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Human(s) On The Loop Demand Aware Robot Scheduling: A Mixed Reality based User Study

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***Abstract*— Scheduling tasks for multiple heterogeneous robots is challenging, especially with human supervision in demand-aware environments. This research aims to understand human decision-making and its impact on scheduling through two studies, the first is a mixed reality based user study to explore how human perception of the scheduling environment influences task scheduling and facilitates personalized resource allocation. Our findings indicate that human task schedulers exhibit enhanced performance when assisted by autonomous agents, compared to scenarios with limited autonomy in robotic systems. To explore the impact of robot planning on human decision-making and scheduling, we conducted the second study which employed a mixed reality-based warehouse environment, where two users controlled different robots with shared objectives. Results showed that visual aids like collision cones improved collision-aware scheduling without compromising demand-aware capabilities.**

I. INTRODUCTION

Multi-robot systems enhance task efficiency and scalability by distributing workloads, enabling parallel task execution, and facilitating robot collaboration. They are popular in applications like emergency rescue, surveying, manufacturing, and logistics [1], [2]. However, these systems may require human supervision for robustness [3]. Efficient task planning, scheduling, motion planning, and control, while maintaining mission objectives, are complex in human-supervised multi-robot systems. Goodrich [4] explored the spectrum of human-robot interactions and the intricacies within human-supervised and human-in-the loop robotic systems.

Human-robot interaction can be human-in-the-loop (HIL) [5]–[9] or human-on-the-loop (HOL) [10]–[12]. In HIL, a human operator actively collaborates with or controls the robot during tasks, whereas in HOL, the operator supervises the robotic system. Our research focuses on HOL systems, particularly human task scheduling for multi-robot systems. Task scheduling has been studied for both single [13]–[15] and multi-robot [7], [16]–[21] systems. Dhanaraj [7] explored HIL task scheduling for fault recovery. Zhang [20] proposed heuristic-based task scheduling for robot coalitions. Sandula [22] introduced a multi-agent multi-armed bandit framework for demand-aware multi-robot scheduling. However, these did not address HOL multi-robot scheduling or integration of human decision-making and collision-aware scheduling in a demand-aware environment.

Human Supervised Multi-Robot Systems (HSMRS) offer several advantages over Unsupervised Multi-Robot Systems (USMRS), as noted by Roldan [24]. They are also adaptable to mission changes, such as scenario or task alterations, unlike USMRS, which may require extensive training for optimal performance [25]. However, HSMRS have disadvantages, such as increased workload for human supervisors when monitoring multiple robots, potentially impacting their performance and situational awareness [25]. Additional tasks can further interrupt supervisors, increasing workload and reducing performance [26]. Maintaining situational awareness is challenging for supervisors viewing the world from a robot's perspective, especially in complex environments like demand-aware scenarios [23]. Although human-in/on-the-loop multi-robot scheduling has been explored [27]–[30], human-on-the-loop demand-aware robot scheduling with precedence constraints remains under-investigated.

Our research addresses the complexities of multi-robot scheduling with a human-centric focus through two distinct studies. We utilized collision cones, as explained in [31], to observe collision-aware capabilities of human users. Collision cones are geometric representations that visualize potential collision scenarios between objects by depicting the range of velocity vectors of one object (Object A) that could lead to a collision with another object (Object B). They help users anticipate and avoid potential collisions by providing visual indications of possible collision paths. The key contributions of this work are:

- Single-person study shows that humans perform better when assisted with autonomous agents compared to working without assistance, gaining higher rewards and reducing robot travel distance.
- Multi-person study shows that visual feedback of collision cones enhances humans' collision-aware scheduling, reducing robots' collision time without affecting demand-aware scheduling.

These findings highlight the relationship between human decision-making and environmental cues in multi-robot scheduling, particularly in demand-aware environments. They provide insights into human factors, robot autonomy, and environmental dynamics. These insights aid

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the development of better HSMRS scheduling algorithms by optimizing task allocation and scheduling, integrating observed human factors, and personalizing the process for human-robot teams.

II. METHODOLOGY

Understanding human scheduling behavior is crucial for effective human-on-the-loop multi-robot systems. This section outlines our methodology, divided into three main subsections. Section II-A describes the development and evaluation of demand-aware scheduling algorithms tailored to human interaction, including the design and theoretical background. To understand human decision-making, we conducted a single-person user study detailed in Section II-B, covering the experimental setup, data collection, and analysis of individual scheduling behaviors. We also examined the impact of visualizing collision cones on human scheduling in a multi-human user study, detailed in Section II-C.

A. Demand aware human user scheduling

We conducted two user studies in order to customize the task scheduling process for a multi-robot task scheduler, by assessing the priorities of a human task allocator. The results of this study can be leveraged to tailor the scheduling process accordingly. A user performs a total of $n(>0)$ iterations or trials. The user is presented with $k(>0)$ reward stations. The reward generated at every station follows a probability distribution. At each trial t, the user selects an arm a_t from the set of arms $1, 2, ..., k$ and obtains a reward $r_{a_t,t}$ based on the value sampled from the probability distribution at the corresponding arm. The reward obtained from arm i at trial t is denoted by $r_{i,t}$. The true mean reward of arm i is denoted by μ_i, where $i \in$ 1,2,...,k, and the standard deviation of the reward distribution of arm i is denoted by σ_i. The reward distributions of each arm are independent and identically distributed across trials. Therefore, we can model the human user's decision-making process in a multi-armed bandit scenario. The cumulative reward obtained after t trials is denoted by $R_t = \sum_{i=1}^{t} r_{a_i,i}$, where a_i is the arm selected by the user at trial i, and $r_{a_i,i}$ is the reward obtained by selecting arm a_i at trial i. The expected value of the total reward obtained after n trials is given by $E[R_n] = \sum_{i=1}^{n} E[r_{a_i,i}]$, where $E[r_{a_i,i}]$ is the expected value of the reward obtained by selecting arm a_i at trial i. The aim of the human user is to maximize this expected cumulative reward over the n trials by selecting the arm with the highest expected reward at each trial. In other words, at each trial t, the user is expected to select the arm a_t with the highest expected reward based on the information available up to that point in time: $a_t = \arg\max_{i \in 1,2,...,k} \hat{\mu}_i(t-1)$, where $\hat{\mu}_i(t-1)$ is the estimate of the true mean reward of arm i based on the rewards obtained up to trial $t-1$.

B. Single person user study

In our setup, users must navigate an environment with unknown reward station distributions, requiring exploration in initial tasks to identify stations with higher rewards. Optimal scheduling targets these stations for higher mean rewards. Figure 1 shows a demand-aware pickup dispatch task with five drop points and one pickup point, typical in warehouse operations. In Subsections II-B and II-C, we explore similar environments. For the user study, we used one pickup point (base location) and five drop points (reward stations), with rewards generated based on task demand probability. We conducted a user study to understand the impact of human decision-making on task scheduling in a human-on-the-loop robotic system. Using a mixed-reality setup, we created a realistic warehouse scenario for a pickup-dispatch task, encompassing three scenarios: (1) Single-robot scheduling, (2) Multi-robot scheduling, and (3) Simulated scheduling with zero robots. We collected data from participants across randomized, demand-aware environments (explained in II-A). In each case, a single human scheduled tasks to maximize the total reward.

Fig. 1: Mixed Reality setup for single robot scheduling.

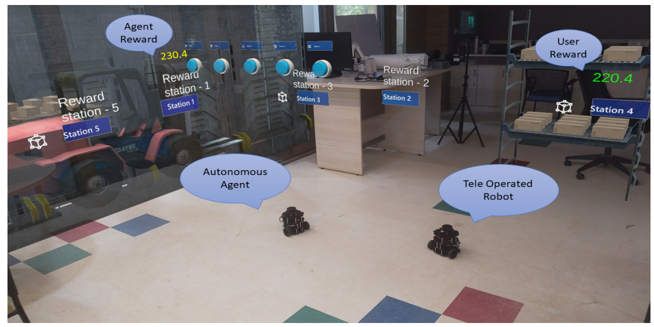

Fig. 2: Mixed reality setup for multi-robot scheduling.

1) Material: We established a mixed reality environment by utilizing Microsoft Hololens [32], Unity [33], Turtlebot [34] and ROS [35] platforms. In this environment, we introduced three distinct scenarios aimed at investigating the influence of human perception on task scheduling.

2) Participants: 8 participants (6 males, 2 females) volunteered from our university, with an average age of 24.37 years and a standard deviation of 2.99. None of the participants had color blindness, and they all granted the required permissions and consent for the study. The users were sampled in a manner ensuring that none of them had prior experience scheduling tasks in a demand-aware task scheduling scenario.

3) Setup: In case 1, known as single-robot scheduling (depicted in Figure 1), participants are assigned the operation of a single robot and tasked with deducing rewards to maximize their collection. Participants control the robots using the virtual buttons, and when a robot reaches a designated station, the reward obtained is revealed in green text atop the station. During this phase, we measure the distance travelled by robot, record task completion times, and calculate the rewards achieved in each iteration.

In case 2, known as multi-robot scheduling, as shown in the Figure 2 we introduce an autonomous agent into the environment. Here, participants observe the actions of the autonomous agent and have the option to incorporate its strategies into their own task scheduling. This stage serves to compare participant performance when acting independently versus when assisted by the autonomous agent. The autonomous agent adopts a multi-agent multi-armed bandit approach for task scheduling, as outlined in [23], due to its superior performance in demand-aware scenarios compared to traditional methods. In this environment, two rewards are displayed: one collected by the autonomous agent (yellow colour) and the other by the user-controlled robot. Participants can utilize the reward data of the autonomous agent to optimize their scheduling processes.

In case 3, simulated scheduling with zero robots, the mixed reality setup is identical to previous cases but without physical robots. Participants instantly see rewards upon pressing virtual buttons, making the total distance traveled by robots irrelevant. This scenario tests if humans can perform better demand-aware scheduling without robots.

The user interface (Figures 1 and 2) has five virtual buttons for task scheduling. In cases 1 and 2, pressing a button prompts the tele-operated robot to perform a pickup-dispatch task, navigating to the base location and then to a station. Rewards are displayed in green for tele-operated robots and yellow for autonomous robots. In the simulated scheduling scenario (case 3), rewards appear instantly on the station when the button is pressed, as no robots are involved. Each case has distinct demand-aware probability distributions. For example, Station One may have the highest mean reward in Case 1, but this can vary in Cases 2 and 3. The rewards in each iteration are calculated based on specific probability distributions unique to each station, all of which are kept confidential from the participants. This information remains undisclosed throughout the study. This remains same across all the Cases 1,2 and 3.

4) Procedure: Participants were briefed about the objectives of the study. Their goal was to maximize rewards, which serves as a parameter for demand-aware scheduling. We documented the total reward for each participant, the execution time of the task, and the travel distance of the robot for all scenarios wherever applicable. The outcomes are detailed in Section III.

C. Multi-person user study

We conducted a multi-person user study to understand how human perception of robot planning space can impact the task scheduling in a human-on-the-loop robotic system. We utilized the concept of collision cones, which are geometric shapes representing the potential collision areas of robots based on their current trajectories and surrounding obstacles. This concept, detailed in [31], was employed for visualizing the collision cones of the robots through the mixed reality device, as shown in Figure 3. The study encompassed two distinct scenarios: (1) Scheduling with Visualized Collision Cones, and (2) Scheduling without Visualized Collision Cones, each elaborated below. Across these scenarios, we employed multiple demand-aware environments (as detailed in Section II-A) and randomized the order in which participant groups encountered them, akin to the previous study. In contrast to the previous study, the workspace accommodated two users simultaneously, with each supervising two distinct robots as shown in the figure 3.

Fig. 3: Mixed reality setup for multi-human user study with visualization of collision cones.

1) Material: We set up a mixed reality environment employing two Microsoft HoloLens devices [32], Unity for developing mixed reality applications [33], two Turtlebot mobile robots [34], and ROS for designing the navigation and policy of the mobile robots [35]. Within this setup, we introduced two distinct scenarios to explore the influence of human perception of collision cones on task scheduling.

2) Participants: 8 participants (6 males, 2 females) from our university, with an average age of 26.25 years and a standard deviation of 1.56. None of the participants had color blindness, and they all granted the required permissions and consent for the study. The participants involved in this user study were distinct from those mentioned in II-B. Conducting with different sets of participants was aimed at mitigating selection bias [36] and enhancing the generalizability of the results. The selection criteria is similar to the previous study, that none of the participants have any prior experience of scheduling robots in a demand-aware scheduling environment.

3) Design: We introduced two distinct scenarios. Contrary to the previous study, this is a multi-human user study. Two human users sharing similar warehouse environment and demand aware task scheduling environment will be controlling two different mobile robots as depicted in the figure 3. The demand-aware probability distributions in both the cases were distinct. The figure II-C represents the software and hardware architecture of the environment created for this study.

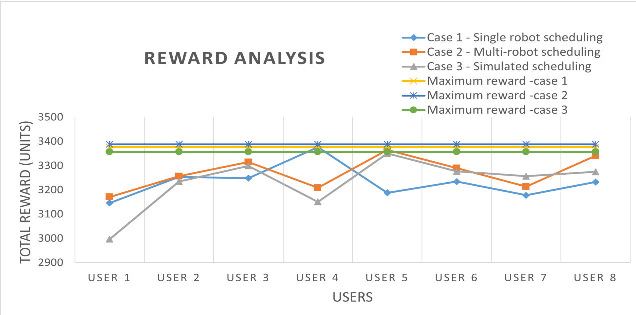

Fig. 4: Reward analysis for single person user study

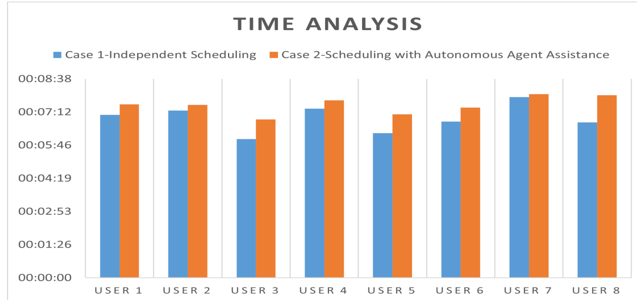

Fig. 5: Time analysis

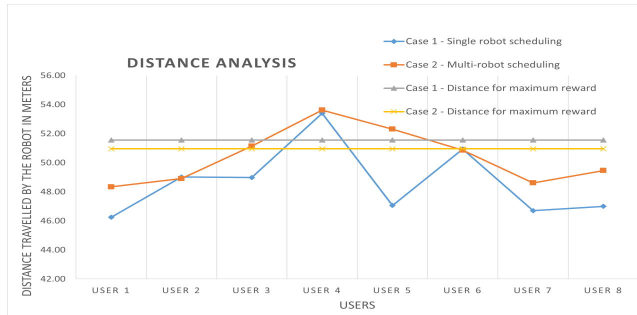

Fig. 6: Distance analysis

In Case 1, known as Multi-Person With Collision cone (MPWC) scheduling, the setup replicates that of the previous case with a crucial addition: alongside the spatial anchor, collision cones are also visualized, as illustrated in Figure 3. These collision cones provide visual cues to indicate potential areas of collision or obstruction. Both the spatial anchor and collision cones remain consistently attached and colocalized with the respective mobile robot, ensuring seamless integration into the mixed reality environment.

In Case 2, known as Multi-Person WithOut Collision cone (MPWOC) scheduling, two human users teleoperate two separate mobile robots using two distinct mixed reality headsets. As the mobile robots are identical and equally capable, a spatial anchor in the form of a hologram is attached to each robot through the respective mixed reality headset, facilitating human control. This setup ensures that each human operator can identify and interact with the specific robot they are teleoperating, enhancing clarity and coordination in the teleoperation process. The spatial anchor, visualized through the mixed reality headset, remains consistently attached to and colocalized with the respective mobile robot as shown in figure 3.

The user interface, as depicted in Figure 3, shares similarities with the interface shown in Figure 1, featuring five virtual buttons designed for task scheduling. However, in Cases 1 and 2, there is a notable difference: the presence of collision cones and spatial anchors integrated into the visualization via the mixed reality headset.

4) Procedure: Participants were briefed about the objectives of the study, which encompass two major goals. The first objective is to maximize the rewards obtained for scheduling, serving as a parameter for demand-aware scheduling. The second objective aims to minimize the total occurrences of robots falling into each other's collision cones, representing a parameter for collision-aware scheduling. The outcomes are detailed in Section III. We documented the total reward of each participant, total time robots are heading towards collision, task execution time, and robot travel distance for both scenarios. The time when robots were heading towards collision was recorded whenever the velocity of the robot fell within the collision cones, and all such instances were continuously added together. The outcomes are detailed in Section III.

III. Results

In this section we detail the results of the user studies single human user study and multi-human user studies in subsections III-A and III-B respectively.

A. Single human user study

The user study has three distinct conditions: (1) Single-robot (no autonomous Agent), (2) Multi-robot scheduling (with autonomous agent) and (3) Simulated scheduling environment with no robots as explained in Section II-B. In total, each participant was responsible for scheduling 45 tasks: 15 tasks independently in case 1, 15 tasks with the assistance of the autonomous agent in case 2 and additionally, participants completed 15 tasks in a simulated environment where there was no robot involved, and the reward was instantly observed by the user. Our analysis encompassed three distinct aspects

Users prioritized minimizing the robot's travel distance, leading to lower rewards in Case 1, observed in 4. However, with autonomous agent assistance, users achieved higher rewards and were less concerned about travel distance of the robots. There was no substantial difference in user performance regarding rewards obtained between Cases 1 and 3. Participants favored quick task completion over optimal scheduling in independent scheduling (Case 1), observed in 5. In Case 2, with autonomous agent assistance, participants took more time but achieved higher rewards. In Case 1, users aimed to minimize the robot's travel distance, observed in 6. In Case 2, with the DARTS algorithm, users focused on maximizing rewards, even if it meant the robot traveled more distance. The robot covered significantly more distance in Case 2, except for user 4.

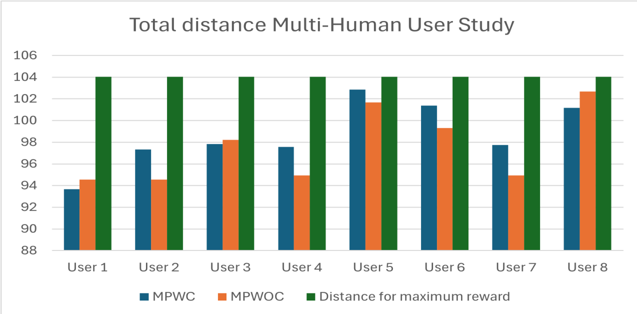

Fig. 7: Distance analysis for multi-human study

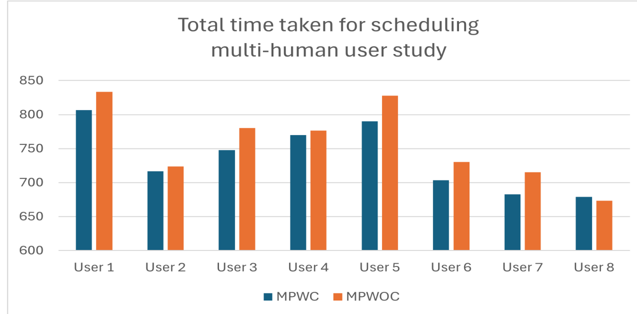

Fig. 9: Time analysis for scheduling in multi-person study

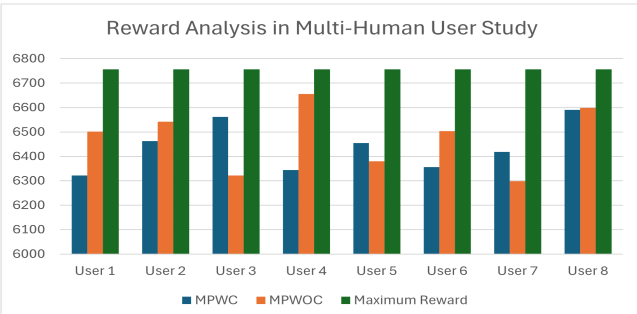

Fig. 8: Reward analysis for multi-person study

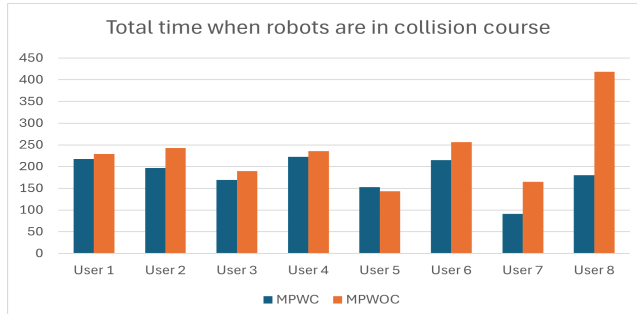

Fig. 10: Collision-bound robot timing analysis

We performed a one-way ANOVA to compare the *total rewards* of users across three cases: 1, 2, and 3. This analysis did not reveal any statistically significant differences. However, when we performed paired T-tests on other dependent variables, namely *total task completion time* and *total distance* traveled by the tele-operated robot, we observed statistical significance among the cases 1 and 2. A paired T-test score for total task completion time indicate that the users took higher time to complete the tasks in case 2, while case 1 is significantly lower ($t = -4.693$, $p < 0.050$, Cohen's $d = -1.369$) than case 2. The paired T-test score for *total distance* traveled by the tele-operated robot indicate that the tele-operated robot travelled significantly higher distance complete the tasks in case 2, while case 1 is significantly lower ($t = -2.759$, $p < 0.050$, Cohen's $d = -0.787$) than case 2. In conclusion, the data suggests that there are significant differences between the means of distances traveled by the tele-operated robot and the time taken by users across the different cases.

B. Multi-human user study

This user study comprises two distinct cases: (1) Multi-Person With Collision cones visualization (MPWC) and (2) Multi-Person WithOut Collision cones visualization (MPWOC), as explained in Section II-C. Each participant was tasked with scheduling 60 tasks: 30 tasks in Case 1 and 30 tasks in Case 2. The analysis of this study encompasses four distinct aspects: the total distance traveled by the robots, the total reward obtained after finishing tasks, which serves as a parameter for demand-aware scheduling, the time taken for scheduling all the tasks and finally, the time during which the robots are heading towards collision. It is important to note that although the demand-aware scheduling environment differed between both cases, the maximum possible reward and the corresponding distance traveled by the optimal agent remain the same for both cases.

From Figure 7 we observe that the robot's total travel distance in the MPWC scenario, where collision cones are visualized, is close to the maximum possible reward. However, a paired T-test showed no statistical significance in this distance. Regarding the total reward obtained by human users, no clear trend was observed. A paired T-test also indicated no statistical significance in the rewards when collision cones were visualized, observed in Figure 8

In Case 1, users took less time to schedule tasks with collision cones visualized, as shown by a paired T-test indicating significantly lower time (t = 3.715, p ¡ 0.050, Cohen's d = 0.274). In Case 1 (MPWC) with collision cones, robots did not intersect each other's paths. A paired T-test for the time when robots were heading towards a collision showed significantly lower times in Case 1 (t = -1.950, p ¡ 0.050, Cohen's d = -0.571) as observed in figures 9 and ,10

IV. Discussion

In the single human user study, participants initially focused on speed and minimizing travel distance for task scheduling. When an autonomous agent was introduced, task scheduling improved with higher rewards but took more time. Participants learned that minimizing robot travel distance did not always yield the best outcomes. The study also showed that participants performed better with an autonomous agent when scheduling tasks for a robot in a multi-robot environment. Visual aids like collision cones in the mixed reality interface enhanced collision awareness without affecting demand-aware scheduling performance. This suggests that collision cones improve collision avoidance without compromising task scheduling efficiency.

V. Conclusion

This study has provided valuable insights into the dynamics of human-robot interaction in multi-robot environments, particularly in the context of task scheduling and collision avoidance. Our findings highlight the benefits of incorporating autonomous agents and visual aids such as collision cones in enhancing task scheduling efficiency and collision awareness among human users. Furthermore, the integration of mixed reality interfaces shows promise in providing intuitive visual feedback to enhance human-robot collaboration and decision-making in complex environments. Future work will delve into integrating the identified sub-optimality factors introduced by human intervention into the design of well-integrated multi-robot scheduling and path planning approaches.

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