2024 33rd IEEE International Conference on
Robot and Human Interactive Communication (RO-MAN)
August 26-30, 2024. Pasadena, California, USA.

2024 33rd IEEE International Conference on Robot and Human Interactive Communication (ROMAN) | 979-8-3503-7502-2/24/$31.00 ©2024 IEEE | DOI: 10.1109/RO-MAN60168.2024.10731266

Multilateral Multimodal Human-Robot Collaboration for Robotic Nursing Assistance: Prototype System and Preliminary User Study

Lorena Maria Genua[1], Nikita Boguslavskii[1] and Zhi Li[1]

***Abstract*— In this paper, we introduce an innovative robotic nursing assistance system with multilateral multimodal human-robot (MMHR) collaboration, enabling nursing robots to be assisted by remote and on-site operators. Through our augmented reality (AR) interfaces, the remote and local operators can monitor the robots' operations, issue task and action commands, and facilitate collaborative assistance and information exchange via AR cues or verbal communication. Our preliminary user study evaluated the usability of the prototype system and validated the efficacy of our MMHR collaboration in a representative nursing assistance task scenario. The results show significant improvements in overall task efficiency for the remote operator and reveal human strategies and rationales in the spontaneous multilateral human-robot collaboration.**

I. Introduction

Over the last decade, robots for nursing assistance have evolved from mobile telepresence to mobile manipulators and humanoid robots [1]. Compared to tele-robotic systems developed for specific and structured intervention (e.g., tele-surgery), nursing robots are expected to be more general-purpose. They are designed to perform a wide range of tasks including communication, mobility, measurement of clinical data, general manipulation and tool use [2], and will need more assistance from humans to operate in dynamic, cluttered, human environments, such as hospitals, nursing facilities and homes. Recently, many mobile manipulators and humanoid robots deployed all over the world (e.g., [3]) have proven their value for pandemic patient care, for mitigating the shortage of caregivers and reducing their infection risks. Beyond pandemic responses, our aging society, which is getting 8-hours older every day on average and facing a shortage of nursing workforce, may increasingly depend on robots to provide more sustainable, affordable, and accessible care [4], because the nursing robots can effectively enable nurses to engage in professional tasks and reduce their turnover intention and time pressure [5], [6].

In the near future, we envision these nursing robots will be deployed at a large scale in hospitals and nursing facilities to perform comprehensive nursing assistance tasks (e.g., patient room cleaning and organization) that demand effective human-robot collaboration and communication. In particular, we need to advance the nursing robots from unilateral to **multilateral** collaborative human-robot system, such that they can leverage a little assistance from both remote and local humans to effectively operate complex tasks otherwise not feasible to their limited autonomy for perception and action. Consider the task of organizing medical supplies in a cluttered storage. During a task, the robot operates autonomously under the remote user's supervision but can request help from both the remote and local users. When the robot encounters a problem (e.g., cannot find the target object), it can alert the remote user who could move robot's camera to search for the missing target, or point and click the mislabeled object in the camera view, to remotely control the robot's action and remove the objects that occlude the target. A local user, called by the remote user or the robot, could also help with all these issues. However, there are also problems only the local users can help with, such as retrieving the target object from a location the robot cannot access, or manipulating the object or storage in ways not feasible with remotely controlled actions.

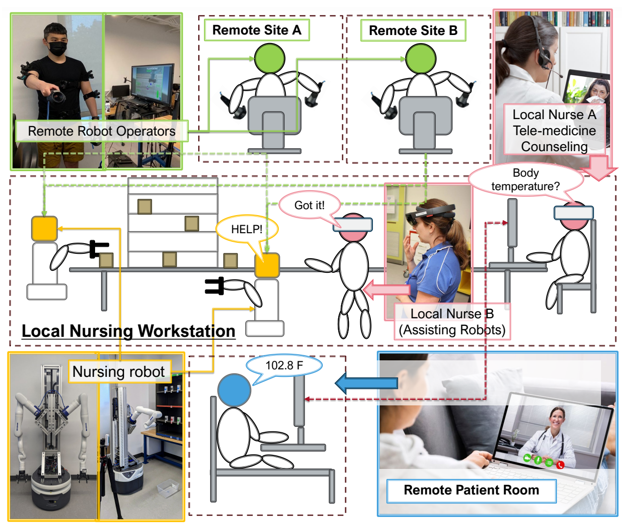


Fig. 1: Multilateral Multimodal Collaboration for Nursing Assistance.

This paper will present an innovative robotic nursing assistance system with multilateral multimodal (MMHR) collaboration. Our prototype MMHR nursing assistance system will enable each nursing robot in the team to be assisted by remote operators and local human nurses through multimodal human-robot interfaces with adjustable levels of autonomy. Shown in Fig. 1, the remote operator can switch the control between multiple robots. The local nurses can also assist any robot in the shared workspace while multitasking on other patient care tasks (e.g., tele-medical counseling). The system also supports natural and intuitive communication (e.g., AR visual cues, verbal communication) among human and robot team members. The significance of our work is to contribute a prototype system that advances the engineering for robotic

[1] Robotics Engineering Department, Worcester Polytechnic Institute (WPI), Worcester, MA 01609, USA {lgenua,nbboguslavskii,zli11}@wpi.edu

nursing assistance and can be deployed for human-robot collaboration across a wide range of industry, maintenance, warehouse and assisted living tasks applications. We further conducted a user study to evaluate the usability of the prototype system, and validated the efficacy of multilateral and multimodal collaboration in a representative nursing assistance task scenario. Our study also reveals how humans decide on task division and delegation in spontaneous multilateral collaboration.

II. Related Work

A. Human-Robot Collaboration for Nursing Assistance

In response to Ebola, Zika and the COVID-19 pandemic crisis, mobile manipulators and humanoids with various levels of autonomy have been developed and deployed for nursing assistance tasks for quarantine patient care (e.g., fetching and delivering medical supplies, preparing and cleaning nursing workspace and patient rooms, taking vital sign measurements) [7]. These robots may operate autonomously on a few tasks (e.g., Moxi [8], autonomous navigation to deliver medical supplies). However, most of them still need to leverage human assistance, either from remote or local operators, to handle tasks that involve more complex and difficult operations. While these more advanced nursing robots have the potential to perform various complicated tasks that involve the robot's base, arm, and camera coordination [9], these tasks could not be feasible or performed efficiently without collaboration between the robot autonomy, remote operators and local operators. To improve the remote human-robot collaboration (HRC) through tele-nursing interfaces, recent research efforts have developed more transparent and intuitive human-robot interfaces that integrate natural gaze and motion control [10], [11], more adaptive human-robot task division based on their performance and workload [12], and investigated the human-robot communication through multimodal interfaces [13], perception and action augmentation [14] and for HRC with various levels of autonomy [15], [16]. Meanwhile, to better collaborate (interact) with nurses (patients) in the shared workspace, recent nursing robots also improved their system integration for more dexterous base-arm coordination [17], autonomy for safe navigation and precise manipulation, haptic sensing for human contact [11], and intelligence for natural verbal communication and social interaction [18]–[20]. In this work, we will advance the HRC for nursing assistance to a more versatile **multi-lateral** collaboration, so that the nursing robots will be able to leverage (a little) assistance from both the remote and local operators to accomplish an otherwise not feasible task due to its limited autonomy for perception and action.

III. Prototype System

A. System Overview

Shown in Fig. 2, our proposed system supports the collaboration of *nursing robots*, *local users* sharing the robot's workspace, and *remote users* operating the robot from a different physical location. Our system utilizes the *nursing robot* IONA (Intelligent rObotic Nursing Assistant), a mobile humanoid nursing robot developed in our recent work [17], which has outstanding manipulation reachability and dexterity to operate in cluttered workspace (e.g., between the high shelves that store medical supplies). A versatile supporting structure allows multiple manipulator arms (Kinova Gen3) to be mounted on the robot's motorized chest, and move autonomously with respect to the mobile base (Freight Research Platform). The robot also has several RGB+D cameras (Realsense D435) on the robot chest and hands to provide sufficient telepresence and autonomous visual perception. The operator console of the *remote users* has a screen-based graphical user interface along with keyboard and mouse control. Meanwhile, the *local users* can control the robot using head-mounted augmented reality interfaces (Microsoft HoloLens 2). Both the remote and local users' interfaces support multimodal communication through augmented reality visual cues, auditory feedback and speech. Our software system uses Ubuntu 20.04 operating system and ROS1 (Robot Operating System) for robot control. The user interfaces were developed using Unity and Microsoft Reality Toolkit (MRTK) 2.7.2, while ROS-TCP Connector package was used to support the communication.

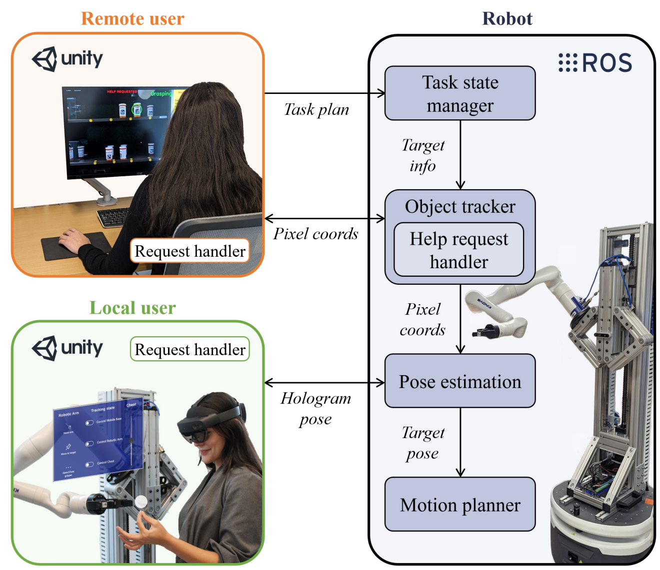


Fig. 2: MMHR system architecture involves a remote user employing a screen-based interface and a local user wearing a mixed-reality headset to interact with each other and with the robotic system.

B. Robotic Systems

Here we describe the essential modules of the robotic systems in Fig. 2 and their communication. The robotic system has a **Task State Manager** module that tracks the list of tasks from the remote operator's control interface. In our setup, the task plan contains the list of the medicines to be handled, including their unique identifier (id), associated names, and expiration dates. The Task State Manager therefore monitors the current target and sends its information to the **Object Tracker** module. The Object Tracker constantly detects all visible markers in the current field of view of the camera mounted on the robot's chest and stores their 2D positions $p_{image} = (p_x, p_y)$, i.e., the marker's pixel coordinates in the camera image. If the current target is detected, the position p_{image} is sent to the Pose Estimation. If not, the Object Tracker will generate a request to the **Help Request Handler** module. The Help Request Handler will compare the error code e_i in the request against the category of errors $e = \{e_1, e_2, \ldots, e_n\}$ to identify the encountered problem. A help request will be sent to either a local or a remote user depending on e_i. When receiving a help request, the interfaces will generate a message based on e_i and display it to the remote or local operator using augmented reality text box (and potentially using speech). Once the current task is handled with human assistance, the Task State Manager updates the target and the robot resumes its autonomous actions. Shown in Fig. 3, besides the help requests from the robot, the remote and local operators can also send help requests to one another if they need to collaboratively resolve the problem.

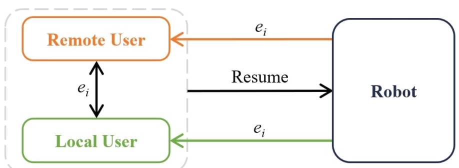


Fig. 3: Help request handler module. The robot sends a help request based on a specific error code e_i. Each user can solve the issue independently or send a request to each other, and resume the task upon resolution.

Our module for **Pose Estimation** handles the frame transformations between the workspace, the robot and the HoloLens, and sends them to the Motion Planner module. We use Azure Spatial Anchor (ASA) and the ASA SDK for Linux to set a common coordinate reference system between the robot and the HoloLens (See Fig. 4). Azure Spatial Anchor is a cloud-based service provided by Microsoft that allows for the creation, storage, and retrieval of digital objects, anchored to precise physical world locations. The Pose Estimation module receives the pixel coordinates p_{image} from the Object Tracker, and computes its 3D position relative to the camera's coordinate frame. For augmenting the local user's view with a digital twin [21], we calculate the transformation T_8^1 from the spatial anchor to the object. The transformation from the target object to the camera frame T_8^7, calculated from the input p_{image}, can be represented as: $T_8^7 = [R_8^7, \vec{t_8^7}; \mathbf{0}, 1]$, where R_8^7 is the 3×3 rotation matrix and $\vec{t_8^7}$ is a translation vector that represents the object's position relative to the camera. We can then retrieve the transformation of the object relative to the spatial anchor T_8^1 as the product of the transformations from the robot's odometry to the ASA system T_1^3, odometry to the base link T_4^3, base link to the robot's chest T_5^4, and the static transformation from the chest to the camera T_7^5. Therefore, we can compute $T_8^1 = (T_1^3)^{-1} \cdot T_4^3 \cdot T_5^4 \cdot T_7^5 \cdot T_8^7$.

The Pose Estimation module also calculates the transformation from the base link of the robot's mobile base to the target object (T_8^4). With the received estimated object pose, the **Motion Planner** module uses RelaxedIK [22] to solve the inverse kinematics for the robot arm and generate the entire motion to handle an object, or to execute the actions

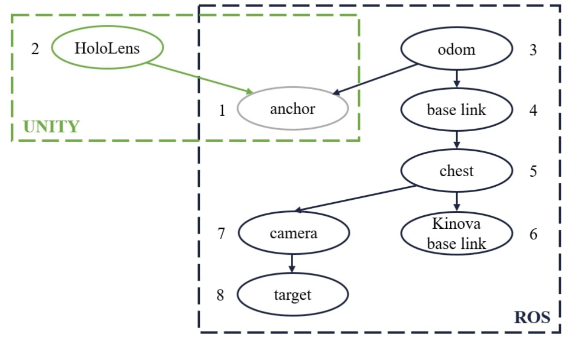


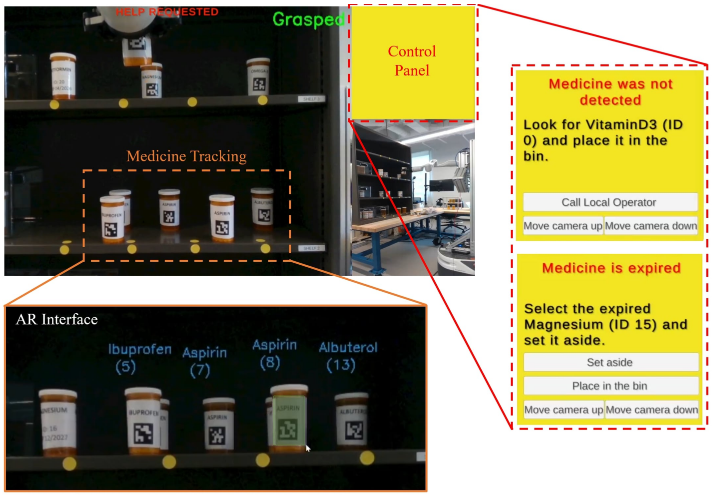
Fig. 4: Transformation Tree of the system. A shared anchor frame is located relative to both the HoloLens world frame and the robot's odometry frame, ensuring synchronized spatial referencing.

commanded by remote or local users. When the task has been completed, the Motion Planner will communicate with the Task State Manager module to update the target and transition to the next task.

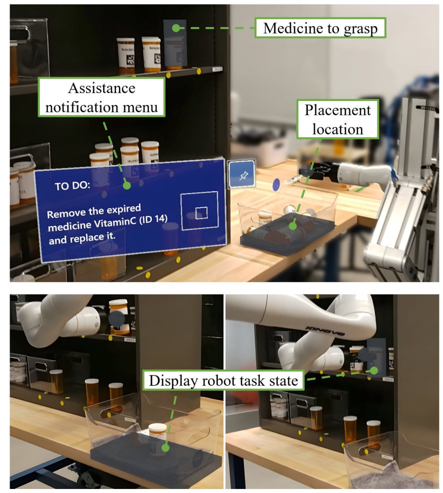
C. Remote and Local User Interfaces

Shown in Fig. 5 (a), the **remote user interface** has a screen-based graphical user interface (GUI), which streams the view from a main camera attached to the chest of the robot and from a secondary standalone camera in the workspace. The main camera view shows the name and the ID of the detected objects, and marks the expired medicines in red. Users can use the mouse cursor to draw a rectangle in the camera view to indicate the object to be grasped or a location to place it. Besides the visual feedback, the interface also provides auditory feedback (e.g., an alert sound when a help request is received). The interface has a control panel that displays messages (e.g., to indicate the errors and suggestions to fix them) and provides buttons for the user to control the camera view and robot's actions. These actions include: 1) *Move camera up/down* — Moving the robot's chest by a predefined distance to adjust the camera view; 2) *Grasp* — Commanding the robot to grasp a selected object on the screen; 3) *Place here* — Placing the object grasped by the robot in a specified location in the field of view; 4) *Set Aside* — Placing the object grasped by the robot in the disposal area in front of the shelves; 5) *Place in the bin* — Placing the object grasped by the robot into a designated container; 6) *Call local operator* — Sending a help request to the local operator.

The **local user interface** uses HoloLens to render several AR entities (on robot, environment, and interfaces) to display task and robot states, and to control the robot. Shown in Fig. 5 (b), the interface provides real-time updates on the task state, using AR to indicate the target object the robot is grasping and of the designated bin where the robot is placing it. When the local user receives a help request (from the robot or the remote user), an AR dialog panel pops up with a notification sound to describe the problem and suggestions to fix it. For example, along with the suggested action "Place here", the interface will also highlight the designated bin to place the object. Once the action for assistance is completed, the user can click the checkmark on the dialog panel to



(a) Remote User Interface



(b) Local User Interface

Fig. 5: User Interfaces. (a) The remote user interface includes two camera views and a control panel to send commands to the robot or call the local operator. (b) The local user HoloLens interface displays hologram overlays for task status and assistance.

resume the robot's autonomous operation for the remaining tasks.

IV. User Study Evaluation

A. Task and Experimental Setup

We conducted a preliminary user study to assess the usability and integration of our prototype system and validate the efficacy of our multilateral, multimodal collaboration system. Our experiment simulated a routine nursing task of collecting an order of medicines from the storage shelves. The robot had to autonomously retrieve and deposit eight specified medicines into a bin in front of the storage shelves. In this preliminary study, one experimenter was designated as the local operator for all the trials to provide optimal and uniform performance across participants. This ensured comparable and consistent interaction behaviors with the participants who acted as the remote operators. The remote operator (i.e., the participant) was instructed to monitor the robot's autonomous operation and to intervene when the robot encountered an error.
The types of errors include: 1) *Expired medicines* — The remote operator must select, grasp, and dispose of the expired medicine, then replace it with a valid one; 2) *Misplaced medicines* — The user needs to control the robot to relocate another misplaced medicine that occludes the target, then select the intended one; 3) *Undetected medicines* — The remote operator has to identify and select the medicine, enabling the robot to grasp it.
Throughout the task, participants were provided with an inventory layout, to help them locate specific medicines while assisting the robot. While supervising the robot, the remote operator was also required to work on the math questions displayed on the same screen. This secondary task was expected to distract their attention and increase their workload for visual processing and critical thinking. The experiment was operated in three different modes, which were randomized for each participant:

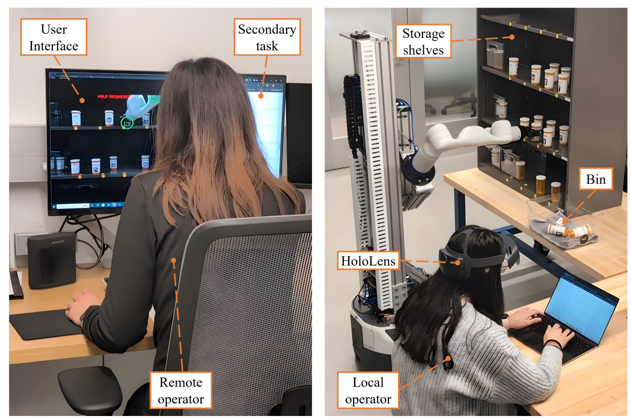


Fig. 6: Experiment Setup: the remote operator (left), and the robotic system and the local operator (right).

- **Mode 1 - Remote only**: the remote operator is responsible for solving every problem the robot encountered.
- **Mode 2 - Remote + Local freeform**: the remote operator can resolve the problem alone or request help from a local operator.
- **Mode 3 - Remote + Local constrained**: the robot decides who to request help from to resolve the problem, and send the request to the chosen operator. In this experiment, the local operator was called for 75% of the encountered errors.

B. Experimental procedure and data collection

We recruited N=20 participants (13 males and 7 females, 26.6 $\pm$ 5.6 years) for our study. The experimenter provided verbal instructions and demonstrations to teach participants the various functionalities of the interface, and how to address each issue (expired, misplaced and undetected medicines). During the formal user study, we conducted two trials for each mode, and the order was randomized for each participant. Between modes, participants filled in some standard and customized questionnaires, including NASA Task Load Index (NASA-TLX) and System Usability Scale (SUS). During the experiment, we recorded task completion

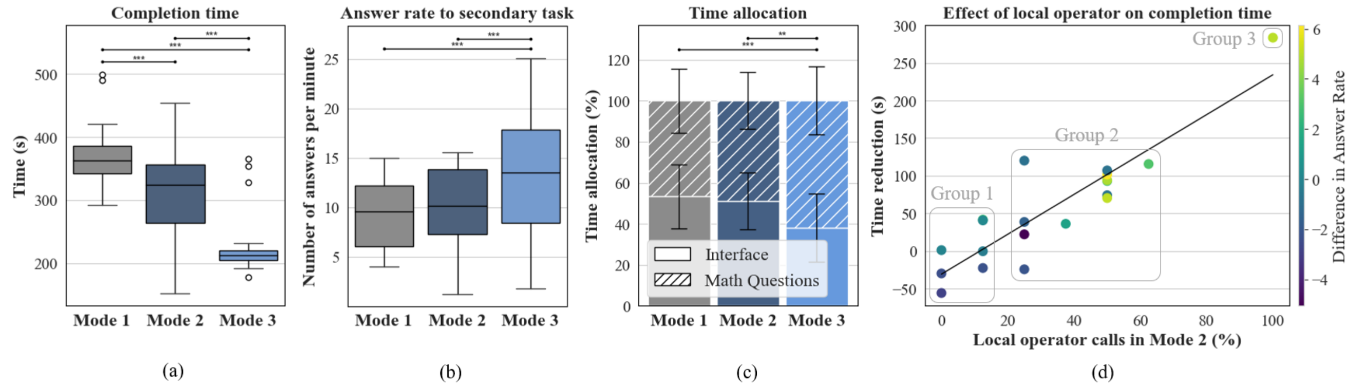


Fig. 7: Performance comparison across modes, **Mode 1**: Remote only, **Mode 2**: Remote + Local freeform, **Mode 3**: Remote + Local constrained. a) Task completion time. b) Secondary task performance, measured as the number of math questions answered per minute. c) Gaze distribution on the screen: percentage of time spent on interface and secondary task. d) Percentage of local operators' calls in Mode 2 versus task completion time reduction compared to Mode 1, for each participant.

time, robot/task states, and interface inputs. Participants' gaze was also tracked to evaluate attention shifts between primary and secondary tasks and their interface engagement. To assess cognitive workload, we collected the pupil diameter as an indication of stress level: an increase in pupil size is associated with increased stress [23]. We therefore compute the cognitive workload as $(D_{\text{real}} - D_{\text{base}})/D_{\max}$, where D_{real} is the real-time pupil diameter, D_{base} is the baseline pupil diameter recorded by looking at a white screen for 30 seconds before the experiment, and D_{max} is the maximum average deviation across all trials for each participant.

V. Results

A. Overall Performance, Workload, and Usability

We used the Paired t-Test with the Benjamini-Hochberg correction, to compare the three modes. Regarding **task performance**, our analysis reveals that the presence of a local operator significantly reduces the task completion time (*p<0.001* across all modes, see Fig. 7 (a)). Fig. 7 (b) compares the secondary task's answer rate, calculated dividing the number of answered questions by the task completion time. The significant difference (*p<0.001*) in answer rates between Mode 1 and Mode 3 indicates that local operator assistance also improves the secondary task performance of the remote operator, as participants were solving the questions quicker. Regarding **workload**, we analyzed the gaze distribution on the screen, represented as the percentage of time focused on the interface versus on the secondary task (Fig. 7 (c)). There is a significant difference between Mode 1 and Mode 3 (*p<0.001*) and between Mode 2 and Mode 3 (*p<0.01*). Because of the local operator's help, participants spent significantly less time looking at the interface and focused more on the secondary task to answer the math questions. However, the cognitive workload has no significant difference across all modes. The subjective data collected through NASA-TLX survey reported a significant difference between Mode 1 and Mode 3 (*p<0.01*), and between Mode 2 and Mode 3 (*p<0.02*). The SUS scores for the three modes suggest participants were satisfied with the overall system and found it to be usable (Mode 1 = 87.63 $\pm$ 10.41, Mode 2 = 86.63 $\pm$ 9.5, Mode 3 = 88.13 $\pm$ 9.65).

B. To Call or Not to Call for Help?

From the comparison of Mode 1 versus Mode 2, we found that having the option to call the local operator for help does not reduce the remote operator's cognitive workload. To the remote operators, to call or not to call the local operator for help was not an easy decision if they are able to help the robot effectively through remote control interfaces. Compared to Mode 1, Mode 2 has significant task completion time reduction (*p<0.001*, see Fig. 7(a)), but the secondary task performance and time allocation between interface and secondary task are comparable. Shown in Fig. 7 (d), we found a monotonic relationship between the frequency of assistance requests and task completion time reduction, confirmed by a *Spearman correlation coefficient* of *0.81*. Overall, more frequent calls to the local operator lead to faster task completion time. The decision to seek help from local operators varied among participants, with post-experiment interviews revealing insights into their strategies and reasoning for either seeking or not seeking assistance. Overall, we noticed three distinct behavioral patterns: **Group 1** participants rarely involved the local user, emphasizing **self-reliance** and efficiency in their tasks. One noted, *"I felt confident in my ability to manage the tasks independently and didn't consider asking for help."* Another highlighted their **ability to multitask**: *"I found I could manage both the robot's operations and the math questions... I saw no reason to delegate unnecessarily."* **Group 2**, on the other side, were more strategic in their approach to delegate. *"I would delegate the hardest tasks... The rest I would handle myself,"* and *"My strategy was based on the number of actions. If a task requires multiple steps, I would prefer to request help."* illustrate their decision to seek local operator assistance for particularly **difficult** or **time-consuming tasks**. Some people in this group also considered **fairness, workload balance,** and **personal capabilities**: *"I didn't want to overload the local operator, and I would delegate unless I felt I could handle the task more quickly myself."* Other participants aimed for an even distribution of tasks. One participant in **Group 3** focused solely on efficiency and trusted the local operator's ability to expedite task completion.

VI. Discussion

Our preliminary user study focused on the impact of local assistance on the remote operator's performance. Findings indicate that enabling a multilateral assistance system significantly decreases task completion time and reduces the mental workload on the remote operator. Additionally, we found that constraining the help requests also benefits the secondary task performance. However, if the remote operator has the option to select whether to handle the issue themselves or delegate it to the local operator, this will introduce an additional layer of complexity as they must expend extra effort to determine who is best suited to address a task failure. Indeed, the cognitive workload of the freeform mode was comparable to Mode 1, and the secondary task performance and attention allocated to the interface remained consistent.

Overall, while our findings validate the importance of this multilateral collaboration, they also suggest that it is preferred to enable the robot (instead of humans) to decide the task division (i.e., when and who to help the robot), because they need to consider a multitude of factors. From the user study, we observed diverse strategies to decide whether to call for help, which may prioritize the overall team performance, the workload of the human collaborator, the efficiency of remotely controlling the robot, the difficulty of the task, etc. We also noticed that some participants called the local operator less often because they found controlling the robot themselves more engaging. Therefore, it will be important to enable robots to dynamically adjust task delegation based on the real-time estimation of remote and local operators workload, the task complexity, and their abilities and availability to assist the robots.

VII. Conclusion and Future Work

We developed an innovative prototype system that transitions nursing robots from unilateral to multilateral collaborative human-robot systems, enabling effective collaboration and communication with both remote and local human operators. While our MMHR collaboration system has demonstrated promising results in improving task efficiency and reducing the remote operator's workload, the challenges of human decision-making suggest a need for adaptive delegation mechanisms to balance autonomy and assistance. Our future work will develop robot autonomy to adapt the task division to human performance, workload, and availability to assist. We will also conduct further user studies to investigate: 1) how to coordinate the MMHR collaboration when the local operators are not experts (as the experimenter) but users novice to the task and interfaces, and 2) how people leverage multimodal communication (i.e., AR and verbal communication).

References

[1] C. Nieto Agraz, M. Pfingsthorn, P. Gliesche, M. Eichelberg, and A. Hein, "A survey of robotic systems for nursing care," *Frontiers in Robotics and AI*, vol. 9, p. 832248, 2022.

[2] K. Hauser and R. Shaw, "How medical robots will help treat patients in future outbreaks," *IEEE Spectrum*, 2020.

[3] F. Betriana, R. Tanioka, J. Gunawan, and R. C. Locsin, "Healthcare robots and human generations: Consequences for nursing and healthcare," *Collegian*, vol. 29, no. 5, pp. 767–773, 2022.

[4] H. Christensen, N. Amato, H. Yanco, M. Mataric, H. Choset, A. Drobnis, K. Goldberg, J. Grizzle, G. Hager, and J. Hollerbach, "A roadmap for us robotics–from internet to robotics 2020 edition," *Foundations and Trends® in Robotics*, vol. 8, no. 4, pp. 307–424, 2021.

[5] H.-Y. Chang, T.-L. Huang, M.-K. Wong, L.-H. Ho, C.-N. Wu, and C.-I. Teng, "How robots help nurses focus on professional task engagement and reduce nurses' turnover intention," vol. 53, no. 2, pp. 237–245, 2021.

[6] T.-L. Huang, C.-N. Wu, I.-C. Lee, A. M.-K. Wong, Y.-I. L. Shyu, L.-H. Ho, G.-Y. Liao, and C.-I. Teng, "How robots impact nurses' time pressure and turnover intention: A two-wave study," *Journal of Nursing Management*, vol. 30, no. 8, pp. 3863–3873, 2022.

[7] E. Ackerman, "How diligent's robots are making a difference in texas hospitals," *IEEE Spectrum*, 2020.

[8] ——, "Moxi prototype from diligent robotics starts helping out in hospitals," *IEEE Spectrum. https://spectrum. ieee. org/automaton/robotics/industrial-robots/moxi-prototype-fro m-diligent-robotics-starts-helping-out-in-hospitals*, 2018.

[9] Z. Li, P. Moran, Q. Dong, R. J. Shaw, and K. Hauser, "Development of a tele-nursing mobile manipulator for remote care-giving in quarantine areas," in *2017 IEEE International Conference on Robotics and Automation (ICRA)*. IEEE, 2017, pp. 3581–3586.

[10] T.-C. Lin, A. U. Krishnan, and Z. Li, "Physical fatigue analysis of assistive robot teleoperation via whole-body motion mapping," in *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2019, pp. 2240–2245.

[11] J. M. Marques, J.-C. Peng, P. Naughton, Y. Zhu, J. S. Nam, and K. Hauser, "Commodity telepresence with team avatrina's nursebot in the ana avatar xprize finals," 2023.

[12] T.-C. Lin, A. U. Krishnan, and Z. Li, "Intuitive, efficient and ergonomic tele-nursing robot interfaces: Design evaluation and evolution," *ACM Transactions on Human-Robot Interaction (THRI)*, vol. 11, no. 3, pp. 1–41, 2022.

[13] ——, "Comparison of haptic and augmented reality visual cues for assisting tele-manipulation," in *2022 International Conference on Robotics and Automation (ICRA)*. IEEE, 2022, pp. 9309–9316.

[14] ——, "Perception and action augmentation for teleoperation assistance in freeform tele-manipulation," *ACM Transactions on Human-Robot Interaction*, 2023.

[15] ——, "The impacts of unreliable autonomy in human-robot collaboration on shared and supervisory control for remote manipulation," *IEEE Robotics and Automation Letters*, 2023.

[16] A. U. Krishnan, T.-C. Lin, and Z. Li, "Human preferred augmented reality visual cues for remote robot manipulation assistance: from direct to supervisory control," in *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2023, pp. 7034–7039.

[17] N. Boguslavskii, Z. Zhong, L. M. Genua, and Z. Li, "A shared autonomous nursing robot assistant with dynamic workspace for versatile mobile manipulation," in *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 2023, pp. 7040–7045.

[18] N. Chatterji, C. Allen, and S. Chernova, "Effectiveness of robot communication level on likeability, understandability and comfortability," in *2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*. IEEE, 2019, pp. 1–7.

[19] J. A. Pepito, H. Ito, F. Betriana, T. Tanioka, and R. C. Locsin, "Intelligent humanoid robots expressing artificial humanlike empathy in nursing situations," *Nursing Philosophy*, vol. 21, no. 4, p. e12318, 2020.

[20] M. E. L. Redondo, R. Niewiadomski, F. Rea, S. Incao, G. Sandini, and A. Sciutti, "Comfortability analysis under a human–robot interaction perspective," *International Journal of Social Robotics*, vol. 16, no. 1, pp. 77–103, 2024.

[21] J. S. Pierce, B. C. Stearns, and R. Pausch, "Voodoo dolls: seamless interaction at multiple scales in virtual environments," in *Proceedings of the 1999 symposium on Interactive 3D graphics*, 1999, pp. 141–145.

[22] D. Rakita, B. Mutlu, and M. Gleicher, "Relaxedik: Real-time synthesis of accurate and feasible robot arm motion." in *Robotics: Science and Systems*. Pittsburgh, PA, 2018, pp. 26–30.

[23] K. Krejtz, A. T. Duchowski, A. Niedzielska, C. Biele, and I. Krejtz, "Eye tracking cognitive load using pupil diameter and microsaccades with fixed gaze," *PLoSOne*, vol. 13, no. 9, 2018.