioned earlier, z_1 represents the fairness of the schedule while z_2 indicates the responsiveness of the schedule to student preferences. The z_3 ensures that no unnecessary assignments. Lastly, in the case of unexpected situations, z_4 captures the number of unsolved cases, which should be minimized.

Table 1: Comparison of experimental conditions

	Experiment 1	**Experiment 2**
Number of students	[35, 55]	[35, 55]
Number of wards	[8, 10]	[8, 10]
Number of urgent requests per week	-	[3, 5]

3.2 Experiment 1: No Unexpected Situations

3.2.1 Experiment results and analysis

The first experiment demonstrated the effectiveness of the CCP-AI-MWS compared to current practice under ideal conditions (i.e., no urgent requests).

Table 2 and Figure 3 presents the experiment results. The results from CCP-AI-MWS are significantly better than the current practice in all metrics. Implementing CCP-AI-MWS showed a reduction in z_1, indicating a more equitable workload distribution. Moreover, z_2 from CCP-AI-MWS is significantly higher than the current practice, i.e., the newly developed protocol better accommodates student preferences. z_3, which is the total number of assignments in the schedule, is also lower, indicating a more efficient allocation of workload and assignments. Note that because of the setting of the experiment, which assumes no unexpected situation happens, there were no unsolved urgent requests (z_4) in either protocol.

The results from experiment 1 highlight the efficiency of the CCP-AI-MWS, especially M_1. The significant reduction in z_1 underlines the system's ability to distribute workloads more evenly among students, potentially reducing burnout and improving satisfaction. The improvement in z_2 suggests that CCP-AI-MWS better meets students' preferences, which could enhance their learning experience and satisfaction with the clinical training program. The decrease in z_3 indicates a more optimal use of student resources, potentially reducing unnecessary work and preventing burnout. The absence of unsolved urgent requests (z_4) in both protocols suggests that both systems can handle the workload under ideal conditions.

Table 2: Experiment 1 results: Performance metrics

Performance metrics	**CCP-AI-MWS**	**Current practice**	***p-value***
z_1	53.59 (8.92)	110.03 (18.09)	***
z_2	11.67 (0.66)	3.67(0.84)	***
z_3	762.47 (106.04)	869.60 (116.07)	**
z_4	0.00 (0.00)	0.00 (0.00)	-

Note: Standard deviations are given in parentheses;
*** Statistically significant at ($p < 0.0001$)
** Statistically significant at ($p < 0.001$)

3.3 Experiment 2: With Unexpected Situations

3.3.1 Experiment results and analysis

Experiment 2 demonstrates a situation where unexpected situations can randomly happen, i.e., the system receives urgent requests.

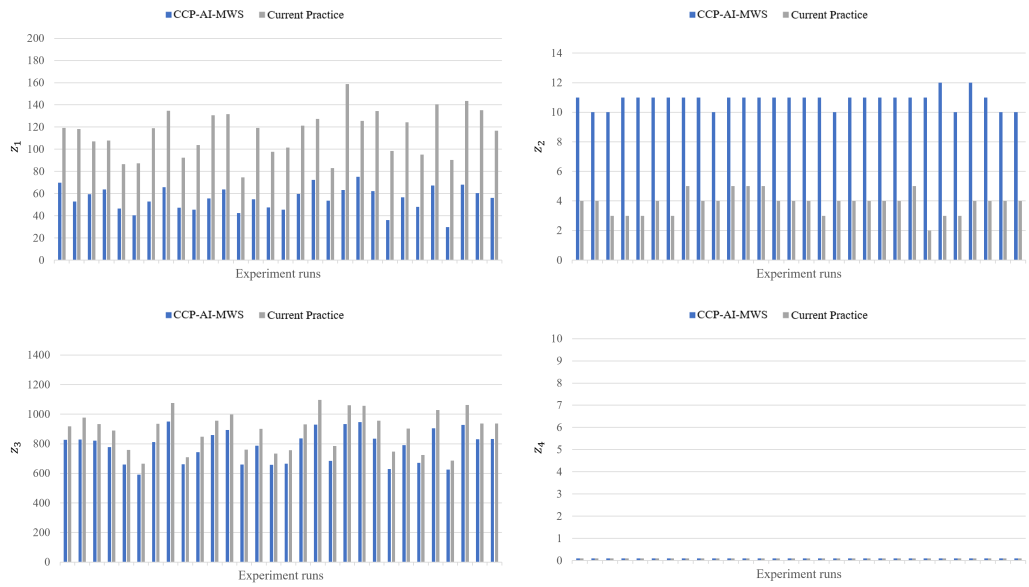

Figure 3: Results of each simulation run from experiment 1

Table 3 and Figure 4 present the results. In the presence of urgent requests, the CCP-AI-MWS also outperformed the current practice. It maintained a more equitable workload distribution (z_1), better accommodated student preferences (z_2), and ensured a more efficient allocation of assignment (z_3).

Importantly, the CCP-AI-MWS showed the ability to handle unexpected situations, which minimize the number of unsolved urgent requests. While the current practice does not have a procedure to deal with unexpected situations, CCP-AI-MWS utilizes M_2 for selecting and solving urgent requests. Note that even though the M_2 is activated to search for standby students to fill in the absent position; in some cases, no replacement happens. The reason may come from the limitation of available students, which may violate specific constraints (e.g., consecutive working days or number of working days per week) if M_2 select them. Therefore, the unsolved cases can be observed in some simulation runs even though CCP-AI-MWS is applied.

The results from experiment 2 show the benefits of CCP-AI-MWS in managing clinical training schedules, particularly in situations with urgent requests. The minimal increase in z_1 and z_3, and the minimal decrease in z_2 from experiment 1 to experiment 2 suggests the system's resilience to unexpected situations. The ability to solve urgent requests in CCP-AI-MWS shows the system's capability for real-time problem-solving. This ability is essential for a system like CCP-AI-MWS which requires the ability to adapt to sudden changes and maintain operational efficiency and fairness.

Table 3: Experiment 2 results: Performance metrics

Performance metrics	**CCP-AI-MWS**	**Current practice**	***p-value***
z_1	55.53 (10.17)	118.17 (16.54)	***
z_2	10.77 (0.50)	3.90(0.84)	***
z_3	771.77 (116.03)	887.93 (134.07)	**
z_4	0.27 (0.45)	4.60 (1.73)	***

Note: Standard deviations are given in parentheses;
*** Statistically significant at ($p < 0.0001$)
** Statistically significant at ($p < 0.001$)

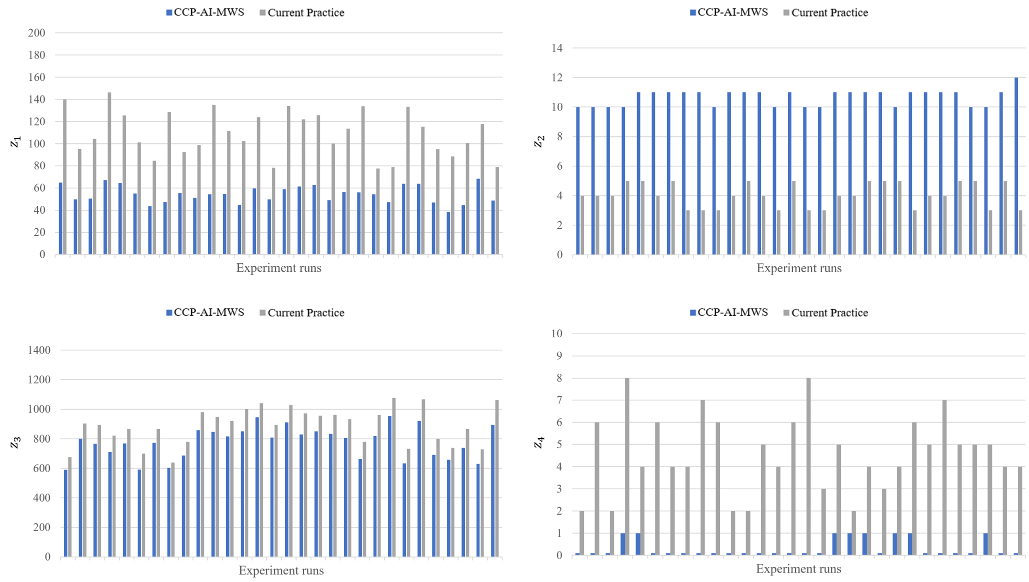

Figure 4: Results of each simulation run from experiment 2

The two experiments demonstrate the effectiveness of the CCP-AI-MWS in creating clinical training schedules for medical students. The CCP-AI-MWS can 1) Ensure equitable workload, 2) Accommodate student preferences, and 3) Effectively handle both expected and unexpected situations. The implementation of CCP-AI-MWS could improve student satisfaction, learning outcomes, and overall system efficiency.

4 Conclusion and Discussion

Clinical training is an important component of medical education. The training offers students hands-on experience, which is necessary for them to become competent healthcare professionals. The complexities of clinical training scheduling, however, have presented significant challenges. These include unbalanced workloads, long working hours, and a lack of flexibility, which can lead to student burnout and drop-out.

This research addresses these critical challenges by focusing on an important aspect of medical education: clinical training scheduling for medical students. We introduced the Collaborative Control Protocol with Artificial Intelligence for Medical Student Work Scheduling (CCP-AI-MWS), a novel method that combines the Collaborative Requirement Planning principle with AI.

The CCP-AI-MWS was validated with two experiments. In addition, the newly developed protocol was compared against current scheduling practice. Our findings show the superior performance of CCP-AI-MWS in several aspects. First, CCP-AI-MWS delivers a more equitable work distribution, addressing a source of student dissatisfaction and promoting workload fairness. Second, CCP-AI-MWS incorporates the preferences of each student into the work schedule. This individual preference incorporation could potentially improve the educational experience of students by maximizing the alignment of each student. Third, CCP-AI-MWS reduces the total workload by eliminating unnecessary assignments, which addresses one of the major causes of student burnout. Finally, CCP-AI-MWS exhibits adaptability to unexpected situations and/or urgent requests, minimizing disruptions to the current schedule.

The implications of this research extend beyond clinical training scheduling problems. Specifically, the CCP-AI-MWS represents an example of a more client-centric, e.g., student-centric; efficient, and adaptable approach to scheduling, with the potential to improve both service outcomes, e.g., educational outcomes, and client well-being, e.g., student well-being. According to our results, similar scheduling challenges across various domains, such as agriculture and logistics systems, can also benefit from integrating CCP and AI.

Building on research's findings, future studies could explore several directions, as follows:

1. **Optimizing resource allocation in response to multiple ward demand fluctuations:** When there are multiple ward demand fluctuations, investigating strategies to dynamically allocate resources (i.e., students) could increase overall system efficiency. For instance, given that some students are idle due to lower actual demand in their assigned wards, it would be better if the system could reassign them to other busier wards. It will improve overall system performance and enhance system service quality. This strategy would require the development of a new protocol for adjusting current assignments according to real-time demand, and, at the same time, considering all requirements and constraints, hence optimizing the utilization of available resources. An example of this approach is the demand-and-capacity sharing protocols developed for supply networks (e.g., [34]).

2. **Developing a new methodology for managing student absences with no standby position:** An important aspect of future research is how to effectively manage situations where some students are absent. The problem becomes more severe and complex when there are no standby students available (i.e., all students are fully assigned to wards). Strategies might include developing a new protocol that can shuffle and/or aggregate medical students from multiple wards and partially operate all wards, as well as establishing a contingency plan to reduce overall disruptions to the existing schedule and minimize the impact on patients.

3. **Exploring nature-inspired, AI, and learning algorithms and protocols for large-scale scheduling problems:** The mathematical model in M_1 may not be able to deliver a solution in a practical time, especially for a large-scale scenario. It might be beneficial to investigate nature-inspired algorithms. Algorithms such as genetic algorithms [1, 16], simulated annealing [17], and other learning protocols [12, 31] can support M_1. This approach will increase scalability by utilizing algorithms to overcome computational challenges and provide optimal or near-optimal solutions.

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Author contributions

The authors contributed equally to this work.

Conflict of interest

The authors declare no conflict of interest.

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