Intuitive, Efficient and Ergonomic Tele-Nursing Robot Interfaces: Design Evaluation and Evolution

TSUNG-CHI LIN, Worcester Polytechnic Institute, Robotics Engineering
ACHYUTHAN UNNI KRISHNAN, Worcester Polytechnic Institute, Mechanical Engineering
ZHI LI, Worcester Polytechnic Institute, Robotics Engineering

Tele-nursing robots provide a safe approach for patient-caring in quarantine areas. For effective nurse-robot collaboration, ergonomic teleoperation and intuitive interfaces with low physical and cognitive workload must be developed. We propose a framework to evaluate the control interfaces to iteratively develop an intuitive, efficient, and ergonomic teleoperation interface. The framework is a hierarchical procedure that incorporates general to specific assessment and its role in design evolution. We first present pre-defined objective and subjective metrics used to evaluate three representative contemporary teleoperation interfaces. The results indicate that teleoperation via human motion mapping outperforms the gamepad and stylus interfaces. The trade-off with using motion mapping as a teleoperation interface is the non-trivial physical fatigue. To understand the impact of heavy physical demand during motion mapping teleoperation, we propose an objective assessment of physical workload in teleoperation using electromyography (EMG). We find that physical fatigue happens in the actions that involve precise manipulation and steady posture maintenance. We further implemented teleoperation assistance in the form of shared autonomy to eliminate the fatigue-causing component in robot teleoperation via motion mapping. The experimental results show that the autonomous feature effectively reduces the physical effort while improving the efficiency and accuracy of the teleoperation interface.

CCS Concepts: • **Human-centered computing → Empirical studies in interaction design**; *Gestural input*; **Interaction design theory, concepts and paradigms**.

Additional Key Words and Phrases: Teleoperation interface, human workload, shared autonomy

1 INTRODUCTION

Tele-nursing robots provide a promising safe and cost-efficient approach for patient-caring in quarantine areas [52]. The recent outbreaks of infectious diseases like Ebola [95], Zika [143] and recently COVID-19 [121] necessitate the evolution of tele-nursing robots for the nursing workplace [178]. For quarantine patient care, tele-nursing robots for routine and assistive tasks (e.g., cleaning patient room, deliver food and supplies, assisting patient motions, etc) can reduce the work time, stress, risk of infection, and discomfort of human workers in quarantine areas. They are also capable of supporting the patient's needs for physical and emotional care, and improving the nursing workers' job satisfaction [1, 60]. With the looming threat of the shortage of nursing workers, tele-nursing robots also have the potential to provide remote care in hospitals, homes and nursing facilities, thus improving the sustainability of healthcare for an aging society [55].

Currently, commercialized nursing robots deployed in the workplace are mostly limited to providing mobile telepresence [42, 160]. A few advanced robot prototypes can perform nursing tasks that require manipulation capability and mobility. However, even equipped with the state-of-the-art autonomy, these robots cannot perform

Authors' addresses: Tsung-Chi Lin, tlin2@wpi.edu, Worcester Polytechnic Institute, Robotics Engineering, 85 Prescott Street, Worcester, Massachusetts, 01605; Achyuthan Unni Krishnan, Worcester Polytechnic Institute, Mechanical Engineering, 100 Institute Road, Worcester, Massachusetts, 01609, aunnikrishnan@wpi.edu; Zhi Li, Worcester Polytechnic Institute, Robotics Engineering, zli11@wpi.edu.

2573-9522/2022/4-ART
https://doi.org/10.1145/3526108

nursing tasks at operational speed, or handle high-complexity tasks. They are also not able to perform reliably without human direct control or intervention [173]. While teleoperation interfaces become a natural and practical solution to this problem, teleoperation interfaces may also become the threshold for human-robot teaming. Unlike surgical robots that are specialized for structured operations, nursing robots are designed for assisting a wide range of tasks which require the coordination of the control of the robot arm, hand, base, as well as the active sensors and telepresence.

Prior research has demonstrated that, the performance of human-robot teaming via teleoperation is limited by the usability of teleoperation interfaces rather than the robot's physical capabilities. The high workload and learning effort associated with robot teleoperation interfaces also prevents nursing workers from using the nursing robots on a daily basis, and imposes barriers to the nursing profession. The recent advances in human-robot interfaces provides a wide range of interfaces for the teleoperation of complex motion coordination. However, it is still unclear which interface design could be the most suitable for nursing robots, nursing tasks and workers.

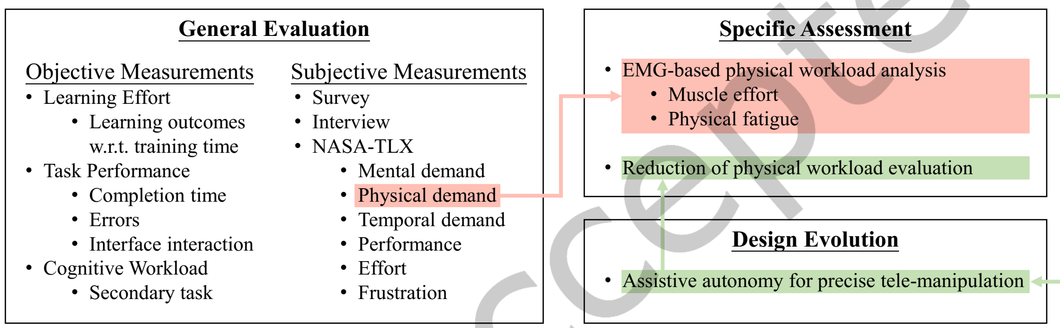


Fig. 1. A proposed hierarchical framework for the evaluation and evolution of human-robot interface.

We hypothesize that the desirable teleoperation interfaces for nursing robots should be efficient (high task performance), ergonomic (low cognitive and physical workload) and intuitive (low learning efforts). We proposed a hierarchical framework for the evaluation and evolution of a human-robot interface. The concept and the procedures are presented in Figure 1. We first conduct a general user study evaluation, to characterize the interfaces based on their performance, workload and learning effort. With the results from this general evaluation, we further conducted an integrated interview and survey with participants to identify the causing factors and the extent of their influence. Robot autonomy is further designed to address the major interface limitations discovered in the general evaluation user study. A specialized evaluation was used to assess the efficacy of the designed robot autonomy.

To demonstrate the efficacy of the proposed framework, we conducted three user studies for the evaluation and evolution of the tele-nursing robot interfaces. Specifically, we compared three representative interfaces designs frequently used for the direct teleoperation of low-autonomy robots (i.e., the robot autonomy is limited to basic collision avoidance and inverse kinematics), including gamepad, stylus/joystick, and whole-body motion mapping via a motion capture system. The evaluations were performed over a set of "psuedo" nursing tasks that require the motion coordination skills frequently performed in a wide range of nursing tasks, including: arm-hand coordination for (object grasping), bimanual coordination (for handling large, deformable and heavy objects), loco-manipulation (for navigating in a cluttered workspace), and camera selection and control to support these tele-actions. Our general evaluation found that: whole-body motion mapping interfaces have the best task performance and learning efforts among freeform teleoperation interfaces for nursing robots. However, it may cause non-negligible physical fatigue and prevent users from teleoperating the robots for a long time. Our integrated participant interview and survey also identified and ranked the fatigue-causing factors, including maintaining steady postures for wrist camera controls and adjusting arm posture for stable object grasping. Our robot autonomy design and specialized evaluation focused on reducing the physical workload of the interface, and improving the ergonomics of the interface. For the specialized evaluation, we proposed a novel Electromyography (EMG)-based muscle effort index, to provide a more detailed, objective, and accurate physical workload assessment. The outcomes of the specialized evaluation validated the efficacy of our robot autonomy design, as well as our proposed framework for interface evaluation and evolution. We believe the proposed framework, including most of the evaluation metrics, are applicable to human-robot teaming interfaces beyond teleoperation.

The main contributions of this article are:

(1) **An Evaluation framework and methods used** — A proposed hierarchical framework that evaluates a human-robot interface from general to specific characteristics; The specific evaluation focuses on addressing the limitation of the characteristics of the interface, rather than augmenting the task-specific robot autonomous functions.
(2) **Integrated design evaluation and evolution** — Apply the proposed evaluation framework to the interface design evolution of general purpose tele-nursing robots. We focus on the skill sets necessary for freeform teleoperation instead of evaluating a large variety of specific nursing tasks; We also consider the needs of the primary user population, the nurses.

The rest of the paper is organized as follows. Section 2 discusses the design of the teleoperation interfaces and methods for performance assessment. Section 3 describes our robot platform, teleoperation interfaces and assistance design as well as the proposed framework. From Section 4 to 6, we evaluate the proposed evaluation of the interface and the design evolution by conducting three independent user studies. In Section 7, we presented the discussion of the results, limitations and future directions. Finally, Section 8 summarizes the important findings of this paper.

2 RELATED WORK

2.1 Teleoperation Interface and Assistance for Nursing Robots

Tele-nursing robots: In response to Ebola, Zika and the COVID-19 pandemic crisis, mobile autonomous robots [9], mobile telepresence robots [11, 12, 157], mobile manipulators and humanoids [7, 10, 72, 103, 145] have been developed and deployed for quarantine patient care. While the current commercialized nursing robots are predominantly mobile telepresence platforms (see review in [94]), more advanced nursing robots of high mobility and manipulation capabilities are in great need to augment the future workforce in quarantine, hospital and nursing facility [72]. Table 1 compares the existing commercial and prototype nursing robots according to the robot platform, their motion capability, level of autonomy and operation interfaces. It shows that for more complex nursing robot platforms, the interface design leans toward supporting more freeform teleoperation of complex motion coordination, with the assistance of general-purpose, low-level autonomy. Most of the contemporary nursing robots (e.g., Intouch RT-Vita [4, 52], Ava [6], BeamPro 2 [8], Vecna VGo [163]) are limited to providing just mobility and telepresence. The combination of GUI interfaces with high-level robot autonomy enables users new to robot operation to control or even supervise the robots for tasks consisting of structured sequence of tasks. However, such interfaces are not sufficient to perform a wide range of unstructured tasks that require various complex motion coordination and involve physical human-robot interactions.

Table 1. An overview of commercial and prototype tele-nursing robots, with their Patient Assessment (A), Communication (C), Navigation (N) and Manipulation (M) capabilities.

Robot platform	Capability	Autonomy	Interfaces
Mobile telepresence [4, 6, 8, 163]	A/C/N	Self-navigation Obstacle avoidance Human-following	Touchpad, joystick
Mobile manipulator [7, 71, 103]	A/C/N/M	Self-navigation Obstacle avoidance Pick-and-place	Gamepad, stylus, GUI, touchpad, motion capture system
Humanoid [5]	A/C/N/M	NA	Exoskeleton

Table 2. Representative interfaces for online control of humanoid robot motion coordination.

Input interface	Controlled motion
Human motions	
Customized cockpits	Whole-body [179]
VR controller	Multiple hand configuration [138]
	Whole-body [82]
Exosuit	Balancing [125]
	Manipulation and positioning [126]
RGB-D camera	Whole-body [53]
	Bi-manual manipulation [144]
Marker-based	Whole-body [104]
IMU-based	Whole-body [132]
Human motor commands	
Myo	Arm pose [162]
BCI	Pick-and-place [147]
	Navigation [15]

Teleoperation interface and assistance: The capabilities of the nursing robots are not fundamentally limited by the hardware, but by the usability of interfaces. Thus far, research efforts on tele-medicine interfaces primarily focuses on tele-surgical robots [136]. Since most of the surgical robots are focused on specific procedures (e.g., [21]), the interface design as well as the evaluation methods and metrics tend to be platform- and task-specific. The state-of-the-art interfaces and teleoperation assistance methods for complex robot platforms (e.g., mobile manipulators and humanoid robots) could be considered for tele-nursing robots of higher motion capabilities [67]. For the online control of motion coordination, these interfaces either map the *human motions* to the robots (using customized cockpits [179], commercial virtual reality and gaming controllers [49, 59, 138, 146], soft/hard exoskeletons [27, 125] and data gloves [57, 107], marker-less or marker-based motion capturing device [27, 43, 50, 53, 56, 80, 92, 93, 104, 115, 132, 175]), or map *human motor commands* using myoelectric devices [91, 138, 162] and brain-computer interfaces [15, 28, 119] (see the the representative interfaces in Table 2). Particularly, motion mapping interfaces such as motion capture systems (e.g., Vicon [104]), portable motion capture devices (e.g., Microsoft Kinect [43, 50, 53, 127], Xsens MVN [92, 93, 132, 155]) and exoskeletons [27, 125] are most natural to control humanoid robots to perform hand-arm coordination, bimanual manipulation, locomotion and whole-body coordination. Within the spectrum of robot autonomy level, ranging from fully manual control to fully autonomous control (see the review in [17]), *action support* and *shared control* are often used to assist the freeform teleoperation using motion mapping interfaces. *Action support* like tremor filtering [177], obstacle avoidance [159] and precise orientation assistance [88, 90], usually assists the execution of a selected action. Shared control is mostly used to assist the operator in actions towards a goal or generating motion along certain trajectories [48, 83, 98, 139, 140].

Overall, the freeform control via motion mapping augmented by robot autonomy results in an interface design that is dexterous, precise, and reliable in motion control, which is desirable for a tele-nursing robot. However, it is hard to specify the design choices of the interface and robot autonomy without appropriate evaluation.

2.2 Metrics and Methods for Robot Teleoperation Interface Evaluation

Evaluation metrics: Prior research efforts have provided many generic frameworks for the evaluation of human-robot teaming (HRT) performance and the usability of interfaces [3, 25, 122, 137, 148, 154, 158, 171]. The evaluation of human-robot interfaces are usually coupled with the assessment of task effectiveness (e.g., time- and error-based [70]) and human performance (e.g., workload [70], situational awareness [61]), and therefore share the same set of metrics [31–35, 66]. Some recent research efforts have also proposed metrics for the evaluation at system level [109, 131], or suggest to evaluate dynamic aspects of the human-robot teaming (e.g., interactivity [81], teaming fluency [75], transparency [172], interface learning efforts [97]). For a particular robotic system, modality of interface, work context and primary user group, the generic framework need to be augmented with domain- and application-specific metrics [13, 16, 16, 18, 77, 79, 96, 101, 124, 149, 151, 153, 164, 166, 170, 176, 181]. Generally speaking, the work on human-robot interface evaluation falls into two categories, which may be: (1) a *general evaluation* which uses a framework of metrics to characterize the interface, or (2) a *specific evaluation* to assess the efficacy of some design choices using the metrics that emphasize the interface improvement. The novel contribution of this work is to propose an evaluation framework that integrates the general and specific evaluations with the interface and robot autonomy design, to close the loop of interface evaluation and evolution.

Evaluation methods: The choice of evaluation metrics depends on the available evaluation methods and data collection approaches. Bethel *et al* reviewed the methods of HRI human studies [19], while Abou reviewed the related work for the approaches for HRI performance assessment [3]. In the nursing research community, there are reviews on the usage of nursing robots [110] and on the evaluation of tele-nursing for its satisfaction, selfcare practices, and cost savings [69]. The recently developed nursing robot platforms are usually presented with lab experiment evaluations [36, 78, 102, 103, 120, 142]. Although both the field study and lab experiments can collect data for quantitative evaluation, the subjective evaluation primarily replies upon interview and survey feedback, while the objective evaluation usually rely upon the measurements of robot, task and human states. The standard practice of evaluating HRT interfaces is to use general-purpose surveys (e.g., NASA-TLX and System Usability Scale [20, 68, 89]), or use a customized questionnaire design only applicable to a specific experiment (e.g., [174]). Participant interview, which has proven to be very useful for connecting human-robot teaming performance to the specific aspects of the interface design characteristics [99, 152], hasn't been well utilized for human-robot interface evaluation.

Recently, the evaluation of HRT interfaces has more objective and quantitative metrics adopted for assessing human performance. For instance, the assessment of physical workload can be estimated based upon objective (neuro-) physiological measurements, including Electromyography (EMG) and Electroencephalograms (EEG) [39, 114]. Eye tracking has also been used for objective and accurate assessment of mental workload [23, 113, 150], attention [100, 117] and situational awareness [58, 128, 129]. Thus far, most nursing robots are (mobile) telepresence robots controlled using GUI interfaces, for which the cognitive workload has more influence on the usability of the interface. As the future tele-nursing robots will demand more complex motion control, interfaces that map human motions to robots will become more desirable for efficient operation of the tasks. The physical workload of using such interfaces on a daily basis will no longer be negligible. Prior research has investigated the physical fatigue associated with conventional tele-robotic interfaces. For instance, the physical fatigue during tele-robotic surgery causes muscle tremors and may result in dangerous situations in critical surgical steps [112]. Besides, fatigue level also negatively affects the Quality of Teleoperation (QoT), which indicates a teleoperator's confidence in commands and decisions [108]. Beyond the teleoperation of medical robots, increased fatigue results in reduced performance during the teleoperation of Unmanned Ground Vehicles (UGV) [86]. The accurate assessment of muscle efforts and physical fatigue therefore becomes critical for evaluating interface usability. Recent robot interfaces have incorporated the physical fatigue assessment using EMG sensing [104, 134, 135] and biomechanical human modeling (e.g., OpenSim [45, 133]). Besides, the learning efforts for the interfaces, measured as the difference in task performance and workload, is also important for the nursing robots to be accepted by nursing workers. To address these needs, our proposed interface evaluation framework will also incorporate novel methods and metrics for the quantitative and objective assessment of the physical workload, and the interface learning efforts of nursing workers.

3 MATERIAL AND METHOD

3.1 Teleoperated Robot

This section describes the robot platform. Shown in Figure 2, the Tele-Robotic Intelligent Nursing Assistant (TRINA) consists of a dual-armed humanoid torso (Rethink Robotics Baxter), and an omnidirectional mobile base (HStar AMP-I). For grasping objects, two Righthand Robotics Reflex grippers were used in the experiments evaluating physical fatigue indices and benefits of automating grasping while two two-fingered soft grippers (UBIROS GentleDuo) were used for evaluating teleoperation interfaces. The visual sensor suite consists of a ELP-USBFHD01M 180° fisheye camera mounted on the robot head, two Intel RealSense D435 cameras on the wrists and a Microsoft Kinect 2 on the middle of the Torso. The RGB-D cameras on the Kinect are used for object detection as will be mentioned in Section 3.3.

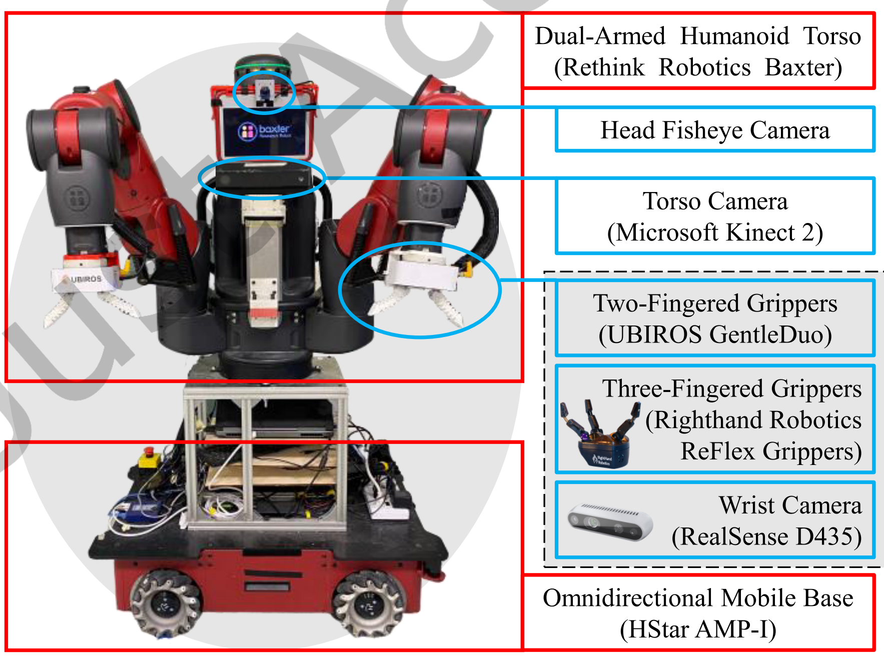


Fig. 2. Tele-robotic Intelligent Nursing Assistant (TRINA) system.

3.2 Teleoperation Interfaces

In the following section the design of the gamepad, stylus-based and motion mapping interfaces that will be used in performing the robot teleoperation for the user studies will be expanded upon. This section will provide a brief overview of the button configuration, design methodology and the control input for each teleoperation interface.

3.2.1 ***Gamepad.*** The TRINA robot is controlled using a gamepad (Logitech F710) as shown in Figure 3. The gamepad control interface consists of 2 modes: arm and base mode. The arm mode controls the motion of the robot arm while the base mode controls the motion of the robot base. There are dedicated buttons to cycle between the two modes, to return the arms to a pre-defined starting position and hold the current gripper pose. The left and right trigger buttons are used to switch between the arm being currently controlled and to control the gripper, respectively. The gripper of the currently active arm will be controlled when operated using the trigger. The joysticks of the gamepad are to control the motion of the base and arms depending on the mode the operator is in currently. In the arm mode, the left joystick moves the arms up and down while the right joystick moves the arm forward, backward, and sideways. In the base mode, the left joystick moves the base forward, backward and sideways while the left gamepad rotates the base clockwise and counterclockwise. Specifically, the end-effector position and base motion is controlled using velocity control based on the location of the joystick on the gamepad:

$$V_x = X_{left}/5 \tag{1}$$

$$V_y = Y_{left}/5 \tag{2}$$

$$V_z = Y_{right}/5 \tag{3}$$

where V_x, V_y and V_z are the velocities in the x,y and z directions, X_{left}, Y_{left} and Y_{right} are the x-coordinate and y-coordinate position of the left joystick and y-coordinate position of the right joystick respectively. When controlling the base V_x, V_y and V_z correspond to the motion of the base in the x and y directions and rotation of base respectively.

Fig. 3. Gamepad controller configuration for teleoperation interface.

As it is not possible to represent cartesian positions of the gripper through the gamepads, the grippers are controlled through velocity control. The direction in which the gamepad is held and the extent to which it is moved from center determines the velocity with which the gripper moves. This principle applies for moving the arm up, down, and sideways. For the gamepad interface, the gripper is designed such that the face of the gripper when open always points downwards. The interface was designed in this manner because this orientation of the gripper enables the robot to pick up even objects that are very small or laundry that can lie flat against the table.

However, this interface is limited in its joint control abilities. The addition of this extra mode to the interface might make the interface more complicated.

To illustrate this interface, we explain how the robot is controlled to pick up an object off a table. The user first switches to the base mode to position the robot near the table and the object using the two joysticks. The user then switches to the arm mode and uses the trigger switch to cycle between the left and the right arm. The user uses the two joysticks to position the arm near the object. The right trigger (RT) button is used to close the gripper and the Hold (A) button is used to lock the gripper's position. The user can then use the joysticks to lift the arm off the table.

3.2.2 ***Stylus Device.*** The TRINA robot is controlled using the stylus device (Geomagic Touch) as shown in Figure 4. Due to the limited amount of user inputs that can be extracted from the device, the interface is split into three modes namely the base, arm, and gripper modes. There are two buttons on both styluses that can cycle between the modes. Once a mode is selected, the dedicated engage button can be used to activate the mode of teleoperation.

Fig. 4. Stylus device (Geomagic Touch) configuration for teleoperation interface.

The motion of the styluses can control the respective arms in the arm mode. To make the interface as intuitive as possible, the orientation of the robot arm from the robot's "elbow" to the gripper is mapped to the orientation of the stylus of the device. To control the robot end-effector positions cartesian position control was used. The position and orientation of the left and right styluses were scaled to the robot frame and the robot limbs were moved to the desired location by solving the Inverse Kinematics of the Baxter robot arms. In the base mode, the left stylus can move the base linearly while the right stylus is used to rotate the base. This means that the base moves forwards, backwards and sideways depending on the way the left stylus is moved. The right stylus is used to rotate the base clockwise and counterclockwise. The base control uses velocity control similar to the one described in Section 3.2.1 where the location of the right and left styluses control the robot base rotation and translation respectively.

To illustrate this interface, we again use the example of grasping an object off a table. The user in the base mode uses the stylus motion to move the base closer to the table and the object. The user then must switch to the arm mode to control the arms using the styluses. Once in a suitable pose, the user can close the gripper in the gripper mode. The gripper can be toggled between fully open and fully closed. Once the object is fully grasped, the user can switch back to the arm mode to lift the arm.

3.2.3 ***Motion Mapping.*** The Vicon Nexus motion capture system is used to develop a motion capture interface to control the TRINA robot (Figure 5). Human motion was captured at 100 Hz by 10 infrared cameras and streamed at 50 Hz for robot control. The subject's physical attributes do not affect the end-effector positions of the robot as only the position and orientation of the wrist and the swivel angle of the teleoperator is mapped to the robot during teleoperation. The swivel angle is defined as the rotation of the elbow of the operator with respect to the axis connecting the centers of the shoulder and wrist joints [161]. This angle is then used as an indicator of the operator's arm posture.

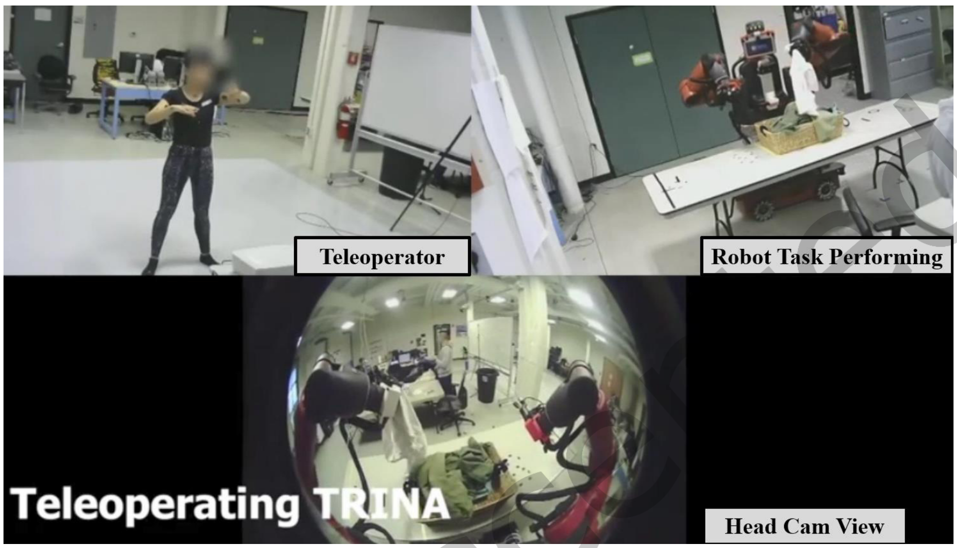


Fig. 5. Overview of robot teleoperation via motion mapping interface.

Table 3. Motion Mapping Teleoperation Interface. The arm posture is measured by the swivel angle, i.e., the rotation of the elbow position with respect to the axis connecting the shoulder and wrist positions [161].

Teleoperation Input	**Robot Function**
Robot's Upper Body	
Hand position and orientation	End-effector position and orientation
Arm posture and orientation	Manipulator arm posture
Rotate upper body	Rotate mobile base orientation
Hand open/close	Gripper opens/closes
Right shank flexion	Activate teleoperation assistance
Robot's Lower Body	
Squat	Engage/Disengage teleoperation
Leg steps forward/backward	Mobile base moves front/back
Left (right) leg steps left (right)	Mobile base moves left (right)
Lift right leg	Switch the camera view

The motion mapping interface developed using the VICON motion capture set-up also used controlled the robot motion using the Cartesian position similar to the method described in Section 3.2.2. The location of the operator's hands in the human skeleton captured by the motion capture system is scaled to the robot frame. The

Inverse Kinematics for the Baxter robot arms is solved to control the motion of the robot end-effectors. The robot base is controlled using desired velocity. The direction and magnitude of offset of the operator's feet from the origin defined in the operator's workspace is the direction and magnitude of velocity with which the base is required to move.

Table 3 defines the controls for the motion mapping interface. Robot teleoperation can be engaged and disengaged by squatting. The operator can control the robot arms by moving their arms in the desired manner and the robot will replicate these movements. The robot base can be moved by the operator stretching their leg out in the desired direction of motion. For example, the operator can move the robot forward, backward, left, and right by stretching their leg out forward, backward, left and right respectively. The robot base can also be moved diagonally depending upon how the operator moves their leg. The opening and closing of the robot grippers can be achieved by the operator opening and closing their fingers.

We shall use the example of picking up an object from a table to explain this interface. The operator moves the robot towards the table and the object by stretching their legs in the necessary direction. Once at a convenient position, the operator can make the robot reach out to the object by reaching out in the corresponding direction in their workspace. The robot replicates this motion and once at the right position the gripper can be closed when the operator closes their fingers.

3.2.4 ***Graphical User Interface.*** A Graphical User Interface is used to provide the teleoperator with the video stream from the fisheye camera (e.g. in the bottom of the Figure 5) and the two wrist cameras. The video stream and the control GUI are presented to the user on a monitor at the teleoperation workstation. This video stream provides the teleoperator with a real-time view of the workspace. The GUI also tells which mode the operator is in while using the gamepad and stylus interface or which arm is being controlled when in the gamepad mode. The current robot state is also provided as a 3D model in a simulated environment. Examples of this GUI in use can be seen in Figures 10 (a) and (b).

3.3 Teleoperation Assistance

The flowchart in Figure 6 describes the design of the autonomous grasping function for teleoperation assistance. The Microsoft Kinect attached to the robot was used for capturing the workspace. Mask-RCNN [2, 73] is used to detect objects and generate bounding boxes of $(2 \times height) \times (3 \times thickness) \times (5 \times width)$ (cm^3) around the center of an object. This enhanced region around the object is where teleoperation assistance is available for the user and is termed as the Teleoperation Assistance Zone (TAZ). The TAZ was designed in this manner based on the inputs from an initial pilot study while designing this interface.

The bounding box generated by the Mask-RCNN model on the Kinect RGB-stream around the detected objects was projected to the depth stream from the Kinect. The center of this bounding box was determined to be the center of the object. The depth value of the center of the object thus obtained can be used to find the remaining two coordinates of the object using the pinhole camera equations [87]. The coordinates of the object formed in the Kinect frame is transformed to the coordinate system of the Baxter. This provides us with the location of the detected object in the three-dimensional workspace. If multiple objects are present in the workspace (e.g. cluttered environment), it will return the coordinate of the closest object as default.

The teleoperator is indicated if the end-effector is in this region by audio and visual notifications. Points on the mid-points of the left and right vertical sides of the original bounding box around the object are identified as target grasping points. Based on where the robot arm present in the TAZ a reaching-to-grasp motion is planned for the corresponding nearest target point by solving the inverse kinematics for this location. The assistance does not control the gripper and this action is left to the discretion of the operator who goes will complete the grasping action if he/she believes the gripper is in an appropriate position for grasping.

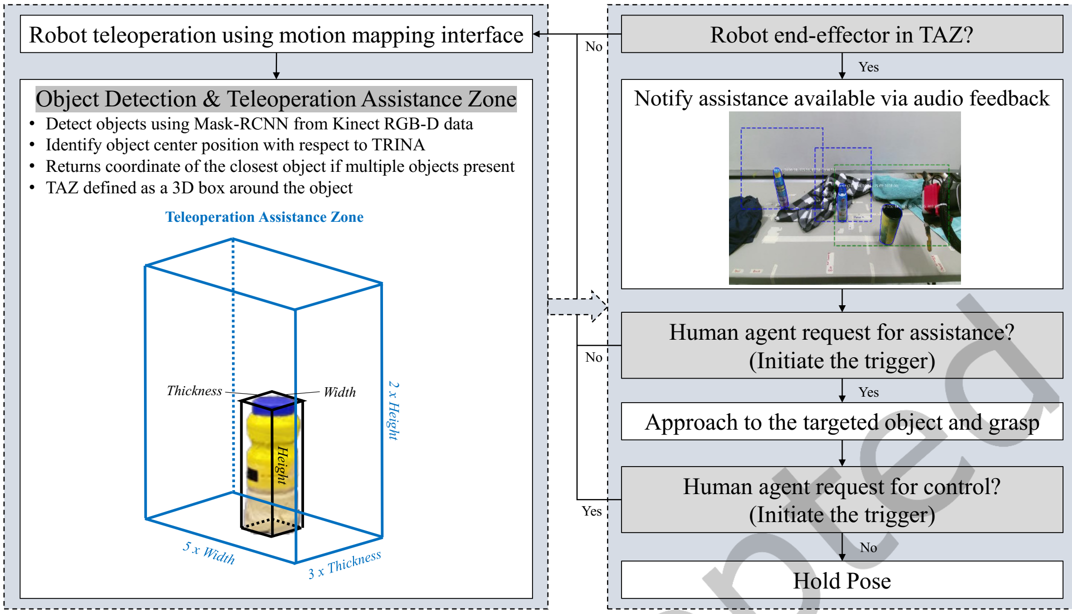


Fig. 6. Autonomous Grasping Function for Teleoperation Assistance.

3.4 General Evaluation Metrics

In order to investigate the most suitable teleoperation interfaces that can be utilized by the non-robotics related populations (e.g. healthcare workers and nurses), we performed the evaluation of three representative designs of contemporary control interfaces (handheld gamepad, stylus-based devices and human motion mapping) by a system of objective and subjective metrics to appraise the learning effort, task performance and operation workload.

3.4.1 *Objective Measurements*.

- For **learning effort** evaluation, we consider the learning outcomes (indicated by the task completion time, numbers of mode switches and errors before and after practice) and practice time used during the training phase for each teleoperation interface. This measurement helps us to quantify how fast the users can build confidence to use the control interface and how much impact training has on task efficiency and accuracy. On the other hand, the investigator could just simply adopt the method of asking the participants to perform multiple trials of the training task and using only the task completion time to evaluate the interface. This is however not sufficient as an index as it will ignore other critical factors that might be essential in influencing the learning curve.
- For **task performance** evaluation, we measure the time required to complete the task, number of interactions with the interface (mode switches in our case) during teleoperation, as well as the number and type of errors. The type of errors that influence the performance include errors that: (1) reduce the efficiency, (2) decrease the accuracy and (3) diminish the safety. For example, in the pick-and-place sub-task in our evaluation task, the types of errors we include are: (1) dropping or knocking over of objects, (2) inappropriate grasps and (3) collisions with the table.
- For **operation workload** evaluation, we used a secondary task where the participants had to solve simple arithmetic questions [30] while teleoperating the robot. Users were allowed to skip questions if they

deemed it too difficult. A mentally demanding task would make the user perceive a problem to be more difficult than they usually would have, and they would answer less questions or have more errors or skip more questions. The longer response time indicates that the user requires a higher cognitive workload for robot teleoperation, and therefore has less capacity for the other aspects of the tasks (e.g. professional decision-making, patient interaction and information inquiry).

3.4.2 ***Subjective Measurements.*** We adopted NASA-TLX as the workload assessment tool that helps record the user's self-evaluation of Mental, Physical and Temporal Demands, Performance, Effort and Frustrations [37]. We further calculated the overall NASA-TLX score to identify the subjective workload by weighting each effort demand. The weighting coefficients were generated by choosing from a series of pairs of rating scale factors that were deemed to be important based on the official instructions. In addition to the NASA-TLX evaluation form, the comprehensive custom questionnaire is an integral part that captures the users' feedback and attitude toward the newly implemented methods and interfaces. Unlike the traditional customized questionnaire in human-robot interaction, we performed a post-study interview to identify the causing factors and features that will improve the interface usability.

3.5 Specific Objective Assessment of Physical Workload

By the general evaluation metrics, robot teleoperation via motion mapping has been demonstrated to be an intuitive, efficient, and low learning curve approach for controlling the motion coordination of the humanoid robots. However, the trade-off with using human motion mapping as a teleoperation interface is the non-trivial physical fatigue associated with this interface and this information is also captured in the NASA-TLX self-evaluation and post-study questionnaire. Muscle fatigue has been defined as any exercise-induced reduction in the maximum capacity to generate force or power output [168]. Assessment of physical fatigue can be based on the measurements of force, power, and torque. Besides, heart rate can also be used to detect muscle contraction and infer overall physical fatigue level [65]. Among all the approaches, sEMG measurement have proven to be more effective as it measures muscle activity in a non-invasive and real-time environment and provides the ability to monitor physical fatigue of a particular muscle [38]. Thus, in addition to the subjective measurements, we developed indices that assess the physical workload objectively using wireless surface EMG sensors (Trigno^{TM} from Delsys Inc. at 1,000 Hz sample rate). Our analysis of the EMG signals aims to: (1) investigate individual muscle effort and physical fatigue development during teleoperation using motion mapping; (2) compare the physical fatigue induced by different tasks and thus identify movements that cause fatigue, giving us the directions to facilitate the fatigue-adaptive interface design. Figure 7 illustrates our data preparation process for the muscle effort and physical fatigue estimation.

3.5.1 ***Muscle Effort Analysis.*** The recorded EMG signals are within the 40 Hz-700 Hz range in the spectrum domain. The raw EMG data was pre-processed using a high pass filter (cutoff frequency 10 Hz), to remove the soft tissue artifact and offset the frequency baseline. The processed signal further went through a full-wave rectification and then a sixth-order elliptical low pass filter (cutoff frequency 50 Hz), to remove noise and transients and develop a linear envelope of the EMG signal. We use the computer-based methods to determine the onset and offset of muscle contraction of the processed EMG signal. The tunable parameters include the threshold value (standard deviation of the baseline signal) and the number of samples (sliding windows in the units of a millisecond) for which the mean must surpass the defined threshold. We choose the combination of three times the standard deviation of the muscle static contraction obtained from the first 200 frames of the EMG signal in the maximum voluntary contraction (MVC) test and 25 milliseconds as the signal sliding window size. This window size has shown similar results to results from the visually derived data [74]. The MVC test also serves as the tool to normalize the EMG signal with respect to the maximum force generated by each muscle [22]. Figure 7(a)

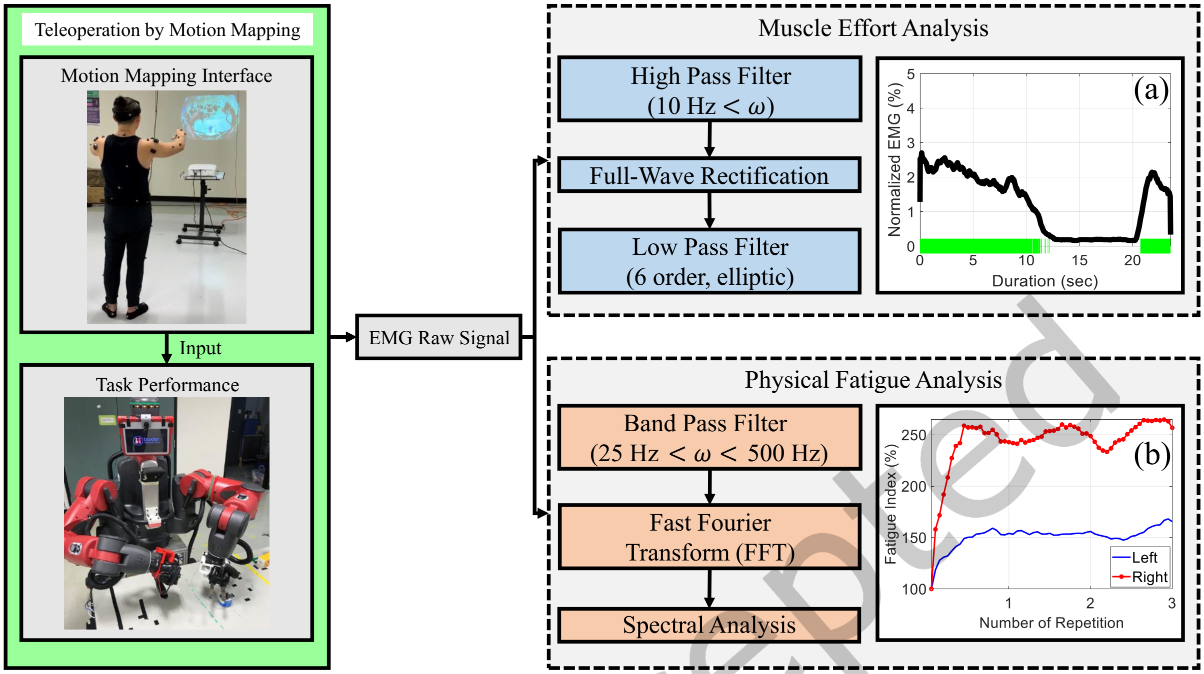


Fig. 7. Process of the muscle effort and physical fatigue analysis.

shows the individual muscle contraction levels (represented as the black line which is the normalized processed EMG signal from the MVC test) and contraction duration (indicated by the green bars).

3.5.2 ***Fatigue Analysis.*** We use the band pass filter (25 to 500 Hz) to filter the recorded EMG signals and apply the conventional fast Fourier transformation to convert the signal from time domain to power spectrum domain to calculate the spectral density. Previous studies have shown that the mean and median frequencies of the surface EMG signals decrease as the muscle contraction duration increases, and therefore can be used to measure the fatigue in isometric contraction [44]. To address the inadequate sensitivity of the transitional fatigue indices during dynamic contractions, increased fatigue can be measured by the highly sensitive Dimitrov spectral fatigue indices (FI_{nsmk}) [46]. These indices are the features extracted from the spectral moments computed from the EMG power-spectral density (PSD) function. The spectral moment (M_k) can be calculated using equation (4):

$$M_k = \int_{f_{\min}}^{f_{\max}} f^k PS(f)df \tag{4}$$

where M_k indicates the spectral moment, f is the frequency, f_{max} and f_{min} represent the bandwidth of the signal and $PS(f)$ is the EMG power-frequency spectrum as a function of frequency and k is the chosen order. The Dimitrov spectral fatigue indices are represented by the ratio of the spectral moments of order (-1) and order k which is in the range of 2-5:

$$FI_{nsmk} = \frac{M_{-1}}{M_k} = \frac{\int_{f_{\min}}^{f_{\max}} f^{-1} PS(f)df}{\int_{f_{\min}}^{f_{\max}} f^k PS(f)df} \quad ,k = 2 \quad to \quad 5 \tag{5}$$

The fifth-order FI_{nsm5} data was selected for generating the objective physical fatigue index since the variation across the repetitions tended to be wider when the order k of the normalizing spectral moment was higher. The relative changes in the fatigue index is calculated against the first repetition within the trial. This means the fatigue index will always start with 100 % and the values increase with increasing fatigue.

$$Objective\ Fatigue\ Index = \frac{FI^{n}_{nsm5}}{FI^{1}_{nsm5}} \times 100\% \quad , n = repetition\ number\ in\ the\ trial \tag{6}$$

Figure 7(b) shows the example output of the fatigue index for the muscle on the left and right sides of the body (blue and red lines in the graph on bottom right).

3.5.3 *Pilot-Testing of the Objective Physical Fatigue Assessment.*

- For **verification of our methods with literature,** we evaluated the effectiveness of the objective indices for measuring fatigue using a validation test. Participants ($N = 5$) were instructed to perform single joint movements like Biceps curls and side lateral raises using their dominant hand to lift a dumbbell (9.5 kg) for 10 repetitions (left in Figure 8), which was expected to fatigue their Bicep and lateral Deltoid in the signals detected by the surface EMG sensors attached. As the fatigue increases, the static fatigue index (for isometric contraction using mean frequencies, F_{mean}) decreases (Figure 8(a) and 8(c) shows the results from a representative participant) while the dynamic fatigue index (for the dynamic contraction using Dimitrov spectral indices, FI_{nsm5}) increases (Figure 8(b) and 8(d) shows the results from a representative participant) that those indices share the same trend with the results reported in previous literature [44, 46]. We choose the dynamic fatigue index based on spectral indices as it is more sensitive and was reported to be more suitable for measuring the fatigue caused due to motion.

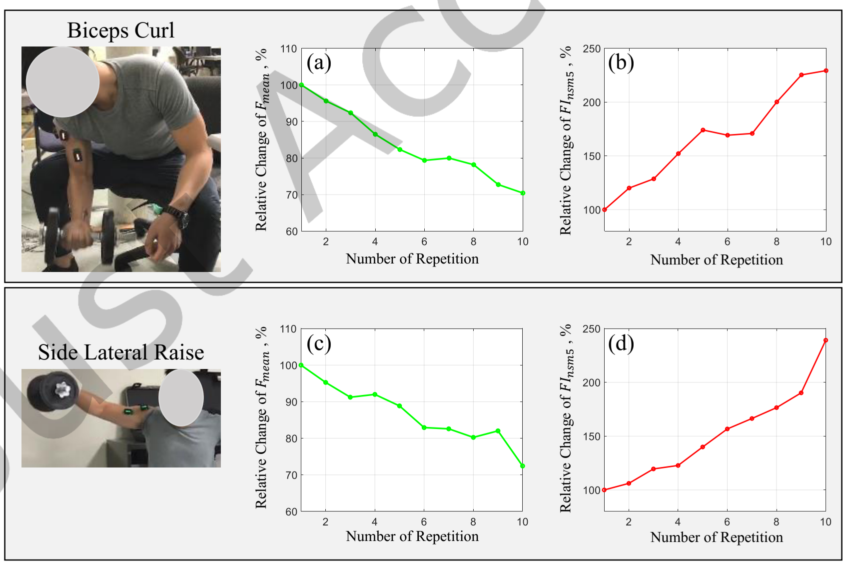
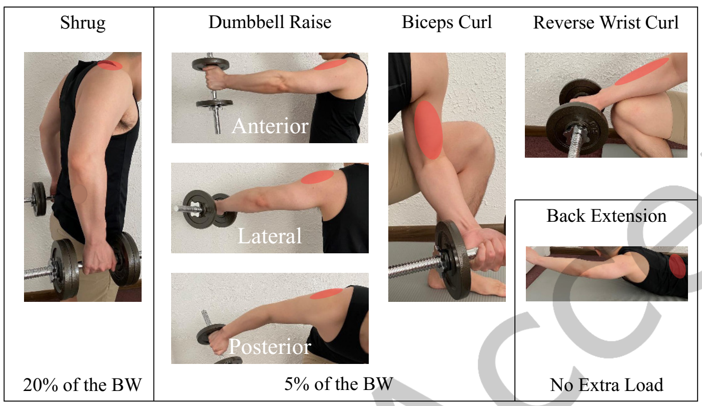


Fig. 8. Objective physical fatigue indices validation.

- For **identification of fatigue threshold,** one important issue in fatigue assessment is to determine an appropriate fatigue threshold which may vary largely across muscle groups. Prior research chose to use a certain percentage of MVC value as the fatigue threshold, which was expected to be suitable for their tasks.

Our robot teleoperation involves tasks that utilize mostly upper body. Thus, we propose an experimental approach to determine the fatigue threshold for each targeted muscle. The participants (two male and one female) were instructed to perform a series of isolation exercises (pictured to the left in Figure 9) using their dominant and non-dominant hand. The participants had to lift a dumbbell (20 percent of the body weight for the trapezius; 5 percent of the body weight for the anterior, lateral, posterior deltoid, biceps and forearm; no extra load for lower back) for 3 sets with 12 repetitions each. They can rest between each repetition for one minute. After the weight-lifting experiment, we asked the participants to point out the specific session and repetition at which they struggled to continue the task. On average, the participants pointed to the 9^{th} repetition in the third set as the fatigue threshold. The ratio (in terms of percentage) between the spectral indices of 9th repetition and the 1st repetition will be used as the threshold for identifying the onset of the physical fatigue. The muscle-specific fatigue threshold is defined as the mean of the index value identified for the dominant and non-dominant hand (Figure 9 in the right).



	Male	Female
Deltoid (Anterior)	150.68	123.64
Deltoid (Lateral)	171.30	137.95
Deltoid (Posterior)	199.85	192.33
Biceps	179.88	201.53
Trapezius	200.65	181.94
Lower Back	268.24	248.82
Forearm	171.04	150.79

Fig. 9. A series of isolation exercises (left) and the muscle-specific fatigue threshold (right). Bodyweight is denoted as BW in the figure.

4 USER STUDY I: TELEOPERATION INTERFACES COMPARISON

To appraise the usability of the general to specific teleoperation interface evaluation framework, we conducted a series of user studies to validate each component step-by-step. In the first user study, we present the usage of the general pre-defined metrics to evaluate three representative designs of contemporary robot teleoperation interfaces. We tried to find a suitable teleoperation interface that is intuitive and easy to learn for the primary users (nursing workers) who usually do not have an engineering background.

4.1 Experimental Setup

First the three teleoperation interfaces are compared to find the best suited interface for the nursing workers. This experiment requires the subject to control the robot platform using the gamepad, stylus and motion capture interfaces (See Figure 10). The teleoperator receive a real time video stream from the fish-eye camera of the robot workspace. The user performs different tasks that involve them manipulating different objects placed on a table in two different experiment stages, the training and performance phase (refer Section 4.4). The task performance time, number and type of errors and number of mode switches were recorded. The responses to arithmetic questions asked during the performance phase are also recorded. After all the tasks, the user answers a survey that captures the user's preferences for the different interfaces.

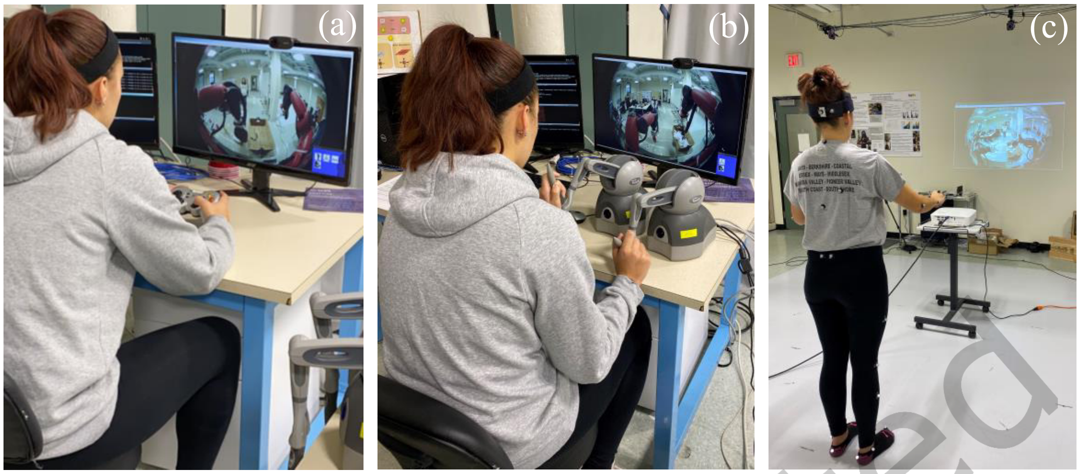


Fig. 10. Nursing robot teleoperation via: (a) Gaempad (b) Stylus-Style Joysticks and (c) Motion Mapping Interface.

4.2 Participants

Our user study involves (N=8) nursing students (eight female, 19-21 years old) who represent the future users for the teleoperation interface. We also recruited three registered nurses to get their feedback and attitude towards the use of tele-nursing assistive robots on a daily basis. All the participants have experience working in healthcare and are familiar with the hospital environment. They also do not have any robotics or engineering expertise and have almost zero gaming experience with the gamepad controller. The experimental protocol was reviewed and approved by the Worcester Polytechnic Institute Institutional Review Board.

4.3 Tasks

The participants in the user study performed two tasks (see Figure 11). The *testing task* (left) is to collect an individual object on the counter workspace and is designed to examine the user's learning effort and the outcome of practice time for each interface. This task is performed both before and after the practice session to evaluate the learning outcome. The *evaluation task* (right) is to clean and organize several objects scattered in the workspace and is designed to evaluate the interface usability. Our prior study shows that most of the tele-nursing tasks require the users to perform: 1) free control of reaching-to-grasp rigid and deformable objects, 2) free control to move the mobile base to facilitate manipulation, and 3) point control to facilitate engaging/disengaging the interface or mode switching. Based on this finding, we set up a "pseudo-task" which incorporates these necessary teleoperation skills in the context of workspace cleaning and organization by a nurse. Specifically, the user will teleoperate the nursing robot to collect several rigid and deformable objects randomly placed on a counter workspace and sort them into two separate bins. This task integrates the free control of precise and gross manipulation in a cluttered environment, locomotion, and point control of robot states, all of which are necessary primitive robot control skills for tele-nursing tasks.

4.4 Experimental Procedure

The user study consists of a *Training Phase* and a *Performance Phase*. The order of interfaces were randomized for each participant. For each user interface, the experimenter introduced and demonstrated the interface functions. In the *Training Phase*, the subject performs the testing task described in the previous section twice. The two trials of testing task is separated by a practice session of 15 minutes. The participants can stop the practice session

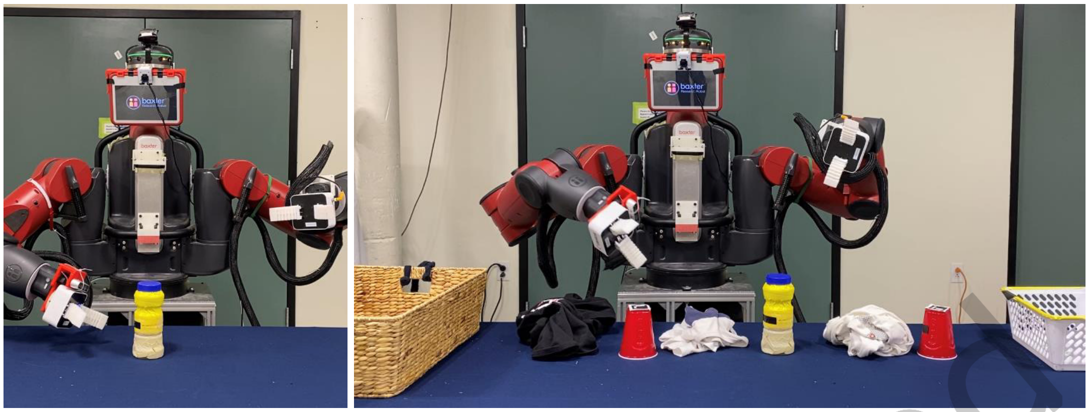


Fig. 11. The tasks of the user study include collecting a single object (left), and cleaning and organizing a counter workspace (right).

anytime they feel comfortable with the interface and are confident in performing the second trial of the training task. The time consumed for practice and the change in performance between the two trials of the testing task are used in evaluating the learning effort associated with the interface. The participants move on to the *Performance Phase* after completing the training phase. In the *Performance Phase* the users will perform the evaluation task, i.e., collecting 3 grocery items and 3 pieces of clothing, and sorting them into two baskets. The participants were required to answer two-digit arithmetic problems continuously for the entirety of the task (as in [30]). This secondary task helps identify the mental effort required for decision-making during robot teleoperation and provides an objective measurement of the cognitive workload of the teleoperators.

4.5 Data Analysis and Results

We used a system of objective metrics to evaluate the usability of each interface, in terms of task performance, user workload and learning efforts. For task performance, we measure the completion time for the evaluation task, number of mode switches during teleoperation, as well as the number and types of errors. The types of errors we consider include: 1) dropping or knocking over objects, 2) inappropriate grasps (failed attempts at grasping) and 3) collisions with the table. For operation workload, we record the time taken to answer each arithmetic question while teleoperating. The longer response time indicates that the user incurs a higher cognitive workload for robot teleoperation, and therefore has less capacity for the other aspects of patient-caring (e.g. professional decision-making, patient information inquiry and emotional care). For learning effort, we consider the learning outcome (indicated by the completion time, numbers of mode switches and errors for the testing task) because of the practice time used for that interface. Harder interfaces require longer practice times and show greater differences between the two trials of the testing task. In addition to the objective metrics, we use the user's responses to NASA-TLX questionnaires (before and after the testing task, as well as after the evaluation task) as the subjective measurement of their performance and workload. The participants also answer a comprehensive custom questionnaire at the end of the user study to evaluate the influence of interface design features.

4.5.1 ***Learning Effort and Outcome.*** Figure 12(a) shows the comparison of interfaces in terms of learning effort. The dotted line indicates the mean of the maximum and minimum value from all participants for both learning effort and outcome. For N=8 nursing students, the motion mapping interface (Mocap) has a better learning outcome and lower learning effort, compared to the other interfaces. Each ellipse plots the mean and standard deviation of the testing task completion time with respect to the mean and standard deviation of the user's practice time. The red, green, and blue colors are for the motion mapping interface (Mocap), stylus and gamepad, respectively. The learning outcomes can be found by comparing the ellipses of the same color. On average, the nursing students spent less time (219±39 sec) to learn the Mocap interface than the gamepad (792±57 sec) and stylus device (870±20 sec) interfaces. ANOVA analysis showed that: 1) The learning effort for Mocap was significantly lower than that for the gamepad ($F(2,21)=71.137$, $p<0.001$) and stylus interfaces ($F(2,21)=71.137$, $p<0.001$); 2) The Mocap interface also had the least completion time (61±6.7 sec) after practice for the testing task, followed by the gamepad (90±8.2 sec), and then the stylus (228±57 sec); 3) In the evaluation task, the Mocap interface also has a significantly faster completion time than the gamepad ($F(1,14)=6.979$, $p<0.05$) and stylus interfaces ($F(1,14)=8.296$, $p<0.05$). We also noticed that the completion time for the testing task before the practice was significantly slower than after practice, when using the gamepad ($F(1,14)=5.624$, $p<0.05$) and stylus device ($F(1,14)=5.442$, $p<0.05$). The significant effects of practice for these two interfaces were confirmed by the participants' reports in the post-study interview. The effect of practice is also more significant for the gamepad than for the stylus interface, which may be because the gamepad is a widely used gaming interface for the public. However, the participants also report that it is difficult to remember the many different functions associated with the gamepad buttons. On the other hand, the Mocap interface has a low learning effort and the trivial effect of practice indicates that this interface is the most intuitive one for nursing robot teleoperation.

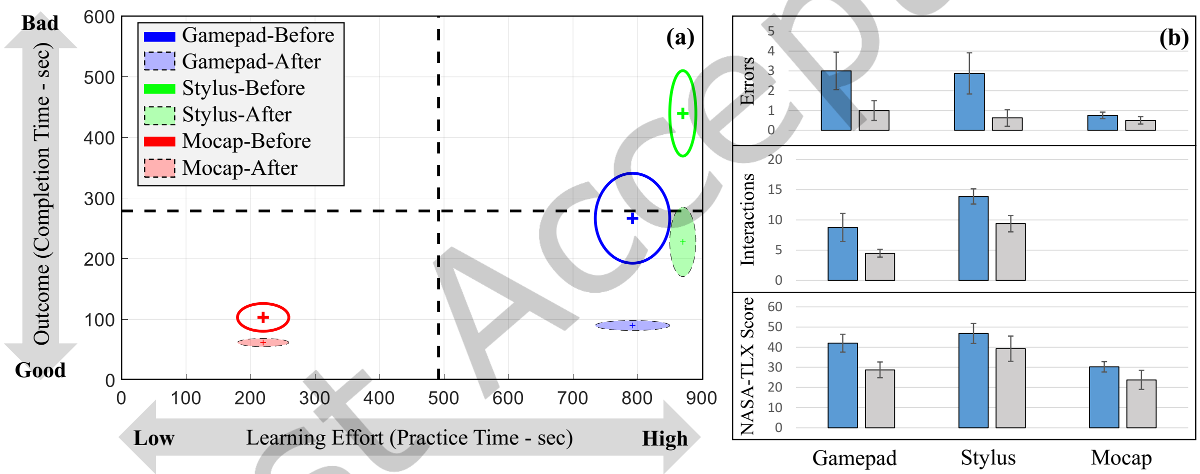


Fig. 12. (a) Practice time vs Completion time for nursing students. (b) Comparison of number of errors, interactions, and subjective workload (NASA-TLX) across interfaces for nursing students.

We further use the weighted NASA-TLX scores to measure the subjective workload before and after practice with the interface. The weighting coefficients were selected as follows: mental demand=5, physical demand=4, temporal demand=0, performance=1, effort=3, frustration=2. In Figure 12(b), the Interactions field refers to the number of times a mode has to be switched while using the interface. A switch from controlling the base of the robot to the right arm of the robot is considered as an interaction when evaluating the gamepad and stylus interfaces. However, for the Mocap interface since the operator can control all aspects of the robot functionality at the same time, this part of the graph is empty as no interactions/mode switching is required. The comparison of all the interfaces for all the nursing students show no significant difference in the number of error and interactions and subjective workload during the testing task performed before and after practice. However, the motion mapping interface allowed users to control the robot arm and mobile base simultaneously eliminating the complexity of mode switches that resulted in lower total subjective workload (23±4.7) than gamepad (29±3.8) and stylus (40±6.2).

4.5.2 ***Task Performance.*** Figure 13(a) compares the performance in the evaluation tasks among all the interfaces, using the following objective metrics: 1) the completion time of evaluation task, and 2) the response time for each math question (i.e., the secondary task). The dotted line indicated the mean of the maximum and minimum value from all participants for both cognitive workload and performance. For nursing students, the task completion time using the Mocap interface was less (404±50 sec) than the gamepad (745±176 sec) and stylus (1367±165 sec). ANOVA analysis shows the significant differences in completion time between Mocap and stylus ($F(2,21)=11.667$, $p<0.001$) and between gamepad and stylus device ($F(2,21)=11.667$, $p=0.015$). The results also indicates that the subjects took lesser time to solve the arithmetic questions while using the Mocap interface (12.8±1.6) than the gamepad (16±1.5) and stylus device (20.3±2.9).

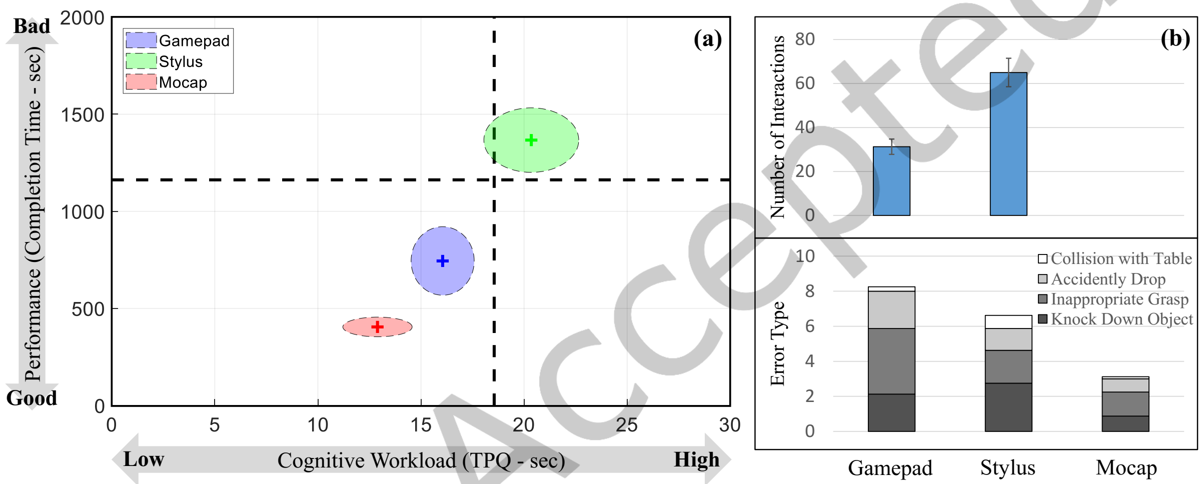


Fig. 13. (a) Completion time vs Cognitive workload based on the time per question answered for nursing students. (b) Number of interactions and type of errors for nursing students.

Figure 13(b) further compares the interfaces by the number of errors and mode switches for the evaluating task. The nursing students have fewer total operation errors using Mocap interfaces (3.1±0.6), compared to using the gamepad (8.6±1.7) and stylus (6.6±1.7). The ANOVA analysis indicated significant differences between the Mocap interface and gamepad ($F(2,21)=3.513$, $p<0.05$). The breaking-down of error types shows that the Mocap and gamepad interfaces tend to cause more inappropriate grasps. Our post-study interviews show that this is due to the lack of depth perception in the visual feedback. Additionally, the stylus interface requires significantly more mode switches during operation than gamepad because the user has only one button to cycle between the hand, arm and base control. The Mocap interface does not need any mode switching as all robot components can be controlled simultaneously via whole-body motion mapping.

4.5.3 ***Subjective Operation Workload.*** As seen in Figure 14(a), the total workload while teleoperating the robot using the Mocap interface was lower (37.4±4.2) than the gamepad (45.8±4.1) and stylus device (56.1±5.8) among nursing students. The ANOVA analysis on the user-reported feedback regarding mental demand shows that the Mocap interface demands significantly lower mental effort than the gamepad ($F(2,21)=9.828$, $p<0.05$) and stylus ($F(2,21)=9.828$, $p<0.001$).

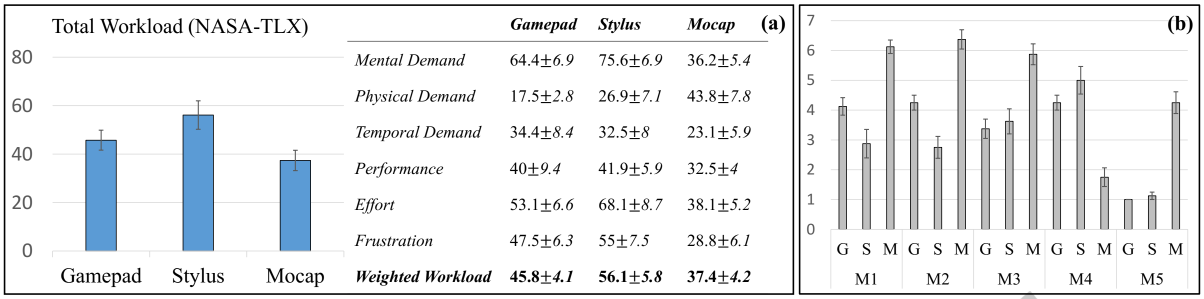


Fig. 14. (a) Subjective workload (NASA-TLX) for nursing students. (b) Users' preference rating for the gamepad (G), stylus device (S) and motion mapping interface (M) based on controllability (M1), efficiency (M2), accuracy (M3), mental demand (M4) and physical demand (M5).

4.5.4 ***Users' Preference***. The survey feedback from the customized questionnaire is shown in Figure 14(b). All nursing students chose the human motion mapping interface as the easiest one to learn and preferred using it as the robot teleoperation interface for future use. Moreover, they reported that the motion mapping interface had better controllability, efficiency, accuracy, and lower mental demand but required greater physical effort.

		Learning Effort							
		Completion Time (s)		*Errors*		*Mode Switch*		*Overall NASA-TLX*	
Nurses	*Practice Time (s)*	*Before Practice*	*After Practice*	*Before Practice*	*After Practice*	*Before Practice*	*After Practice*	*Before Practice*	*After Practice*
				Gamepad					
1	900	157	177	2	4	8	14	88	55
2	900	372	201	8	4	14	10	43	31
3	900	231	414	2	11	1	12	42	47
				Stylus Devices					
1	900	915	213	10	2	33	6	100	80
2	900	259	212	1	1	9	12	38	34
3	900	356	153	0	0	12	7	37	22
				Motion Mapping					
1	420	54	64	0	0	0	0	12	21
2	292	76	35	0	0	0	0	44	29
3	472	63	44	1	1	0	0	28	26

Table 4. Learning effort and outcome of registered nurses.

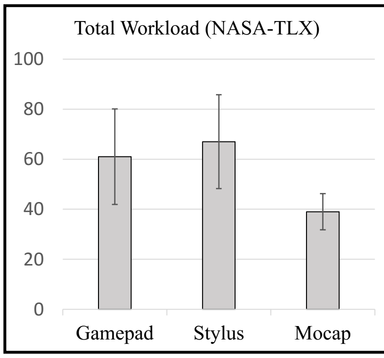
4.5.5 ***Registered Nurses' Performance and Feedback***. Table 4 shows the practice time, learning effort (testing task completion time, number of error and mode switches) and subjective workload for three registered nurses across all interfaces. Due to the small population, we are not able to conclude anything significant. However, the practice time and testing task completion time after practice indicates that: 1) registered nurses require more effort to learn the interface, particularly for gamepad and stylus indicated by the greater usage of the practice time; 2) for the gamepad interface, practicing the interface does not have as much an impact as it had for the nursing students; 3) the motion mapping interface is still the easiest to learn among all the interfaces for elder nursing workers as identified by the lower practice time, testing task completion time and errors during teleoperation; (4) the overall weighted workload after practice tends to be lower while using motion mapping interface.

For registered nurses, Figure 15(a) shows the performance in the evaluation tasks among all the interfaces using the same metrics used for the nursing students as described in Section 4.5.2. The motion mapping interface outperforms the gamepad and stylus devices in terms of faster task completion time, fewer errors and mode

(a)

Task Performance				
Nurses	*Completion Time (s)*	*Errors*	*Mode Switch*	*Secondary Task (s)*
		Gamepad		
1	1150	7	36	46
2	579	5	20	17.5
3	1360	10	38	30.9
		Stylus Devices		
1	1903	2	55	50.1
2	1624	7	56	25.4
3	1474	7	64	32
		Motion Mapping		
1	400	1	0	14.8
2	325	3	0	15.5
3	377	4	0	17.1

(b)



	Registered Nurses		
	Gamepad	*Stylus*	*Mocap*
Mental Demand	80±*13.2*	75±*18*	40±*17.3*
Physical Demand	40±*30*	55±*22.9*	50±*5*
Temporal Demand	60±*20*	50±*25*	35±*13.2*
Performance	55±*17.3*	70±*15*	30±*10*
Effort	60±*21.7*	80±*20*	35±*13.2*
Frustration	60±*26.4*	50±*25*	25±*8.6*
Weighted Workload	**61±*19***	**67±*18.7***	**39±*7.2***

Fig. 15. (a) Task performance of registered nurses. (b) Subjective workload (NASA-TLX) for registered nurses.

switches. The secondary task results also demonstrate that the nurses can solve the arithmetic questions faster while using the motion mapping interface than the gamepad and stylus devices. The total workload while teleoperating the robot using the motion mapping interface was lower than the gamepad and stylus device (Figure 15(b)) and the motion mapping interface demands lower mental effort than the gamepad and stylus device interfaces based on the user-reported feedback. All registered nurses chose the motion mapping interface as the most intuitive and easiest to learn. They also preferred using it for nursing assistive robot teleoperation on a daily basis to help them with routine tasks. Furthermore, they also reported that the motion mapping interface had better controllability, efficiency, accuracy and lower cognitive workload but were concerned about the heavier physical demand, especially for extended usage.

5 USER STUDY II: PHYSICAL WORKLOAD ANALYSIS

The results from User Study I show that teleoperating the robot via human motion mapping interface outperforms the handheld gamepad and stylus-based devices in terms of better task performance and lower learning effort as well as cognitive workload. However, non-trivial physical fatigue may prevent such interfaces from being widely used for robot teleoperation, particularly for a daily usage made of long work hours. In the second user study, we propose the objective assessment of muscle effort and physical fatigue while teleoperating the robot using surface EMG to investigate the fatigue-causing components. The work presented in this section is an extension of our prior work in [104]. However unlike the work presented in [104] where the fatigue threshold was set constant across all the muscle groups, in this analysis the fatigue threshold was determined based on the specific muscle group, helping us develop more muscle specific fatigue indices. This gave us different results as will be highlighted in Section 5.5.2.

5.1 Experimental Setup

The experimental setup for this user study is illustrated in the left side of the Figure 7, where the participant was asked to teleoperate the robot by standing in the center of the motion capture workspace (10 Vero cameras coupled with the Nexus platform from VICON). The real-time visual feedback was projected in front of the participant with the default view being the feed from the fisheye camera. The participant can also cycle through two cameras places on the wrists of the robot arms to provide depth perception.

During the experiment, the Vicon motion capture system records human motion at 100 Hz and streams human motion for robot control at 50 Hz. As shown in Figure 16, wireless sEMG sensors (Trigno^{TM} from Delsys Inc.) are used to record the EMG signals at 1,000 Hz of 14 individual muscles (Anterior, Lateral and Posterior Deltoids, Biceps, Brachioradialis, Trapezius and Erector Spinae Muscles of the left and right sides of the body). These 14 muscle groups are most involved in controlling the motion of the upper body.

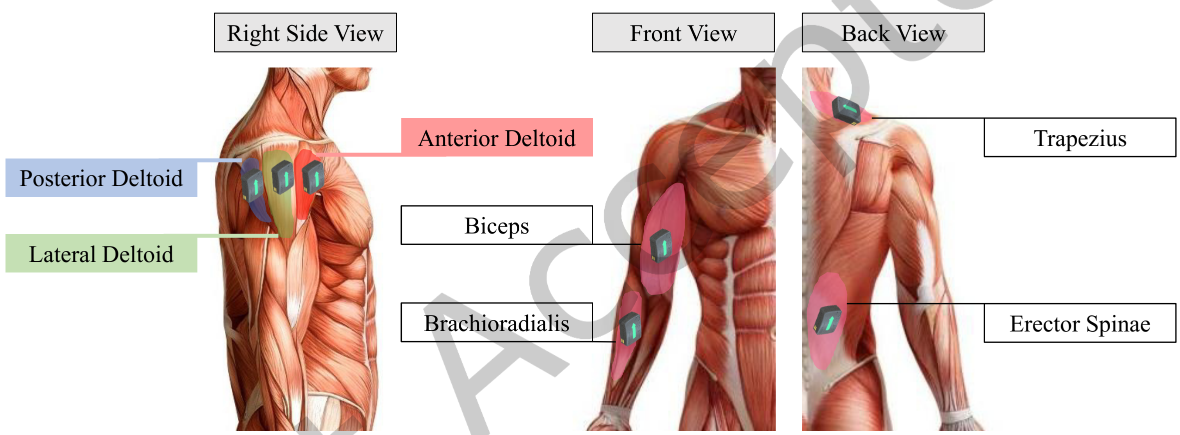


Fig. 16. Surface EMG placement.

5.2 Participants and Preparation

Our experiment involved 6 male (25 ± 3 years old) and 2 female participants (28—29 years old). Seven participants had engineering-related background and one female participant had no experience in engineering or robot control. All the participants had a normal skeletal muscle system in the upper extremities and normal trunk function. The experimental protocol was approved by the Worcester Polytechnic Institute Institutional Review Board.

After the EMG sensor attachment, all the participants were asked to perform the set of subject-specific maximum voluntary contraction test to record the maximum force generated by each targeted muscle. The MVC test involved a series of single-joint motion to isolate the contraction from each muscle. The experimenter tries to resist the subject's single joint motion during the MVC test by applying a resisting force. The MVC movements include: (1) shoulder front raise, (2) shoulder lateral raise, (3) shoulder reverse fly, (4) shoulder shrug, (5) biceps curl, (6) wrist extension and (7) lower back extension. These MVC signals served as the baseline to normalize the EMG signal recorded during the task performance.

5.3 Tasks

As shown in Figure 17, the participants are instructed to perform three robot teleoperation tasks in the experiment, namely: (1) Collecting: collect six scattered grocery items on a large table into a container; (2) Stacking: stack food containers in the instructed order; (3) Laundry: collect towels and blankets (3 pieces of laundry) into a laundry basket and take them out in a pre-defined sequence. Each participant performs each task for three times. For each iteration of each task, the items were replaced in the same position to ensure that the tasks were executed in largely the same manner. The first repetition of each task was used to analyze the muscle usage during the robot teleoperation.

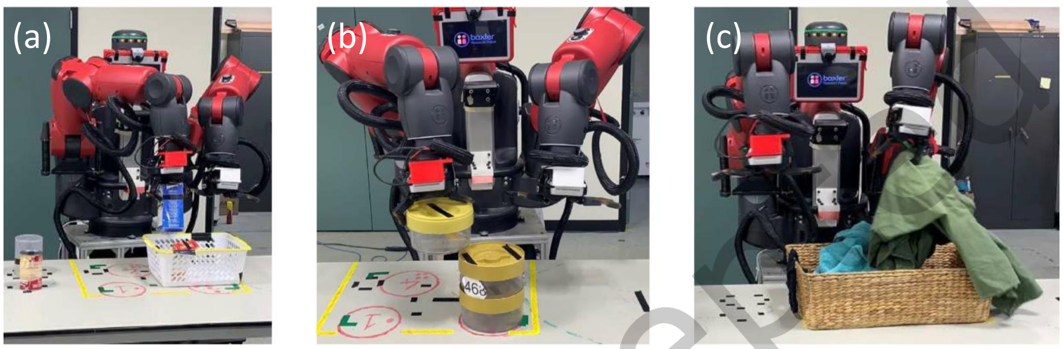


Fig. 17. Robot teleoperation tasks: (a) collecting, (b) stacking and (c) laundry.

5.4 Experimental Procedure

At the start of the user study, each participant was briefed about the capabilities of the robot platform, the way to use the motion mapping interface and the objectives of the experiment. Each participant was attached with surface EMG sensors on the muscle groups as mentioned in Section 5.1 and reflective markers for tracking human motion. Then, we performed a MVC test for each participant to normalize the EMG signal as described in Section 5.2.

Before the experiment, participants could become familiar with the TRINA system through a training session. Participants first performed a quick practice session that lets them use the functions listed in Table 3. The training tasks were similar to the performance tasks described in Section 5.3 but with fewer items. They could practice in this training session until they felt confident and comfortable using the motion mapping interface independently to teleoperate the robot to accomplish the tasks.

The order of the tasks was randomized, and participants took a minute's break after finishing each task iteration. They moved on to the next task only if they felt completely rested and they felt no fatigue in any area of their body. After accomplishing the experiment, each participant answered a custom questionnaire. The task completion time for each task was also monitored.

5.5 Data Analysis and Results

5.5.1 ***Muscle Effort Analysis.*** The muscle effort is analysed using the methodology described in Section 3.5.1. Figure 18 highlights how long the different muscle groups were contracted as a percentage of task completion time while performing different trials of the Collecting, Stacking and Laundry tasks averaged across all the participants. The lateral and anterior deltoid muscles, bicep muscles, trapezius muscles and forearm muscles showed considerable activity during the execution of the teleoperation tasks.

As seen in Figure 19, the subjects were separated into two groups. P1-P3 were users who were familiar with the teleoperation interface while P4-P8 were users who were relative novices to teleoperation. The results show that familiarity with the teleoperation interface reduces task completion time. The effect of familiarity with teleoperation on task performance requires further investigation with greater number of subjects, but the preliminary results show that it has a positive effect on task completion times.

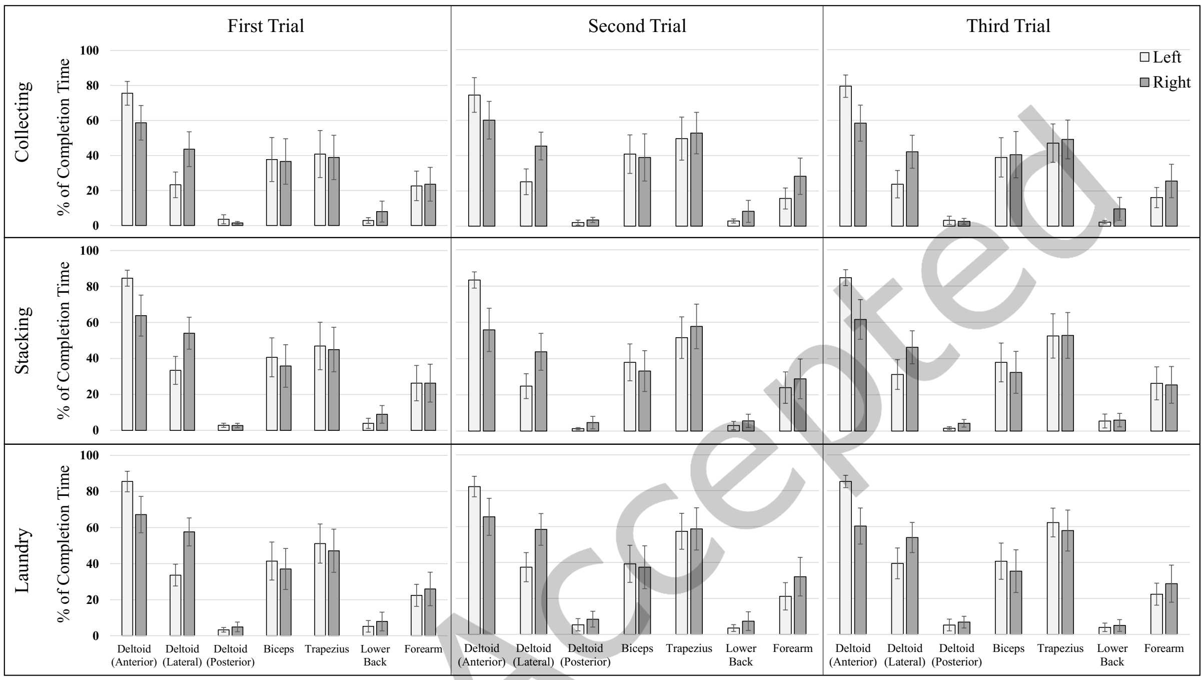


Fig. 18. The muscle effort across all muscle groups averaged across all the participants for the three trials and three tasks. Muscle effort is identified as the percentage of task completion time that the muscle is contracted.

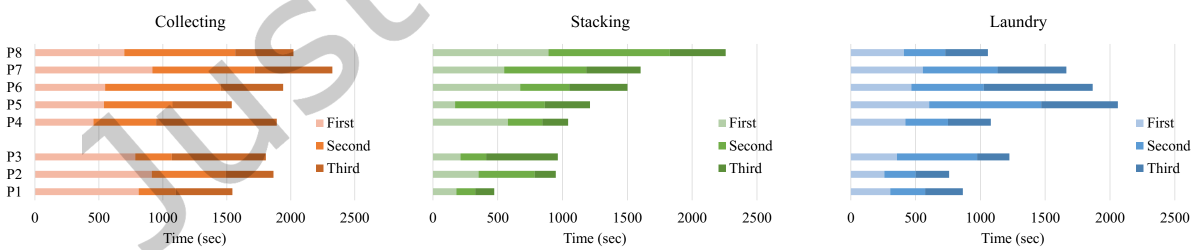


Fig. 19. The task completion time across usage groups and tasks.

5.5.2 ***Physical Fatigue Analysis.*** We compared the physical fatigue level for all the muscle groups using the methodology described in Section 3.5.2. As shown in Figure 20 for novice and expert representative participant, the area in red in the figure indicates the time when the fatigue index is above the fatigue threshold for the particular muscle identified using the technique described in Section 3.5.3. It must be noted that in our previous work [104] the fatigue threshold was set constant across all the muscle groups whereas in this analysis the fatigue threshold was determined based on the specific muscle group. As a result the Anterior and Lateral Deltoids were found to have been muscle groups susceptible to physical fatigue in addition to the Biceps and Trapezius. The novice and experts groups were created based on the subject's familiarity with teleoperation as described in Section 5.5.1. This user study shows that physical fatigue developed in the users is lesser if the familiarity with teleoperation is more. In Figure 21, it is clear that the novice users incur greater fatigue across the Anterior and Lateral Deltoids, Biceps, Trapezius and Forearms while the expert users show considerably less fatigue across these same muscle groups. The users might become more efficient with their motions with increased familiarity. Similar to identifying how task completion time is related to interface familiarity, further testing is required to identify how physical fatigue of the muscles reduces with interface familiarity.

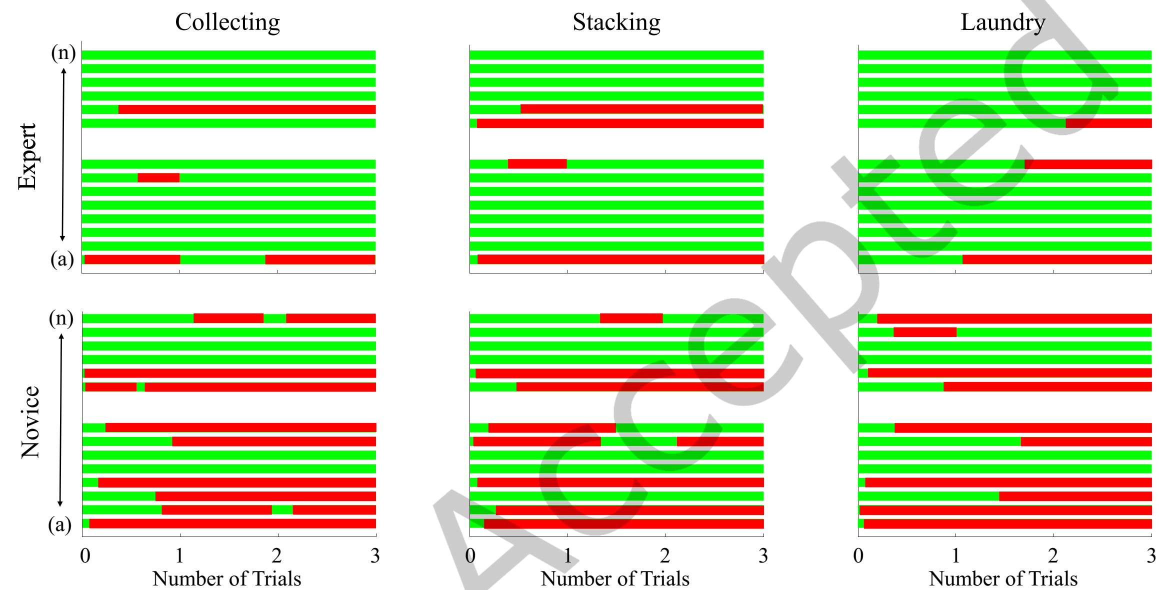


Fig. 20. Representative participant result of physical fatigue across tasks and muscle groups of the (a) left anterior deltoid, (b) right anterior deltoid, (c) left lateral deltoid, (d) right lateral deltoid, (e) left posterior deltoid, (f) right posterior deltoid, (g) left biceps, (h) right biceps, (i) left trapezius, (j) right trapezius, (k) left lower back, (l) right lower back, (m) left forearm and (n) right forearm.

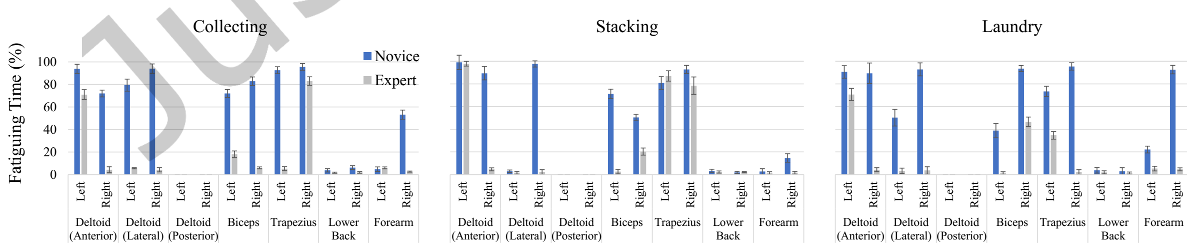


Fig. 21. The duration of muscle fatigue across all three trials as a percentage of the total task performance time.

5.5.3 ***Survey Results***. We surveyed the level of physical demand for each task, and the impact of several possible fatigue-causing factors. The reported physical demand of the three tasks is ordered as: Stacking >

Collecting > Laundry, corresponding to the amount of precise manipulation and active perception each task requires. The teleoperation actions that cause most fatigue (above a 3 rating out of 5 in the survey) include: (a) holding a steady pose of the wrist camera for observation, (b) aligning objects, (c) raising arm up for a long time during teleoperation, (d) grasping small objects, and (e) adjusting camera view for the best perspective. The less fatigue-causing actions (below 3 in rating out of 5) include: (f) picking objects from the top, (g) grasping large objects, (h) picking up objects from the side, (i) placing objects, (j) carrying grasped objects, and (k) lifting leg to change camera. The results confirm the fatigue-causing task characteristics and teleoperation actions, implied in the muscle effort and fatigue analysis.

6 USER STUDY III: SHARED AUTONOMY EVALUATION

The results from User Study II identify the actions that cause the most physical fatigue, namely steady arm postures for wrist camera control and precise manipulation for grasping objects. This physical fatigue as previously mentioned will deter future adoption of teleoperation techniques and needs to be addressed. In this study, an interface was developed that automated the robotic grasping of objects. This will eliminate the need for depth perception through wrist camera control and reduce the teleoperator's effort for manipulation. In our prior work [105], we identified the impact of automation through reduced muscle activity. In this paper, we further investigate the physical fatigue developed across all the muscle groups in the dominant and non-dominant arms while teleoperating with and without teleoperation assistance (shared autonomy) which can be used to objectively validate the effectiveness of interface design.

6.1 Experimental Setup

The experimental setup in this user study is similar to the previous one (see Section 5.1), where the participant teleoperated the robot by standing in the motion capture workspace, with the real-time fisheye camera feed of the workspace projected in front of them (see the left half of Figure 7). In addition to visual feedback, we also provided the camera feed from the Kinect which provides the detected objects and the location of the teleoperation assistance zone for the users (described in Section 3.3). Audio cues are also played when the robot end-effector is within the TAZ.

Wireless sEMG sensors are used to monitor muscle activity during the experiments to evaluate the physical effort. We focused on 10 individual muscles, namely the Anterior and Lateral fibers of the Deltoid, the Biceps, the Brachioradialis (Forearm) and the Trapezius of the left and right sides of the body (see Figure 16). Comparing muscle activity with and without teleoperation helps us understand the impact of teleoperation assistance on the teleoperation experience.

6.2 Participants and Preparations

Our experiment included 6 male (ranging from 22 to 25 years old) and 2 female participants (29 and 31 years old). The Six male participants had engineering-related background and both female participants had no experience in engineering or robot control. All the participants had a normal skeletal muscle system in the upper extremities and normal trunk function. The experimental protocol was approved by the Worcester Polytechnic Institute Institutional Review Board. Out of the 8 participants in this experiment, 1 male and 1 female participants had also participated in the User Study II mentioned in Section 5. Prior to the start of each experiment, all participants also went through a training stage where they were allowed to become familiar with the interface and thus the past experiences of some participants did not inherently make them better than the participants without prior experiences.

After the EMG sensor attachment, all the participants were asked to perform the subject-specific maximum voluntary contraction test to record the maximum force generated by each targeted muscle. The MVC test was conducted similar to the exercise done in Section 5.4.

6.3 Tasks

As shown in Figure 22, the participants performed the following tasks: (a) reaching to grasp an individual object, and (b) grasping multiple objects (bottles and cups) in a cluttered workspace. User Study II has indicated that precise manipulation is one of the most fatigue-causing factors in teleoperation. We choose these tasks because precise orientation control in reaching-to-grasp is challenging for the operators during teleoperation and requires careful design of teleoperation interface assistance (e.g., [88]).

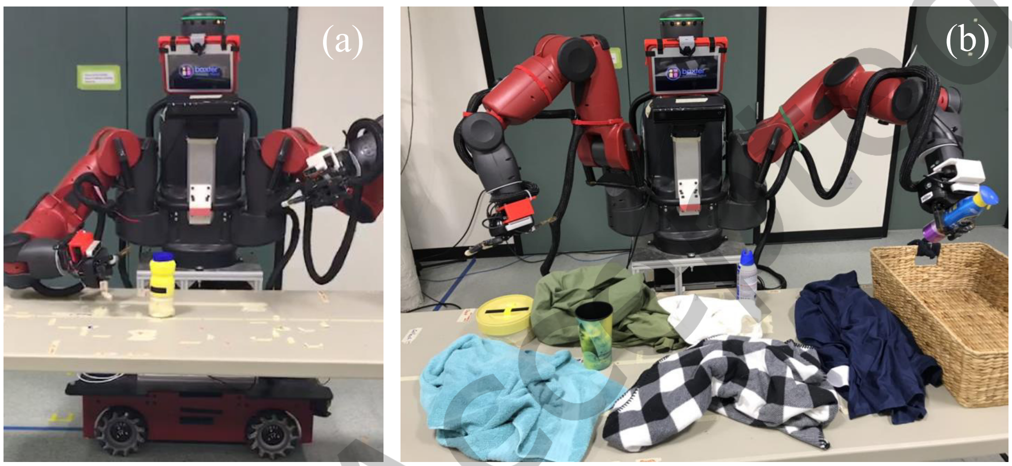


Fig. 22. Teleoperation tasks: (a) reaching-to-grasp an individual object; (b) collecting multiple objects in a cluttered counter workspace.

6.4 Experimental Procedure

Training. Each participant undergoes a training session to get familiar with the teleoperation interface, the autonomous grasping function and the robot. The training task is to pick up a bottle on the counter and place it in a basket. The participants can practice in this training session until they feel confident and comfortable to use the teleoperation interface and assistive function.

Session 1 — Object Grasping. In this session, a participant was instructed to reach and grab a bottle placed on the counter (Figure 22(a)). The participants were asked to grab the object for five repetitions each, under the following conditions: (a) using their dominant and non-dominant arms; (b) with and without the teleoperation assistance (Total number of trials = 5 repetitions × 2 arms × 2 modes). The order of arms and the availability of assistance was randomized. All the repetitions of the object grasping task had the same initial robot arm configuration, initial and final location of the object. The participants were required to pick up and place the object in a stable manner. During each trial, we record the time for completing the task, the number of times the object was knocked down and the EMG signal of the muscle groups for physical workload analysis (described in Section 3.5). The participants also answered survey questions about their teleoperation experience, in the NASA Task Load Index (NASA-TLX) format.

Session 2 — Cleaning the Workspace. In this session, the user has to pick up three cylindrical objects in a cluttered workspace and place it in a basket (see Figure 22(b)). This task was to simulate a real-world scenario in which a nursing robot needs to clean and organize a workspace with medical supplies, patient room debris and laundry (based on the tasks identified in [103]). The participant could choose between picking up the object manually or using teleoperation assistance. If the object was dropped, they are allowed to pick it up unless the object falls off the counter. We counted the number of times that the user uses teleoperation assistance. We also scored the participant's task performance in the following way: (1) +10 points for picking up each object and placing it in the basket; (2) -20 points for knocking an object down or dropping an object when moving it to the basket. The scoring system helps compare quantitatively the performance of the participants who use assistance and don't use assistance by comparing the scores they were able to achieve.

6.5 Data Analysis and Results

Our analysis of the sEMG data aims to evaluate physical workload (muscle effort and fatigue) during teleoperation using motion mapping with and without the assistance feature. Figure 7 illustrates our data analysis process where we have determined individual muscle contraction duration and individual physical fatigue level.

We compared the physical efforts, task completion time and numbers of errors in Session 1 (object grasping task), to objectively and quantitatively assess the teleoperators' physical workload reduction when using teleoperation assistance. We further use the results from the NASA-TLX survey and customized questionnaires in Session 1 and 2 to assess their perception of workload, preference for teleoperation assistance and their change in attitude toward teleoperated robot technologies.

6.5.1 ***Performance and Efforts of the Object Grasping Task***.

Objective Indices. We analyzed the recorded data to evaluate the teleoperator's efficiency, accuracy and effort to perform the object grasping task in Experiment Session 1. For *Efficiency* (T) and *Accuracy* (A), we averaged task completion time and the number of errors across all five repetitions in the four discrete conditions (with and without assistance, and for both the dominant and non-dominant hands). The *Effort* (E) is measured by the average contraction duration for all the muscle groups. For each participant, these three indices were then normalized to range between 0 and 1, with respect to the difference between maximum and minimum values across all the conditions. Figure 23 compares the performance Radar Charts across participants. Overall, the teleoperation assistance improves the task *Efficiency* and *Accuracy* for all the participants and for teleoperation using both the non-dominant and dominant arms. The reduction of **Effort** is more prominent and consistent for the non-dominant arm across the teleoperators.

Our ANOVA analysis further reveals the improvement in task Efficiency and Accuracy when using teleoperation assistance for the object grasping task. This can be seen by the recorded task completion times (non-dominant arm: $F(1,12)= 33.87$, $P< 0.01$; dominant arm: $F(1,12)= 52.35$, $P< 0.01$), number of errors (non-dominant arm: $F(1,12)= 6.02$, $P< 0.05$; dominant arm: $F(1,12)= 9.85$, $P< 0.01$) and duration of muscle contraction (non-dominant arm: $F(1,12)= 5.93$, $P< 0.05$; dominant arm: $F(1,12)= 7.93$, $P< 0.05$). Overall, grasping without teleoperation assistance took 13.3 seconds longer for the non-dominant arm and 11.9 seconds longer for the dominant arm on average. This is mostly because the teleoperation assistance reduced the risk of knocking down the object during grasping and the effort for precise manipulation.

We further compared the muscle efforts and physical fatigue between teleoperation with and without the assistance across all muscle groups for each participant. The different levels of muscle effort was calculated using the Kullback-Leibler (KL) divergence measurement based on muscle contraction duration and all the results were normalized by the maximum value. As shown in Figure 24, most of the muscles had a significant reduction in physical effort (marked as green) with a higher level of relaxation for the deltoids and biceps of the

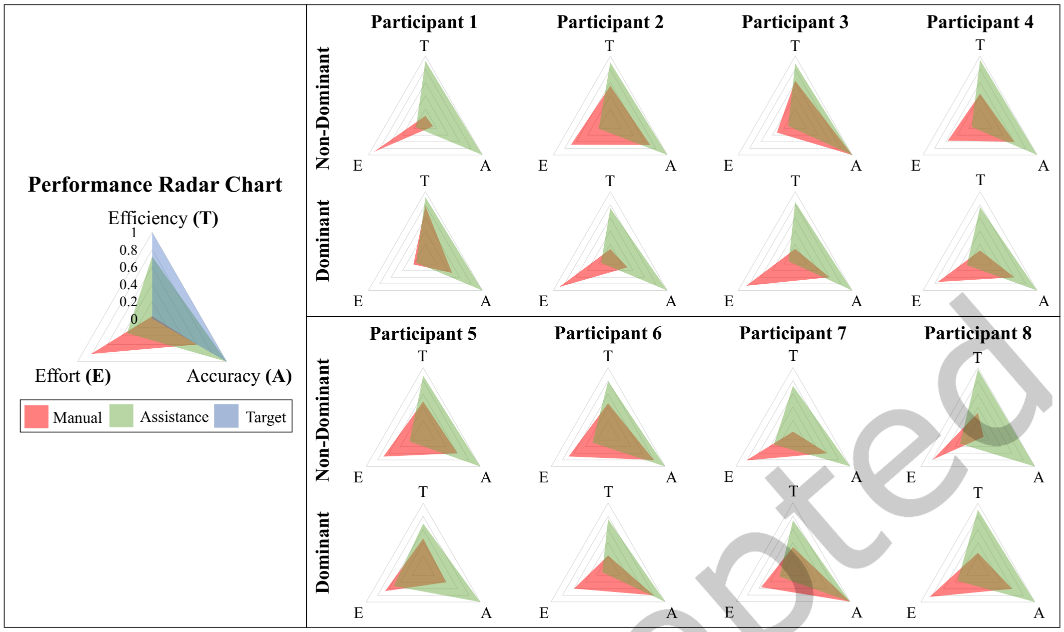


Fig. 23. Performance evaluation procedure and summary for object grasping across all subjects.

dominant/non-dominant hand. It is noted that the trapezius muscle however has reduced reduction (marked as white) or increased physical effort as shown by the red marks for 2 participants. Overall, the assistance function performed equally effectively on both arms for all participants.

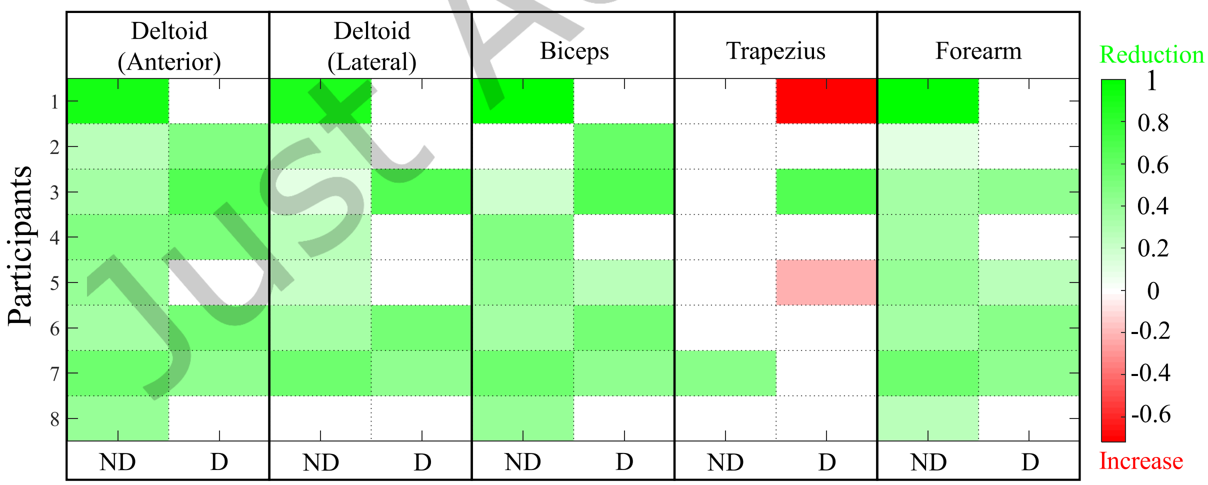


Fig. 24. Comparison of physical effort across all muscles with dominant (D) and non-dominant (ND) hand.

The level of physical fatigue was computed using the fatigue index (described in Section 3.5.2) for all repetitions. Figure 25 presents the physical fatigue developed across all the muscle groups for a representative participant.

The magnitude of the fatigue index was lower while using the teleoperation assistance for most of the repetitions for the both dominant and non-dominant arms. The duration for each repetition of the task was relatively small and hence the fatigue index did not pass the fatigue threshold. However, these results can be used to predict the potential physical fatigue developed due to extended teleoperation duration and is a part of our planned future work. The area under the curve represents the total accumulated fatigue. As shown in Figure 26(a), most of the muscles had significantly less accumulated fatigue (non-dominant arm: anterior and lateral Deltoid, Trapezius and Forearm, $P < 0.01$; dominant arm: anterior and lateral Deltoid and Forearm, $P < 0.01$) while using teleoperation assistance.

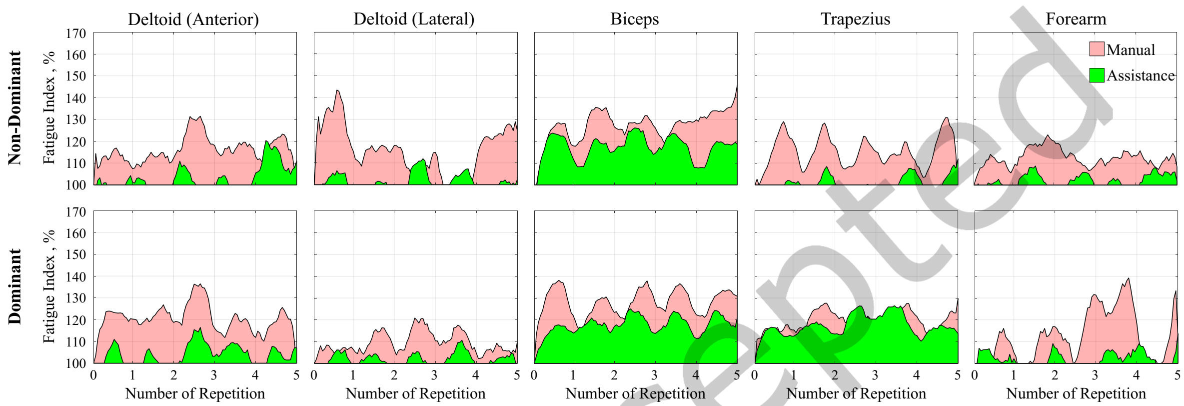


Fig. 25. Representative participant result of physical fatigue across all muscles with dominant (D) and non-dominant (ND) hand.

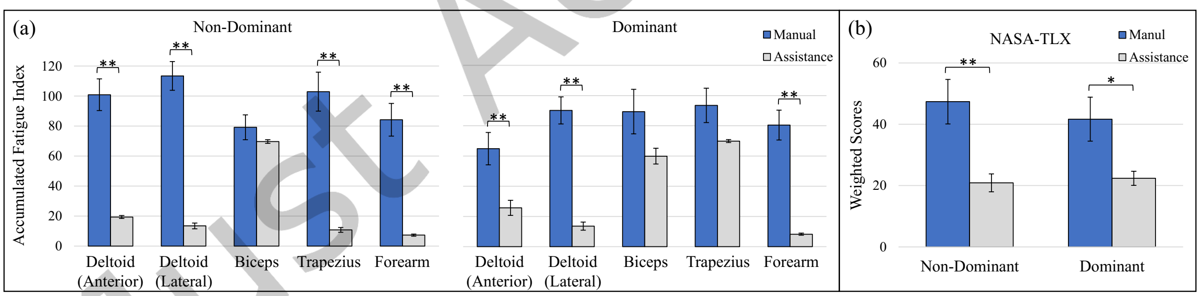


Fig. 26. (a) Comparison of accumulated fatigue across all muscles in the dominant (D) and non-dominant (ND) hands. (b) Subjective workload from weighted NASA-TLX scores.

Subjective Indices. We also used the weighted NASA-TLX scores to evaluate the teleoperators' perception of task performance and workload. The weighting coefficients were selected as follows: mental demand=4, physical demand=5, temporal demand=0, performance=2, effort=3, frustration=1. Shown in Figure 26(b), the teleoperators have answered the survey in support of the usability of the assistance function. Participants reported the significant lower workload while using the teleoperation assistance for the non-dominant ($P < 0.01$) and dominant ($P < 0.05$) hands. The lower workload rating for the assistance function is understandable as there was no errors during operation and the need to manually execute the precise manipulation to perform grasping is eliminated. Additionally, as the assistance function reduces the duration of muscle contraction the mental fatigue incurred due to teleoperation also reduces. As a result, the operation times are reduced as there are no errors and user motion are more efficient. The users may have reported reduced physical workload in their surveys because of these advantages.

6.5.2 ***Preference for the Teleoperation Assistance.*** In Experiment Session 2, participants could choose whether or not to use the teleoperation assistance to pick and place objects. As shown in Figure 27, we found that (1) more participants prefer to use teleoperation assistance (16 times out of 24), (2) participants who used assistance more (more than two times out of three, P4-P8) had higher scores than the participants who performed the tasks more manually (P1-P3), (3) participants who completed the tasks more manually (55.3±7.4) reported higher subjective workload than using assistance (24.6±6.8).

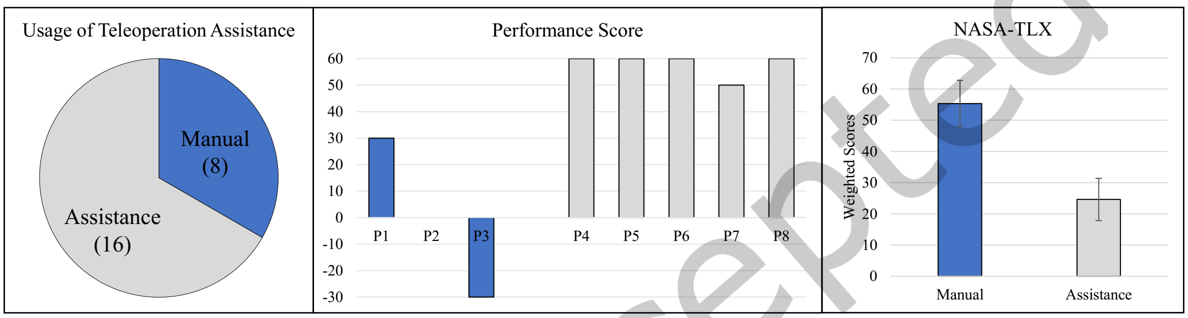


Fig. 27. Performance of score system for collecting three objects.

After Experiment Session 2, participants rated in hindsight their preference for teleoperation assistance and manual control during robot teleoperation on a 1-7 Likert scale with 1 being the least and 7 being the most in terms of agreement. As there was a greater preference for the assistive function (6.6±0.6) than purely manual control (3.6±0.7), the users were questioned on what factors made them favor teleoperation assistance more. They point out that the teleoperation assistance can (1) increase the success rate; (2) reduce the task completion time; (3) reduce the cognitive workload; and (4) reduce the physical workload. The results highlight the participant's belief that teleoperation assistance improves performance.

7 DISCUSSION

The paper fits our prior work on the assessment of physical fatigue for nursing robot teleoperation via motion mapping [104] into a complete framework that integrates interface evaluation and evolution in a closed-loop and potentially iterative process. Beyond the work presented in [104], we compared the motion mapping interface with several widely used tele-medical robot interface modalities. To the best of our knowledge, this is the first user study that evaluates nursing robot interfaces with nursing students and practitioners. We also design and evaluate robot autonomy for reducing the physical fatigue in robot teleoperation [105], as physical fatigue is a non-trivial problem when human motion tracking interfaces becomes more widely used for teleoperating co-robots in the near future. In this paper, we further investigate the physical fatigue developed across all the muscle groups in the dominant and non-dominant hand while teleoperating with and without teleoperation assistance (shared autonomy) which can be used to objectively validate the effectiveness of interface design. In the novel framework presented in this paper, we present a novel way of integrating the identification of the ideal teleoperation interface for healthcare/nursing duties through user studies and interviews, using EMG signals to identify the sources of physical discomfort and designing teleoperation assistance based on the findings from the EMG signals. In this section, we will further discuss the desirable characteristics of the three teleoperation interfaces based on participant interviews and our experience with these interfaces, the impact of assistance designed to reduce physical workload on the teleoperation experience and suitability of our evaluation metrics for designing teleoperation interfaces for nursing applications.

7.1 Desirable Characteristics of Tele-nursing Robot Interface

Tele-nursing robots should preferably be efficient and accurate while being intuitive with bi-directional communication. These components will increase the nursing workers' preference for using such robots as their proxy to perform repetitive daily tasks so that the risks of disease infection, physical strain and injuries are reduced. However, the increased functionality also increases the complexity of the tele-nursing robot hardware and software. It is important to implement a suitable control interface for nursing workers who usually have limited experience with robot control or limited engineering expertise. Right now, the current and future population of nursing workers is pre-dominantly made of women and the female to male ratio is about 9:1 [141, 156]. The average age of the current nursing population is around 49 years [123]. About 50% of full-time nursing faculty are 50 years or older [24]. Research has consistently shown that women and elders tend to perform worse in tasks that require spatial skill [106, 116], which is used to estimate robot teleoperation skills [47, 85, 130, 167, 169]. Elders also tend to have less experience with newer technology [41, 54] and are less willing to adopt them [29, 40, 51, 63, 64, 84, 111, 118]. Gender stereotypes are often perpetuated because women may not be included in the design process or test populations [26, 76, 165]. The lack of transparent and intuitive interfaces leads to not only low task performance of nursing tasks, but also creates intimidating cognitive and physical efforts for the users. The negative experience with traditional and contemporary robot interfaces may further reinforce the age and gender biases that discourage the current and future nursing workers to envision the future of human-robot teaming in a nursing workplace, and integration of robots into nursing education.

We showed the advantage of using human motion mapping as the tele-nursing robot control interface by comparing it with a handheld gamepad and stylus-based device (User Study I). The lower learning effort among nursing workers new to robot operation and the intuitive freeform motion control could also make the teleoperation experience more immersive. Interestingly, from the post-study interview, the participants stated that they felt the operational effort was *reduced* because they *were able to* simultaneously control manipulation and navigation when using the motion mapping interface. The interviews also mentioned that participants appreciated being able to control the robot arms to perform complex orientations with ease. It is understandable that in a realistic patient-caring scenario, the nursing workers often need to take care of multiple tasks simultaneously. Nevertheless, we noticed that the control interface using a gamepad is suitable for more structured tasks since it can precisely and slowly control each motion for each degree of freedom. Interviews of the participants indicated that the ability to use different buttons to control different functions of the robot made teleoperation simpler. They felt this would prevent unintended motions of the arms or the base. The participants also stated that the ability to move the robot in small discrete increments via the joystick input gave them more confidence while performing delicate operations like picking up objects. This is unlike the motion control observed with the Vicon interface and the stylus-based interface where precise control is harder to achieve. On the other hand, when the workspace of the task is limited to a certain area, the stylus device will be a good fit to control the robot to perform tasks with small movements. Additionally, the buttons on the stylus hardware helps integrate discretized base and arm control while also enabling teleoperation through intuitive motion mapping of the stylus. Compared to the gamepad interface the motion mapping of the stylus interface was reported as being more intuitive to use according to some participant surveys. However, for nursing tasks that involve unstructured and large range of movement (e.g. laundry in the cluttered environment), freeform control (human motion mapping) is preferred.

Our future work will explore other wearable/portable interfaces for whole-body motion mapping. Although the motion capture systems are accurate for human motion tracking, the cost of hardware and effort required to setup makes them less desirable. We also noticed that the teleoperation performance and nursing workers' preference might be affected by lots of factors (e.g. age, gender, gaming experiences, spatial skills, etc.). We will further investigate the impact of each identified factor to further the development of desirable teleoperation interfaces. A user study will also be devised to study how immersive each teleoperation interface will be as immersion will play a great role in improving the situational awareness of the operator while teleoperating. Through the three user studies presented in this paper we have verified the usability of our interface design and evaluation framework. To quantitatively evaluate the usability of the different interfaces, we will also work on developing a user study where the performance of these teleoperation interfaces for a diverse array of tasks will be analyzed.

7.2 Teleoperation Assistance for Reducing Physical Workload

Motion mapping as a teleoperation interface proves to be the most intuitive and preferred means of teleoperation. However, the physical fatigue developed because of using this interface cannot be ignored and it can result in the rejection of this interface as a means of everyday sustained use. As identified in this paper (User Study II), physical fatigue is developed primarily in the Anterior Deltoid, Trapezius and Biceps muscle groups due to teleoperation actions like steady arm postures for camera control and small-object manipulation. The squatting action was performed only when the operator had to pause teleoperation which only occurred at the start and end of the trials. Thus, the EMG signals of the leg muscles were not monitored for analyzing the physical workload. However, since standing for extended durations might be a possible source of fatigue, monitoring the EMG signals to verify this aspect of teleoperation can be an interesting direction of future research.

We used a shared autonomous control interface to tackle the issue of physical fatigue. Nursing tasks require a lot of decision-making skills and occur in an unstructured environment. As a result, the entire task cannot be automated as current automation techniques do not capture the nuances of operator controlled teleoperation. In this paper (User Study III), we have proposed how automating reach-to-grasp reduces physical effort and fatigue in the operator and improves their perception towards teleoperation. Aspects of teleoperation like locomotion and gross manipulation is left to the operator while the finer manipulation involved with object grasping is automated and can be triggered on and off base on the operator's needs.

We have demonstrated that augmenting the direct, freeform interfaces for robot control with a little bit of robot autonomy will lead to flexible and reliable robot control for complex tasks. Our proposed robot autonomy effectively reduced the operator's physical workload in the control of reaching-to-grasp motions. Our future work will further develop a variety of robot autonomy to other fine motor skills necessary for quarantine patient care (see the fine manipulation tasks listed in [72]). We will also explore how to design robot autonomy to be fatigue-adaptive, such as triggering the autonomous function based on task context, inferred user intents, and estimated physical fatigue level.

7.3 Evaluation Metrics for Nursing Workers and Tasks

The general framework (in User Study I) of the current human-robot teaming evaluation system we used in this paper evaluates the robot task performance and human workload. The different levels of controllability, efficiency, accuracy, intuitiveness, and effort will affect the users' preference and attitude toward using tele-nursing technologies. Among the nursing workers, the weight of each teleoperation factor may change depending on the usage. For instance, most of the registered nurses from the post-study interview reported that the operational workload is their highest priority since they work in a tense environment where they handle multiple inputs and outputs in a nurse-patient interaction. In this paper, we demonstrated the effectiveness of using evaluation-in-the-loop in the evolution of teleoperation interface design. We focused on the teleoperation interface with lower mental workload (human motion mapping) and tried to learn more about its limitations by evaluating physical fatigue through the use of sEMG sensors.

The use of sEMG sensors helps us monitor the physical workload objectively. In this paper, we showed the potential for sEMG as an offline analysis tool that can evaluate physical workload. It helped us to identify the fatigue-causing factors (User Study II) and helped us generate a novel objective index to evaluate physical fatigue. These results helped us identify the direction in which the shared autonomy must be designed (as seen in User Study III). Our work is similar to [135] in that we prioritize reducing muscle efforts in human-robot collaborative tasks. However, we focus on the tasks that involve more complex motor skills and dynamic muscle contractions.

Our future work will incorporate more advanced methods for the accurate estimation of physical fatigue. Traditionally, physical fatigue is measured using amplitude-based parameters and time-frequency distributions of non-linear parameters. These metrics are suitable for evaluating isometric fatigue. We will consider the novel approaches which are more suitable for assessing dynamic muscle fatigue. These approaches may utilize dynamic muscle fatigue model, differential equations, mechanomyography [180], inertial measurement unit (IMU) measurements [62], power spectral indices and kinetics and kinematics [14] from motion data.

8 CONCLUSION

In this paper, we discussed a framework of evaluation procedures used for continuously improving robot teleoperation interfaces. We initially identify through a user study comparing three different representative teleoperation interfaces that motion mapping is the most intuitive form of teleoperation for nursing tasks. This lets us determine that the best means of input for a teleoperation interface for nursing workers (subjects of the user study) is mapped human motion.

Motion mapping as a means of teleoperation results in non-trivial physical fatigue in the operator. This reduces the feasibility of extended use of teleoperation on a daily basis. In the second level of our evaluation methodology, using EMG measurements and a novel fatigue index, we found that actions like steady arm postures and fine manipulation cause physical fatigue in different muscles groups of the operator.

Finally, we created an autonomous assistance function into this interface that automates the reach to grasp function in the robot teleoperation eliminating the fatigue causing actions (steady arm postures and fine manipulation for object grasping) identified in the previous user study. A user study confirms the benefits of this autonomous interface as it improve the efficiency and accuracy of the motion mapping interface while reducing physical fatigue. We also identified that these automation features improves the operators preference for future use of the teleoperation interface. In this manner, we have developed a robust and competent motion mapping interface to control a humanoid robot for nursing tasks.

REFERENCES

[1] IH Monrad Aas. 2000. Working with telemedicine: user characteristics and attitudes. Journal of telemedicine and telecare 6, 1_suppl (2000), 66–68.

[2] Waleed Abdulla. 2017. Mask R-CNN for object detection and instance segmentation on Keras and TensorFlow. https://github.com/matterport/Mask_RCNN.

[3] Jamil Abou Saleh. 2012. A Novel Approach for Performance Assessment of Human-Robotic Interaction. (2012).

[4] E Ackerman. 2012. iRobot and InTouch Health announce RP-VITA telemedecine robot. IEEE Spectrum (2012).

[5] Evan Ackerman. 2017. Toyota Gets Back Into Humanoid Robots With New T-HR3. IEEE Spectrum (2017).

[6] E Ackerman. 2018. Ava Robotics Introduces Autonomous Telepresence Robot. IEEE Spectrum (2018).

[7] E Ackerman. 2018. 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).

[8] E Ackerman. 2018. Suitable Tech Introduces BeamPro 2 Telepresence Platform. IEEE Spectrum (2018).

[9] E Ackerman. 2020. Autonomous Robots Are Helping Kill Coronavirus in Hospitals. IEEE Spectrum: Technology, Engineering, and Science News (2020).
[10] E Ackerman. 2020. How Diligent's Robots Are Making a Difference in Texas Hospitals. IEEE Spectrum (2020).
[11] E Ackerman. 2020. Telepresence Robots Are Helping Take Pressure Off Hospital Staff. IEEE Spectrum (2020).
[12] E Ackerman, Guizzo E., and F Shi. 2020. Video Friday: Robots Help Keep Medical Staff Safe at COVID-19 Hospital. IEEE Spectrum (2020).
[13] Amir Aly, Sascha Griffiths, and Francesca Stramandinoli. 2017. Metrics and benchmarks in human-robot interaction: Recent advances in cognitive robotics. Cognitive Systems Research 43 (2017), 313–323.
[14] Tommy Apriantono, Hiroyuki Nunome, Yasuo Ikegami, and Shinya Sano. 2006. The effect of muscle fatigue on instep kicking kinetics and kinematics in association football. Journal of sports sciences 24, 9 (2006), 951–960.
[15] Nik Khadijah Nik Aznan, Jason D Connolly, Noura Al Moubayed, and Toby P Breckon. 2019. Using variable natural environment brain-computer interface stimuli for real-time humanoid robot navigation. In 2019 International Conference on Robotics and Automation (ICRA). IEEE, 4889–4895.
[16] Lucile Bechade, Guillaume Dubuisson-Duplessis, Gabrielle Pittaro, Mélanie Garcia, and Laurence Devillers. 2019. Towards metrics of evaluation of pepper robot as a social companion for the elderly. In Advanced Social Interaction with Agents. Springer, 89–101.
[17] Jenay M Beer, Arthur D Fisk, and Wendy A Rogers. 2014. Toward a framework for levels of robot autonomy in human-robot interaction. Journal of human-robot interaction 3, 2 (2014), 74–99.
[18] Momotaz Begum, Richard W Serna, David Kontak, Jordan Allspaw, James Kuczynski, Holly A Yanco, and Jacob Suarez. 2015. Measuring the efficacy of robots in autism therapy: How informative are standard hri metrics'. In Proceedings of the Tenth Annual ACM/IEEE International Conference on Human-Robot Interaction. 335–342.
[19] Cindy L Bethel and Robin R Murphy. 2010. Review of human studies methods in HRI and recommendations. International Journal of Social Robotics 2, 4 (2010), 347–359.
[20] Raghav Bhat, Vishal Pandey, Akash K Rao, and Sushil Chandra. 2017. An evaluation of cognitive and neural correlates for indirect vision driving and rover teleoperation. In 2017 2nd International Conference on Man and Machine Interfacing (MAMI). IEEE, 1–5.
[21] J Bodner, H Wykypiel, G Wetscher, and T Schmid. 2004. First experiences with the da Vinci™ operating robot in thoracic surgery. European Journal of Cardio-thoracic surgery 25, 5 (2004), 844–851.
[22] Craig E Boettcher, Karen A Ginn, and Ian Cathers. 2008. Standard maximum isometric voluntary contraction tests for normalizing shoulder muscle EMG. Journal of orthopaedic research 26, 12 (2008), 1591–1597.
[23] Sharon Claxton Bommer and Mary Fendley. 2018. A theoretical framework for evaluating mental workload resources in human systems design for manufacturing operations. International Journal of Industrial Ergonomics 63 (2018), 7–17.
[24] Jill S Budden, Patricia Moulton, Kimberly J Harper, M Brunell, and Richard Smiley. 2016. The 2015 national nursing workforce survey. Journal of Nursing Regulation 7, 1 (2016), S1–S90.
[25] Jennifer Burke, Matt Lineberry, Kevin S Pratt, Meng Taing, Robin Murphy, and Brian Day. 2008. Toward developing hri metrics for teams: Pilot testing in the field. Metrics for Human-Robot Interaction 2008 (2008), 21.
[26] S Carty. 2011. Many Cars Tone Deaf To Women's Voices. AOL Autos (2011).
[27] Andrés Cela, J Javier Yebes, Roberto Arroyo, Luis M Bergasa, Rafael Barea, and Elena López. 2013. Complete low-cost implementation of a teleoperated control system for a humanoid robot. Sensors 13, 2 (2013), 1385–1401.
[28] Yongwook Chae, Jaeseung Jeong, and Sungho Jo. 2012. Toward brain-actuated humanoid robots: asynchronous direct control using an EEG-based BCI. IEEE Transactions on Robotics 28, 5 (2012), 1131–1144.
[29] Neil Charness, Catherine L Kelley, Elizabeth A Bosman, and Melvin Mottram. 2001. Word-processing training and retraining: Effects of adult age, experience, and interface. Psychology and aging 16, 1 (2001), 110.
[30] Yuhang Che, Heather Culbertson, Chih-Wei Tang, Sudipto Aich, and Allison M Okamura. 2018. Facilitating Human-Mobile Robot Communication via Haptic Feedback and Gesture Teleoperation. ACM Transactions on Human-Robot Interaction (THRI) 7, 3 (2018), 1–23.
[31] Jessie YC Chen. 2010. Robotics operator performance in a multi-tasking environment. Human-Robot Interactions in Future Military Operations (2010), 294–314.
[32] Jessie YC Chen and Michael J Barnes. 2014. Human–agent teaming for multirobot control: A review of human factors issues. IEEE Transactions on Human-Machine Systems 44, 1 (2014), 13–29.
[33] Jessie YC Chen, Michael J Barnes, and Michelle Harper-Sciarini. 2010. Supervisory control of multiple robots: Human-performance issues and user-interface design. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 41, 4 (2010), 435–454.
[34] Jessie YC Chen, Ellen C Haas, and Michael J Barnes. 2007. Human performance issues and user interface design for teleoperated robots. IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews) 37, 6 (2007), 1231–1245.
[35] Jessie Y Chen, Ellen C Haas, Krishna Pillalamarri, and Catherine N Jacobson. 2006. Human-robot interface: Issues in operator performance, interface design, and technologies. Technical Report. ARMY RESEARCH LAB ABERDEEN PROVING GROUND MD.

[36] Tiffany L Chen and Charles C Kemp. 2010. Lead me by the hand: Evaluation of a direct physical interface for nursing assistant robots. In 2010 5th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 367–374.
[37] Sonia Chernova and Andrea L Thomaz. 2014. Robot learning from human teachers. Vol. 8. Morgan & Claypool Publishers, Chapter 10, 1–121.
[38] Mario Cifrek, Vladimir Medved, Stanko Tonković, and Saša Ostojić. 2009. Surface EMG based muscle fatigue evaluation in biomechanics. Clinical biomechanics 24, 4 (2009), 327–340.
[39] Chris S Crawford, Marvin Andujar, and Juan E Gilbert. 2017. Neurophysiological Heat Maps for Human-Robot Interaction Evaluation. In 2017 AAAI Fall Symposium Series.
[40] Stephen J Cutler, Jon Hendricks, and Amy Guyer. 2003. Age differences in home computer availability and use. The Journals of Gerontology Series B: Psychological Sciences and Social Sciences 58, 5 (2003), S271–S280.
[41] Sara J Czaja, Neil Charness, Arthur D Fisk, Christopher Hertzog, Sankaran N Nair, Wendy A Rogers, and Joseph Sharit. 2006. Factors predicting the use of technology: Findings from the center for research and education on aging and technology enhancement (CREATE). Psychology and aging 21, 2 (2006), 333.
[42] Torbjørn S Dahl and Maged N Kamel Boulos. 2014. Robots in health and social care: A complementary technology to home care and telehealthcare? Robotics 3, 1 (2014), 1–21.
[43] Behzad Dariush, Michael Gienger, Arjun Arumbakkam, Youding Zhu, Bing Jian, Kikuo Fujimura, and Christian Goerick. 2009. Online transfer of human motion to humanoids. International Journal of Humanoid Robotics 6, 02 (2009), 265–289.
[44] Carlo J De Luca. 1997. The use of surface electromyography in biomechanics. Journal of applied biomechanics 13, 2 (1997), 135–163.
[45] Scott L Delp, Frank C Anderson, Allison S Arnold, Peter Loan, Ayman Habib, Chand T John, Eran Guendelman, and Darryl G Thelen. 2007. OpenSim: open-source software to create and analyze dynamic simulations of movement. IEEE transactions on biomedical engineering 54, 11 (2007), 1940–1950.
[46] George V Dimitrov, Todor I Arabadzhiev, Katya N Mileva, Joanna L Bowtell, Nicola Crichton, and NONNA A Dimitrova. 2006. Muscle fatigue during dynamic contractions assessed by new spectral indices. Medicine and science in sports and exercise 38, 11 (2006), 1971.
[47] Mark Draelos, Brenton Keller, Cynthia Toth, Anthony Kuo, Kris Hauser, and Joseph Izatt. 2017. Teleoperating robots from arbitrary viewpoints in surgical contexts. In IEEE International Conference on Intelligent Robots and Systems (IROS). Vancouver, 2549–2555.
[48] Anca D Dragan and Siddhartha S Srinivasa. 2013. A policy-blending formalism for shared control. The International Journal of Robotics Research 32, 7 (2013), 790–805.
[49] Guanglong Du, Ping Zhang, and Xin Liu. 2016. Markerless human-manipulator interface using leap motion with interval Kalman filter and improved particle filter. IEEE Transactions on Industrial Informatics 12, 2 (2016), 694–704.
[50] Guanglong Du, Ping Zhang, Jianhua Mai, and Zeling Li. 2012. Markerless kinect-based hand tracking for robot teleoperation. International Journal of Advanced Robotic Systems 9, 2 (2012), 36.
[51] Jennifer L Dyck and Janan Al-Awar Smither. 1994. Age differences in computer anxiety: The role of computer experience, gender and education. Journal of educational computing research 10, 3 (1994), 239–248.
[52] Ryhan Ebad and KSA Jazan. 2013. Telemedicine: Current and Future Perspectives Telemedicine: Current and Future Perspectives. (2013).
[53] Reda Elbasiony and Walid Gomaa. 2018. Humanoids skill learning based on real-time human motion imitation using Kinect. Intelligent Service Robotics 11, 2 (2018), 149–169.
[54] R Darin Ellis and Jason C Allaire. 1999. Modeling computer interest in older adults: The role of age, education, computer knowledge, and computer anxiety. Human Factors 41, 3 (1999), 345–355.
[55] Sara Falleni, Alessandro Filippeschi, Emanuele Ruffaldi, and Carlo Alberto Avizzano. 2017. Teleoperated multimodal robotic interface for telemedicine: A case study on remote auscultation. In 2017 26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN). IEEE, 476–482.
[56] Bin Fang, Fuchun Sun, Huaping Liu, Di Guo, Wendan Chen, and Guodong Yao. 2017. Robotic teleoperation systems using a wearable multimodal fusion device. International Journal of advanced robotic systems 14, 4 (2017), 1729881417717057.
[57] Kerstin Fischer, Franziska Kirstein, Lars Christian Jensen, Norbert Krüger, Kamil Kukliński, Maria Vanessa aus der Wieschen, and Thiusius Rajeeth Savarimuthu. 2016. A comparison of types of robot control for programming by demonstration. In 2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 213–220.
[58] Ulrik Franke and Joel Brynielsson. 2014. Cyber situational awareness–a systematic review of the literature. Computers & security 46 (2014), 18–31.
[59] Lars Fritsche, Felix Unverzag, Jan Peters, and Roberto Calandra. 2015. First-person tele-operation of a humanoid robot. In 2015 IEEE-RAS 15th International Conference on Humanoid Robots (Humanoids). IEEE, 997–1002.
[60] Robert Garcia and Olayele Adelakun. 2019. A Conceptual Framework and Pilot Study for Examining Telemedicine Satisfaction Research. Journal of medical systems 43, 3 (2019), 51.
[61] Yiannis Gatsoulis, Gurvinder S Virk, and Abbas A Dehghani-Sanij. 2010. On the measurement of situation awareness for effective human-robot interaction in teleoperated systems. Journal of cognitive engineering and decision making 4, 1 (2010), 69–98.

[62] Marcus Georgi, Christoph Amma, and Tanja Schultz. 2015. Recognizing Hand and Finger Gestures with IMU based Motion and EMG based Muscle Activity Sensing.. In Biosignals. 99–108.
[63] MV Giuliani, M Scopelliti, and Ferdinando Fornara. 2005. Coping strategies and technology in later life. Companions: Hard Problems and Open Challenges in Robot-Human Interaction (2005), 46.
[64] Maria Vittoria Giuliani, Massimiliano Scopelliti, and Ferdinando Fornara. 2005. Elderly people at home: technological help in everyday activities. In IEEE Workshop on Robot and Human Interactive Communication, (RO-MAN). IEEE, Nashville, US, 365–370.
[65] VF Gladwell and JH Coote. 2002. Heart rate at the onset of muscle contraction and during passive muscle stretch in humans: a role for mechanoreceptors. The Journal of physiology 540, 3 (2002), 1095–1102.
[66] Matthew Gombolay, Anna Bair, Cindy Huang, and Julie Shah. 2017. Computational design of mixed-initiative human–robot teaming that considers human factors: situational awareness, workload, and workflow preferences. The International journal of robotics research 36, 5-7 (2017), 597–617.
[67] Michael A Goodrich, Jacob W Crandall, and Emilia Barakova. 2013. Teleoperation and beyond for assistive humanoid robots. Reviews of Human factors and ergonomics 9, 1 (2013), 175–226.
[68] Akif Hacinecipoglu, E Ilhan Konukseven, and A Bugra Koku. 2013. Evaluation of haptic feedback cues on vehicle teleoperation performance in an obstacle avoidance scenario. In 2013 World Haptics Conference (WHC). IEEE, 689–694.
[69] Louise Hagan, Diane Morin, and Rachel Lépine. 2000. Evaluation of telenursing outcomes: satisfaction, self-care practices, and cost savings. Public Health Nursing 17, 4 (2000), 305–313.
[70] Caroline E Harriott. 2015. Workload and task performance in human-robot peer-based teams. Ph.D. Dissertation. Vanderbilt University.
[71] Kunimatsu Hashimoto, Fuminori Saito, Takashi Yamamoto, and Koichi Ikeda. 2013. A field study of the human support robot in the home environment. In 2013 IEEE Workshop on Advanced Robotics and its Social Impacts. IEEE, 143–150.
[72] K. Hauser and R Shaw. 2020. How Medical Robots Will Help Treat Patients in Future Outbreaks. IEEE Spectrum (2020).
[73] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. 2017. Mask r-cnn. In Proceedings of the IEEE international conference on computer vision. 2961–2969.
[74] Paul W Hodges and Bang H Bui. 1996. A comparison of computer-based methods for the determination of onset of muscle contraction using electromyography. Electroencephalography and Clinical Neurophysiology/Electromyography and Motor Control 101, 6 (1996), 511–519.
[75] Guy Hoffman. 2019. Evaluating fluency in human–robot collaboration. IEEE Transactions on Human-Machine Systems 49, 3 (2019), 209–218.
[76] Ayanna Howard and Jason Borenstein. 2018. The Ugly Truth About Ourselves and Our Robot Creations: The Problem of Bias and Social Inequity. Science and Engineering Ethics 24, 5 (01 Oct 2018), 1521–1536.
[77] Ayanna M Howard. 2005. A methodology to assess performance of human-robotic systems in achievement of collective tasks. In 2005 IEEE/RSJ International Conference on Intelligent Robots and Systems. IEEE, 90–95.
[78] John Hu, Aaron Edsinger, Yi-Je Lim, Nick Donaldson, Mario Solano, Aaron Solochek, and Ronald Marchessault. 2011. An advanced medical robotic system augmenting healthcare capabilities-robotic nursing assistant. In 2011 IEEE international conference on robotics and automation. IEEE, 6264–6269.
[79] Curtis M Humphrey, Christopher Henk, George Sewell, Brian W Williams, and Julie A Adams. 2007. Assessing the scalability of a multiple robot interface. In 2007 2nd ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 239–246.
[80] Chih-Lyang Hwang and Guo-Hsuan Liao. 2018. Real-time pose imitation by mid-size humanoid robot with servo-cradle-head RGB-D vision system. IEEE Transactions on Systems, Man, and Cybernetics: Systems 49, 1 (2018), 181–191.
[81] Jung-Hoon Hwang, KangWoo Lee, and Dong-Soo Kwon. 2007. A formal method of measuring interactivity in hri. In RO-MAN 2007-The 16th IEEE International Symposium on Robot and Human Interactive Communication. IEEE, 738–743.
[82] Yasuhiro Ishiguro, Kunio Kojima, Fumihito Sugai, Shunichi Nozawa, Yohei Kakiuchi, Kei Okada, and Masayuki Inaba. 2018. High speed whole body dynamic motion experiment with real time master-slave humanoid robot system. In 2018 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 1–7.
[83] Shervin Javdani, Henny Admoni, Stefania Pellegrinelli, Siddhartha S Srinivasa, and J Andrew Bagnell. 2018. Shared autonomy via hindsight optimization for teleoperation and teaming. The International Journal of Robotics Research 37, 7 (2018), 717–742.
[84] Gina M Jay and Sherry L Willis. 1992. Influence of direct computer experience on older adults' attitudes toward computers. Journal of Gerontology 47, 4 (1992), P250–P257.
[85] Aaron W. Johnson, Kevin R. Duda, Thomas B. Sheridan, and Charles M. Oman. 2017. A Closed-Loop Model of Operator Visual Attention, Situation Awareness, and Performance Across Automation Mode Transitions. Human Factors: The Journal of the Human Factors and Ergonomics Society 2 (2017), 229–241.
[86] Chanyoung Ju and Hyoung Il Son. 2019. Evaluation of Haptic Feedback in the Performance of a Teleoperated Unmanned Ground Vehicle in an Obstacle Avoidance Scenario. International Journal of Control, Automation and Systems 17, 1 (2019), 168–180.

[87] Juho Kannala, Janne Heikkilä, and Sami S Brandt. 2007. Geometric camera calibration. Wiley Encyclopedia of Computer Science and Engineering (2007), 1–11.
[88] David Kent, Carl Saldanha, and Sonia Chernova. 2017. A comparison of remote robot teleoperation interfaces for general object manipulation. In Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction. 371–379.
[89] David Kent, Carl Saldanha, and Sonia Chernova. 2020. Leveraging depth data in remote robot teleoperation interfaces for general object manipulation. The International Journal of Robotics Research 39, 1 (2020), 39–53.
[90] Karan H Khokar, Redwan Alqasemi, Sudeep Sarkar, and Rajiv V Dubey. 2013. Human motion intention based scaled teleoperation for orientation assistance in preshaping for grasping. In 2013 IEEE 13th International Conference on Rehabilitation Robotics (ICORR). IEEE, 1–6.
[91] Min Kyu Kim, Kwanghyun Ryu, Yonghwan Oh, Sang-Rok Oh, and Keehoon Kim. 2014. Implementation of real-time motion and force capturing system for tele-manipulation based on sEMG signals and IMU motion data. IEEE, 5658–5664.
[92] Jonas Koenemann and Maren Bennewitz. 2012. Whole-body imitation of human motions with a nao humanoid. In Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction. ACM, 425–426.
[93] Jonas Koenemann, Felix Burget, and Maren Bennewitz. 2014. Real-time imitation of human whole-body motions by humanoids. In 2014 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2806–2812.
[94] Annica Kristoffersson, Silvia Coradeschi, and Amy Loutfi. 2013. A review of mobile robotic telepresence. Advances in Human-Computer Interaction 2013 (2013).
[95] Adam J Kucharski, Anton Camacho, Stefan Flasche, Rebecca E Glover, W John Edmunds, and Sebastian Funk. 2015. Measuring the impact of Ebola control measures in Sierra Leone. Proceedings of the National Academy of Sciences 112, 46 (2015), 14366–14371.
[96] I-Han Kuo, Chandimal Jayawardena, Elizabeth Broadbent, Rebecca Q Stafford, and Bruce A MacDonald. 2012. Hri evaluation of a healthcare service robot. In International Conference on Social Robotics. Springer, 178–187.
[97] Daniel Labonte, Patrick Boissy, and François Michaud. 2010. Comparative analysis of 3-D robot teleoperation interfaces with novice users. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics) 40, 5 (2010), 1331–1342.
[98] Marco Laghi, Michele Maimeri, Mathieu Marchand, Clara Leparoux, Manuel Catalano, Arash Ajoudani, and Antonio Bicchi. 2018. Shared-autonomy control for intuitive bimanual tele-manipulation. In 2018 IEEE-RAS 18th International Conference on Humanoid Robots (Humanoids). IEEE, 1–9.
[99] Min Kyung Lee, Karen P Tang, Jodi Forlizzi, and Sara Kiesler. 2011. Understanding users! perception of privacy in human-robot interaction. In 2011 6th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 181–182.
[100] Séverin Lemaignan, Fernando Garcia, Alexis Jacq, and Pierre Dillenbourg. 2016. From real-time attention assessment to "with-me-ness" in human-robot interaction. In 2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI). Ieee, 157–164.
[101] Michael Lewis. 2013. Human interaction with multiple remote robots. Reviews of Human Factors and Ergonomics 9, 1 (2013), 131–174.
[102] Jianqiao Li, Zhi Li, and Kris Hauser. 2017. A study of bidirectionally telepresent tele-action during robot-mediated handover. In 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 2890–2896.
[103] Zhi Li, Peter Moran, Qingyuan Dong, Ryan J Shaw, and Kris Hauser. 2017. 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, 3581–3586.
[104] Tsung-Chi Lin, Achyuthan Unni Krishnan, and Zhi Li. 2019. 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, 2240–2245.
[105] Tsung-Chi Lin, Achyuthan Unni Krishnan, and Zhi Li. 2020. Shared Autonomous Interface for Reducing Physical Effort in Robot Teleoperation via Human Motion Mapping. In to appear in the 2020 IEEE International Conference on Robotics and Automation (ICRA). IEEE.
[106] Marcia C Linn and Anne C Petersen. 1985. Emergence and characterization of sex differences in spatial ability: A meta-analysis. Child development (1985), 1479–1498.
[107] Jie Liu and Yuru Zhang. 2007. Mapping human hand motion to dexterous robotic hand. In 2007 IEEE International Conference on Robotics and Biomimetics (ROBIO). IEEE, 829–834.
[108] Shuang Liu, Yu Xie, Yunyi Jia, Ning Xi, and Yaonan Li. 2015. Effect of training on the quality of teleoperator (QoT). In 2015 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems (CYBER). IEEE, 1928–1933.
[109] Manja Lohse, Marc Hanheide, Katharina J Rohlfing, and Gerhard Sagerer. 2009. Systemic interaction analysis (SInA) in HRI. In Proceedings of the 4th ACM/IEEE international conference on Human robot interaction. 93–100.
[110] Noel Maalouf, Abbas Sidaoui, Imad H Elhajj, and Daniel Asmar. 2018. Robotics in Nursing: A Scoping Review. Journal of Nursing Scholarship 50, 6 (2018), 590–600.
[111] Robert R Mackie and C Dennis Wylie. 1988. Factors influencing acceptance of computer-based innovations. In Handbook of human-computer interaction. Elsevier, 1081–1106.
[112] Jacques Marescaux, Joel Leroy, Francesco Rubino, Michelle Smith, Michel Vix, Michele Simone, and Didier Mutter. 2002. Transcontinental robot-assisted remote telesurgery: feasibility and potential applications. Annals of surgery 235, 4 (2002), 487.

[113] Gerhard Marquart, Christopher Cabrall, and Joost de Winter. 2015. Review of eye-related measures of drivers' mental workload. Procedia Manufacturing 3 (2015), 2854–2861.
[114] Amirhossein H Memar and Ehsan T Esfahani. 2018. Physiological measures for human performance analysis in human-robot teamwork: Case of tele-exploration. IEEE Access 6 (2018), 3694–3705.
[115] Nathan Miller, Odest Chadwicke Jenkins, Marcelo Kallmann, and Maja J Mataric. 2004. Motion capture from inertial sensing for untethered humanoid teleoperation. In 4th IEEE/RAS International Conference on Humanoid Robots, 2004., Vol. 2. IEEE, 547–565.
[116] Scott D Moffat. 2009. Aging and spatial navigation: what do we know and where do we go? Neuropsychology review 19, 4 (2009), 478.
[117] Mohammad Mehdi Moniri, Fabio Andres Espinosa Valcarcel, Dieter Merkel, and Daniel Sonntag. 2016. Human gaze and focus-of-attention in dual reality human-robot collaboration. In 2016 12th International Conference on Intelligent Environments (IE). IEEE, 238–241.
[118] Roger W Morrell, Christopher B Mayhorn, and Joan Bennett. 2000. A survey of World Wide Web use in middle-aged and older adults. Human Factors 42, 2 (2000), 175–182.
[119] Katharina Muelling, Arun Venkatraman, Jean-Sebastien Valois, John E Downey, Jeffrey Weiss, Shervin Javdani, Martial Hebert, Andrew B Schwartz, Jennifer L Collinger, and J Andrew Bagnell. 2017. Autonomy infused teleoperation with application to brain computer interface controlled manipulation. Autonomous Robots 41, 6 (2017), 1401–1422.
[120] Toshiharu Mukai, Shinya Hirano, Hiromichi Nakashima, Yo Kato, Yuki Sakaida, Shijie Guo, and Shigeyuki Hosoe. 2010. Development of a nursing-care assistant robot RIBA that can lift a human in its arms. In 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems. IEEE, 5996–6001.
[121] Vincent J Munster, Marion Koopmans, Neeltje van Doremalen, Debby van Riel, and Emmie de Wit. 2020. A novel coronavirus emerging in China—key questions for impact assessment. New England Journal of Medicine (2020).
[122] Robin R Murphy and Debra Schreckenghost. 2013. Survey of metrics for human-robot interaction. In 2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 197–198.
[123] NCSBN. 2016. The 2015 National Nursing Workforce Survey. Technical Report. NCSBN. www.journalofnursingregulation.com
[124] Adam Norton, Brian Flynn, and Holly Yanco. 2019. Implementing Human-Robot Interaction Evaluation Using Standard Test Methods for Response Robots. In Homeland Security and Public Safety: Research, Applications and Standards. ASTM International.
[125] Jaesung Oh, Inho Lee, Hyobin Jeong, and Jun-Ho Oh. 2019. Real-time humanoid whole-body remote control framework for imitating human motion based on kinematic mapping and motion constraints. Advanced Robotics 33, 6 (2019), 293–305.
[126] Jaesung Oh, Okkee Sim, Hyobin Jeong, and Jun-Ho Oh. 2019. Humanoid whole-body remote-control framework with delayed reference generator for imitating human motion. Mechatronics 62 (2019), 102253.
[127] Yongsheng Ou, Jianbing Hu, Zhiyang Wang, Yiqun Fu, Xinyu Wu, and Xiaoyun Li. 2015. A real-time human imitation system using kinect. International Journal of Social Robotics 7, 5 (2015), 587–600.
[128] Lucas Paletta, Amir Dini, Cornelia Murko, Saeed Yahyanejad, and Ursula Augsdörfer. 2019. Estimation of situation awareness score and performance using eye and head gaze for human-robot collaboration. In Proceedings of the 11th ACM Symposium on Eye Tracking Research & Applications. 1–3.
[129] Lucas Paletta, Amir Dini, Cornelia Murko, Saeed Yahyanejad, Michael Schwarz, Gerald Lodron, Stefan Ladstätter, Gerhard Paar, and Rosemarie Velik. 2017. Towards real-time probabilistic evaluation of situation awareness from human gaze in human-robot interaction. In Proceedings of the Companion of the 2017 ACM/IEEE International Conference on Human-Robot Interaction. 247–248.
[130] Nicholas Paperno, Michael Rupp, Edgard M. Maboudou-Tchao, Janan Al Awar Smither, and Aman Behal. 2016. A Predictive Model for Use of an Assistive Robotic Manipulator: Human Factors Versus Performance in Pick-and-Place/Retrieval Tasks. IEEE Transactions on Human-Machine Systems 46, 6 (2016), 846–858.
[131] Julia Peltason, Nina Riether, Britta Wrede, and Ingo Lütkebohle. 2012. Talking with robots about objects: a system-level evaluation in hri. In 2012 7th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 479–486.
[132] Luigi Penco, Brice Clément, Valerio Modugno, E Mingo Hoffman, Gabriele Nava, Daniele Pucci, Nikos G Tsagarakis, J-B Mouret, and Serena Ivaldi. 2018. Robust real-time whole-body motion retargeting from human to humanoid. In 2018 IEEE-RAS 18th International Conference on Humanoid Robots (Humanoids). IEEE, 425–432.
[133] Luka Peternel, Cheng Fang, Nikos Tsagarakis, and Arash Ajoudani. 2019. A selective muscle fatigue management approach to ergonomic human-robot co-manipulation. Robotics and Computer-Integrated Manufacturing 58 (2019), 69–79.
[134] Luka Peternel, Nikos Tsagarakis, and Arash Ajoudani. 2017. A human–robot co-manipulation approach based on human sensorimotor information. IEEE Transactions on Neural Systems and Rehabilitation Engineering 25, 7 (2017), 811–822.
[135] Luka Peternel, Nikos Tsagarakis, Darwin Caldwell, and Arash Ajoudani. 2018. Robot adaptation to human physical fatigue in human–robot co-manipulation. Autonomous Robots 42, 5 (2018), 1011–1021.
[136] Brian S Peters, Priscila R Armijo, Crystal Krause, Songita A Choudhury, and Dmitry Oleynikov. 2018. Review of emerging surgical robotic technology. Surgical endoscopy 32, 4 (2018), 1636–1655.
[137] P Pina, M Cummings, J Crandall, and M Della Penna. 2008. Identifying generalizable metric classes to evaluate human-robot teams. In Workshop on Metrics for Human-Robot Interaction, 3rd Ann. Conf. Human-Robot Interaction. 13–20.

[138] Oliver Porges, Mathilde Connan, Bernd Henze, Andrea Gigli, Claudio Castellini, and Máximo A Roa. 2019. A wearable, ultralight interface for bimanual teleoperation of a compliant, whole-body-controlled humanoid robot. In Proceedings of ICRA-International Conference on Robotics and Automation.
[139] Daniel Rakita, Bilge Mutlu, Michael Gleicher, and Laura M Hiatt. 2018. Shared dynamic curves: A shared-control telemanipulation method for motor task training. In Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction. 23–31.
[140] Daniel Rakita, Bilge Mutlu, Michael Gleicher, and Laura M Hiatt. 2019. Shared control–based bimanual robot manipulation. Science Robotics 4, 30 (2019), eaaw0955.
[141] Emily Rappleye. 2015. Gender ratio of nurses across 50 states. https://www.beckershospitalreview.com/human-resources/gender-ratio-of-nurses-across-50-states.html
[142] Anja Richert, Michael Schiffmann, and Chunrong Yuan. 2019. A Nursing Robot for Social Interactions and Health Assessment. In International Conference on Applied Human Factors and Ergonomics. Springer, 83–91.
[143] Isabel Rodriguez-Barraquer, Federico Costa, Eduardo JM Nascimento, Nivison Nery, Priscila MS Castanha, Gielson Almeida Sacramento, Jaqueline Cruz, Mayara Carvalho, Daiana De Olivera, José E Hagan, et al. 2019. Impact of preexisting dengue immunity on Zika virus emergence in a dengue endemic region. Science 363, 6427 (2019), 607–610.
[144] Emily-Jane Rolley-Parnell, Dimitrios Kanoulas, Arturo Laurenzi, Brian Delhaisse, Leonel Rozo, Darwin G Caldwell, and Nikos G Tsagarakis. 2018. Bi-Manual Articulated Robot Teleoperation using an External RGB-D Range Sensor. In 2018 15th International Conference on Control, Automation, Robotics and Vision (ICARCV). IEEE, 298–304.
[145] M Romero. 2020. Tommy the robot nurse helps Italian doctors care for COVID-19 patients. The World (2020).
[146] Eric Rosen, David Whitney, Elizabeth Phillips, Gary Chien, James Tompkin, George Konidaris, and Stefanie Tellex. 2019. Communicating and controlling robot arm motion intent through mixed-reality head-mounted displays. The International Journal of Robotics Research 38, 12-13 (2019), 1513–1526.
[147] Andres F Salazar-Gomez, Joseph DelPreto, Stephanie Gil, Frank H Guenther, and Daniela Rus. 2017. Correcting robot mistakes in real time using EEG signals. In 2017 IEEE International Conference on Robotics and Automation (ICRA). IEEE, 6570–6577.
[148] Jamil Abou Saleh and Fakhreddine Karray. 2010. Towards generalized performance metrics for human-robot interaction. In 2010 International Conference on Autonomous and Intelligent Systems, AIS 2010. IEEE, 1–6.
[149] Jamil Abou Saleh and Fakhreddine Karray. 2011. Towards unified performance metrics for multi-robot human interaction systems. In International Conference on Autonomous and Intelligent Systems. Springer, 311–320.
[150] Marc Schneider and Barbara Deml. 2017. Analysis of a multimodal human-robot-interface in terms of mental workload. In Advances in ergonomic design of systems, products and processes. Springer, Berlin, Heidelberg, 247–260.
[151] Debra Schreckenghost, Tod Milam, and Terrence Fong. 2010. Measuring performance in real time during remote human-robot operations with adjustable autonomy. IEEE Intelligent Systems 5 (2010), 36–45.
[152] Takanori Shibata and Kazuo Tanie. 2000. Influence of a priori knowledge in subjective interpretation and evaluation by short-term interaction with mental commit robot. In Proceedings. 2000 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS 2000)(Cat. No. 00CH37113), Vol. 1. IEEE, 169–174.
[153] Doreen Ying Ying Sim and Chu Kiong Loo. 2015. Extensive assessment and evaluation methodologies on assistive social robots for modelling human–robot interaction–A review. Information Sciences 301 (2015), 305–344.
[154] Sharon Singer and David Akin. 2011. A survey of quantitative team performance metrics for human-robot collaboration. In 41st International Conference on Environmental Systems. 5248.
[155] Anoop Kumar Sinha, Sujit Kumar Sahu, Rakesh Kumar Bijarniya, and Karali Patra. 2017. An effective and affordable technique for human motion capturing and teleoperation of a humanoid robot using an exoskeleton. In 2017 2nd International Conference on Man and Machine Interfacing (MAMI). IEEE, 1–6.
[156] STATISTICSTATS. 2019. Male Nursing Statistics 2019. https://www.statisticstats.com/health/male-nursing-statistics/
[157] N Statt. 2020. Boston Dynamics' Spot robot is helping hospitals remotely treat coronavirus patients. The Verge (2020).
[158] Aaron Steinfeld, Terrence Fong, David Kaber, Michael Lewis, Jean Scholtz, Alan Schultz, and Michael Goodrich. 2006. Common metrics for human-robot interaction. In Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction. 33–40.
[159] Justin Storms, Kevin Chen, and Dawn Tilbury. 2017. A shared control method for obstacle avoidance with mobile robots and its interaction with communication delay. The International Journal of Robotics Research 36, 5-7 (2017), 820–839.
[160] Russell H Taylor. 2006. A perspective on medical robotics. Proc. IEEE 94, 9 (2006), 1652–1664.
[161] Deepak Tolani and Norman I Badler. 1996. Real-time inverse kinematics of the human arm. Presence: Teleoperators & Virtual Environments 5, 4 (1996), 393–401.
[162] Stefano Tortora, Michele Moro, and Emanuele Menegatti. 2019. Dual-myo real-time control of a humanoid arm for teleoperation. In 2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI). IEEE, 624–625.
[163] K Tsui, Adam Norton, David Brooks, H Yanco, and Daniel Kontak. 2011. Designing telepresence robot systems for use by people with special needs. In Int. Symposium on Quality of Life Technologies: Intelligent Systems for Better Living.
[164] Edward Tunstel. 2007. Operational performance metrics for mars exploration rovers. Journal of Field Robotics 24, 8-9 (2007), 651–670.

[165] Elizabeth CJ van Oost, NEJ Oudshoorn, and T Pinch. 2003. Materialized gender: how shavers configure the users' feminity and masculinity. How users matter. The co-construction of users and technology (2003), 193–208.
[166] Jonathan Velez, Hyun Ka, and Dan Ding. 2015. Toward developing a framework for standardizing the functional assessment and performance evaluation of assistive robotic manipulators (ARMs). In Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Vol. 59. SAGE Publications Sage CA: Los Angeles, CA, 986–990.
[167] Igor Verner and Sergei Gamer. 2018. Spatial Learning of Novice Engineering Students Through Practice of Interaction with Robot-Manipulators. In Online Engineering & Internet of Things. Vol. 22. 359–366.
[168] Nina K Vøllestad. 1997. Measurement of human muscle fatigue. Journal of neuroscience methods 74, 2 (1997), 219–227.
[169] Chunhui Wang, Yu Tian, Shanguang Chen, Zhiqiang Tian, Ting Jiang, and Feng Du. 2014. Predicting performance in manually controlled rendezvous and docking through spatial abilities. Advances in Space Research 53 (2014), 362–369.
[170] Jijun Wang and Michael Lewis. 2008. Assessing cooperation in human control of heterogeneous robots. In Proceedings of the 3rd ACM/IEEE international conference on Human robot interaction. 9–16.
[171] Astrid Weiss, Regina Bernhaupt, and Manfred Tscheligi. 2011. The USUS evaluation framework for user-centered HRI. New Frontiers in Human–Robot Interaction 2 (2011), 89–110.
[172] Robert H Wortham, Andreas Theodorou, and Joanna J Bryson. 2017. Robot transparency: Improving understanding of intelligent behaviour for designers and users. In Annual Conference Towards Autonomous Robotic Systems. Springer, 274–289.
[173] Julia L Wright, Jessie YC Chen, and Shan G Lakhmani. 2019. Agent transparency and reliability in human–robot interaction: the influence on user confidence and perceived reliability. IEEE Transactions on Human-Machine Systems (2019).
[174] Yuqiang Wu, Pietro Balatti, Marta Lorenzini, Fei Zhao, Wansoo Kim, and Arash Ajoudani. 2019. A Teleoperation Interface for Loco-Manipulation Control of Mobile Collaborative Robotic Assistant. IEEE Robotics and Automation Letters 4, 4 (2019), 3593–3600.
[175] Katsu Yamane and Jessica Hodgins. 2009. Simultaneous tracking and balancing of humanoid robots for imitating human motion capture data. In 2009 IEEE/RSJ International Conference on Intelligent Robots and Systems. IEEE, 2510–2517.
[176] Holly A Yanco, Jill L Drury, and Jean Scholtz. 2004. Beyond usability evaluation: Analysis of human-robot interaction at a major robotics competition. Human–Computer Interaction 19, 1-2 (2004), 117–149.
[177] Chenguang Yang, Jing Luo, Yongping Pan, Zhi Liu, and Chun-Yi Su. 2017. Personalized variable gain control with tremor attenuation for robot teleoperation. IEEE Transactions on Systems, Man, and Cybernetics: Systems 48, 10 (2017), 1759–1770.
[178] Guang-Zhong Yang, Bradley J Nelson, Robin R Murphy, Howie Choset, Henrik Christensen, Steven H Collins, Paolo Dario, Ken Goldberg, Koji Ikuta, Neil Jacobstein, et al. 2020. Combating COVID-19—The role of robotics in managing public health and infectious diseases.
[179] Kazuhito Yokoi, Katsumi Nakashima, Masami Kobayashi, Humisato Mihune, Hitoshi Hasunuma, Yoshitaka Yanagihara, Takao Ueno, Takuya Gokyuu, and Ken Endou. 2006. A tele-operated humanoid operator. The International Journal of Robotics Research 25, 5-6 (2006), 593–602.
[180] Y Yoshitake, H Ue, M Miyazaki, and T Moritani. 2001. Assessment of lower-back muscle fatigue using electromyography, mechanomyography, and near-infrared spectroscopy. European journal of applied physiology 84, 3 (2001), 174–179.
[181] Andrea Maria Zanchettin, Nicola Maria Ceriani, Paolo Rocco, Hao Ding, and Björn Matthias. 2015. Safety in human-robot collaborative manufacturing environments: Metrics and control. IEEE Transactions on Automation Science and Engineering 13, 2 (2015), 882–893.