OPTIMIZATION APPROACH FOR MULTIMODAL SENSORY FEEDBACK IN ROBOT-ASSISTED TASKS

by

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A Thesis

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Master of Science in Biomedical Engineering

Weldon School of Biomedical Engineering

West Lafayette, Indiana

August 2021

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Dedicated to my family

ACKNOWLEDGMENTS

This thesis would not have been possible without a strong system of guidance and support. I would like to extend my sincerest thanks to my advisors, Prof. Bradley Duerstock and Prof. Juan Wachs for their guidance and mentorship through the course of this project, and for making this valuable learning opportunity available to me. Their advice, encouragement, and knowledge fueled this work from start to finish, and greatly enriched my graduate studies.

I would also like to thank my thesis committee member, Prof. Ramses Martinez for making time to provide valuable feedback on this work. A special thank you also to Dr. Ting Zhang for her valuable input and mentorship in the early stages of this project, and for being supportive and available even after graduating.

My sincere thanks to my lab mates (past and present), Ting, Shruthi, Aditya, Ana, and Mitch for their continued support and encouragement, for being great sounding boards, and for contributing to a warm lab atmosphere. Thank you also to undergraduate students Shivani and Caroline who contributed to various aspects of this project.

Last but certainly not least, a heartfelt thank you to my friends and family for being constant sources of strength and encouragement during my graduate school experience. Their simple, invaluable presence in my life, and especially through these last two years, played a key role in helping me see this project and my graduate studies through.

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ABSTRACT

Individuals with disabilities and persons operating in inaccessible environments can greatly benefit from the aid of robotic manipulators in performing activities of daily living (ADLs) and other remote tasks. Users relying on robotic manipulators to interact with their environment are restricted by the lack of sensory information available through traditional operator interfaces. These interfaces only allow visual task access and deprive users of somatosensory feedback that would be available through direct contact. Multimodal sensory feedback can bridge these perceptual gaps effectively. Given a set of object properties (e.g. temperature, weight) to be conveyed and sensory modalities (e.g. visual, haptic) available, it is necessary to determine which modality should be assigned to each property for an effective interface design. However, the effectiveness of assigning properties to modalities has varied with application and context. The goal of this study was to develop an effective multisensory interface for robot-assisted pouring tasks, which delivers nuanced sensory feedback while permitting high visual demand necessary for precise teleoperation. To that end, an optimization approach is employed to generate a combination of feedback properties to modality assignments that maximizes effective feedback perception and minimizes cognitive load. A set of screening experiments tested twelve possible individual assignments to form the combination. Resulting perceptual accuracy, load, and user preference measures were input into a cost function. Formulating and solving as a linear assignment problem, a minimum cost combination was generated. Results from experiments evaluating efficacy in practical use cases for pouring tasks indicate that the solution is significantly more effective than no feedback and has considerable advantage over an arbitrary design.

1. INTRODUCTION

1.1 Overview

Robot-assisted manipulation has applications in diverse tasks and environments. In the last decade, applications of high significance have emerged, such as in robot-assisted surgical procedures [1] [2] and space or undersea exploration [3] [4]. Remote robot manipulation is also useful for situations that are hazardous to humans such as toxic waste clean-up sites [5] or situations where humans may adversely affect the environment such as clean rooms [6] [7].

One other field where remote robot operation is emerging to be of significant interest is assistive technology. Robot manipulators can significantly enhance the quality of life of individuals with disabilities [8]. Robot-assisted pouring tasks belong to a class of tasks that are critical to activities of daily living (ADLs) such as feeding and meal preparation [9] [10] and is also applicable in many of the other remote operation environments discussed above. In this thesis, we selected the application of robot-assisted pouring tasks in ADLs as the focus of our investigations due to its high relevance and the ability to simulate accurate everyday conditions without factors such as physical barriers, toxic gases or chemicals, and physical environmental properties such as gravity and pressure that other relevant applications may impose.

Users relying on robotic manipulators to interact with the environment are deprived of an experience comparable to direct object manipulation due to the lack of access to sensory information such as tactile, thermal, and force feedback. Such sensory deprivation may result in poor situation awareness and consequently affect decisions relevant to the task being executed [11]. Somatosensory feedback that conveys information such as thermal and tactile properties of the object being manipulated may contribute to enhancing situational awareness and enabling better decisions to be made by the user [10] [12]. Multimodal feedback interfaces may provide effective solutions to bridging this gap and have been explored previously in several applications such as human-computer interaction and teleoperation [13] [14].

The theoretical premise of multimodal feedback displays is to avoid overloading a single perceptual pathway and/or provide additional information that cannot be obtained by a single modality alone. This is supported by cognitive models of information processing [15] [16]. However, modality assignment solutions from such studies have proven to vary with the application and context, and studies specific to assistive robotic manipulators in decision-based ADLs remain underexplored.

The primary objective of this project was to develop an effective multisensory interface for robot-assisted pouring tasks, which delivers nuanced sensory feedback while permitting high visual demand necessary for precise robot operation. To that end, an optimization approach is employed to generate a combination of feedback property to modality assignments that maximizes effective delivery and minimizes load. A system was developed, integrating a robotic arm with a haptic device, vibrating tactors, a visual display, and a thermal feedback module as modalities to provide weight, temperature, and liquid level properties in a pouring task. An initial survey was conducted to support the relevance of the selected properties for situation awareness. A set of metrics including perception accuracy and resolution, and cognitive attention factors in such as distraction and load were selected to model the cost to be optimized. A detection response task was used to collect measures of attentional load. A linear assignment problem was used to solve for the optimal mapping based on the selected metrics. Two sets of experiments were conducted. The first set collected data for the selected metrics from which a minimum cost solution was generated. The second experiment evaluated the efficacy of the generated solution for decision making tasks against a control case of no feedback and an arbitrary design.

1.2 Research Problem

Consider the daily execution of the simple task of pouring milk manually (Figure 1.1). The individual grasps and lifts the milk carton, assesses the surface temperature and the amount of liquid contained in it using tactile and force information, determines an angle to tilt based on the force information, and tilts the carton to pour milk into a glass without spilling. Much of the information relevant to these assessments is communicated from the contact surface to the individual via thermal, haptic, and visual receptors, and is used to inform the decision-making process relevant to the task. Such daily tasks are committed to muscle memory, and do not require an average, experienced individual significant conscious effort for execution.

Figure 1.1: Feedback in a direct pouring task.

Individuals with partial upper limb impairments resulting from conditions such as stroke or spinal cord injury may lack the somatosensory feedback and motor control abilities to perform such tasks without aid and may therefore look towards robot assistance. Remote robot assistance may also be sought by individuals working on toxic waste cleanup, space, undersea, surgical, or clean room operations. For these individuals, only visual feedback during pouring would be readily available which is typically limited by field of view, greater distance than when performed manually, and other applicable environmental conditions (Figure 1.2). This leaves a significant gap in non-visual sensory feedback identified in Figure 1.1, that may be integral to task-related decisions. For example, without this information the user will not know whether the liquid is too hot for drinking or how far to tilt the vessel for controlled pouring of liquid. This will force the user to spend time testing or to slow down the task to control the outcome. In this project, we attempt to ameliorate this gap by developing a framework for designing a multimodal feedback interface capable of effectively conveying relevant object properties that enhance situational awareness and better inform robot operated task-related decisions.

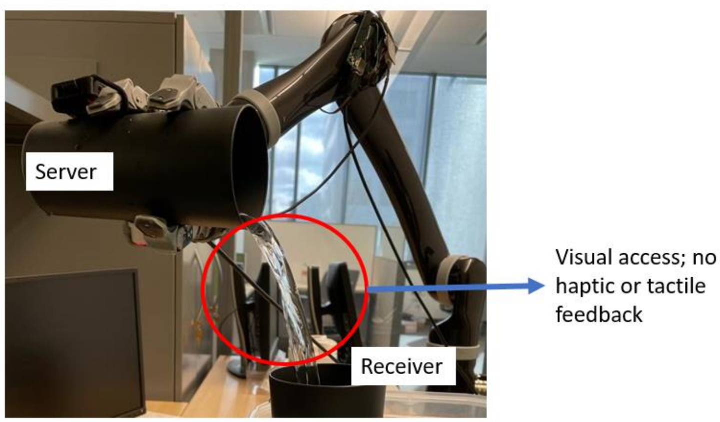

Figure 1.2: Feedback in a robot-aided pouring task

1.2.1 **Research Questions**

In this thesis, a set of selected cost metrics and an assignment problem were used to develop and test an effective multimodal interface for a robot-assisted pouring task. To that end, the following research questions were addressed through this study:

1) Which property-modality assignment will be most effective in delivering each of the identified object properties (i.e. temperature, weight, liquid level) through selected sensory feedback modalities (i.e. visual, haptic, audio, vibration, thermal)?

Hypothesis: An effective assignment combination can be generated by using an analytical model developed through empirical testing

2) Does the developed interface show improved decision-making performance and user experience in a pouring task compared to when executing the task without feedback?

Hypothesis: The developed interface will improve performance and user experience compared to a control of no feedback and an arbitrary assignment of properties to modalities.

1.3 Contribution

In this thesis, an approach to developing multimodal feedback interfaces for robot operation tasks is identified. This approach optimizes for visual distraction and may be generalized to other multimodal interfaces in other visual-manual tasks that demand visual attention, such as driving, human-computer interaction, and virtual reality applications. An effective solution for the defined application is produced and evaluated. The relevance of feedback for decision making, an overlooked aspect so far in robot-assisted tasks is also demonstrated in this project. Further insights into the design considerations for such interfaces are generated from experimental findings, and results may also contribute towards further understanding of cognitive limitations associated with multisensory processing and attention.

1.4 Thesis Structure

The remainder of this thesis is structured as follows:

Chapter 2 provides a background and literature review of the applications, neurocognitive theories, human factors tools, and the assignment problem relevant to this work. At the end of each section, the relevant aspects included in this project are described. This chapter also introduces the results of a thought experiment conducted to establish an initial basis of for this research problem. Chapter 3 describes the system architecture, feedback mappings, and solution approach. Chapter 4 presents the design of preliminary studies and main experiments, referred to from here on as screening experiments and validation experiments. Chapter 5 discusses the results of the experiments discussed in Chapter 4. Chapter 6 summarizes the conclusions of this project and discusses possible investigations for future work.

2. BACKGROUND AND LITERATURE REVIEW

2.1 Assistive robot manipulators

Assistive robot manipulators have the potential to aid in numerous tasks and many solutions have been developed over the years [17] [18]. In this section, the use of assistive robotic manipulators in activities of daily living and other remote operations applications is reviewed. Existing solutions for feeding and related tasks are identified and modalities for controlling the robotic devices are also explored.

2.1.1 Assistive robot manipulators for individuals with upper limb impaired impairments

According to the most recent Americans with Disabilities Report [17], 5.6% of the adult population experience difficulties with activities of daily living (ADLs) stemming from manipulation tasks. These include critical activities such as feeding, bathing, and dressing. Individuals with such upper limb motor impairments are often rely on aids and assistants for help with everyday activities. Assistive technologies, including assistive robotic solutions [18] [19] [20] have shown potential to enhance their autonomy significantly [8] and may also provide cost savings and economic benefits relative to a dependent lifestyle [21].

Among assistive robots, manipulators are particularly relevant because they allow the user to perform manipulation tasks that are crucial for many ADLs. A number of user surveys have been conducted in the past to identify critical tasks relevant to assistive robotic manipulators. Pre- and post-development studies reviewed in [9] identify meal preparation, eating, and drinking tasks to be ranked among the top five highest priority tasks. These are accompanied by tasks such as picking up and carrying objects and personal hygiene-related tasks such as bathing. Another survey reviewed in [9] found the most desirable tasks identified by users to be picking up objects, pouring liquid, fetching objects from shelves, turning knobs, drinking from a cup or glass, use cutlery, and grasping and releasing objects. Surveys conducted on caregivers of the target population also rated eating and drinking tasks and pouring liquid to be of high importance in addition to tasks such as brushing teeth or typing. In [10], wheelchair transfer, gripping objects, and drinking were ranked highest priority, and when asked to express free ideas, the most popularly identified tasks were food preparation, household activities, and grasping objects. These surveys highlight both the wide variety of tasks that would benefit from an assistive robot and the significance of those tasks for carrying out essential functions of daily life routines.

A majority of the ADLs identified above require upper limb motion and/or dexterity to manipulate tools and objects relevant to the task. One set of tasks particularly demanding of upper limb control are feeding and meal preparation. Assistive robot manipulators have been configured and tested specifically for this category of tasks in previous work. Commercial solutions capable of assisting with feeding tasks include recent seven degree of freedom (DOF) manipulators such as the iArm [22] and JACO [18], and simpler spoon-feeding mechanisms such as Handy1 [23], the Winsford Feeder [24], Meal Buddy [25] and MySpoon [26].

Many of the development efforts targeting feeding tasks using six or seven DOF arms have focused on control algorithms suited for these tasks. In [18] a drinking mode is implemented in the JACO robot to synchronize complex drinking and pouring motions. Other control implementations such as spasm filtering and automatic orientation are also implemented in this work to improve usability by an upper limb-impaired population. A reactive control strategy using vision to track the human is implemented in [27] to prevent risk of injuries during autonomous robot-assisted feeding tasks. In [28] a robot arm simulator is demonstrated to avoid obstacles and enable successful transfer of food in self-feeding tasks using a cup and spoon. A vision-augmented control algorithm is introduced in [29] to improve food acquisition efficiency and delivery.

2.1.2 Other robot-assisted manipulation tasks

Robot-assisted manipulation tasks extend beyond the domain of upper limb-impaired individuals. In the last decade, a heavy focus has been placed on improving minimally invasive robot-assisted surgical procedures such as endovascular procedures [1] [30] [31], retinal surgeries [32] [33], biopsies [34], and more [2] [35] [36]. Teleoperated robot manipulators have been used for remote tasks such as space exploration [3] [37], undersea exploration [4] [38], dismantling bombs [39] [40], and safe maintenance of electricity infrastructure [41]. Remote robot manipulation is also useful for situations that are hazardous to humans such as toxic waste clean-up sites and nuclear reactors [5] [42] [43] [44] or situations where humans may adversely affect the environment such as clean rooms [6] [7] [45], fume hoods, or hospital isolation rooms. Many of these environments deal with tasks that involve manipulating containers. Specific examples may include cleaning contaminated water bodies or soil, handling sensitive fluids, chemicals, and cell samples, or tending to an isolated patient.

Because of its wide applicability to many tasks relevant to robot-assisted manipulation including in feeding and other remote operation environments, in this project, a pouring task was selected as the test case for developing a multimodal feedback interface.

2.1.3 Assistive robot control modalities

Control modalities implemented in assistive manipulator solutions have varied widely depending on the targeted population and tasks. A vast majority of these solutions rely on joystick only or joystick and customized keyboard inputs [18] [22] [24] [26] [10]. Other control modalities explored and implemented have included a head-controlled joystick [25], mouse inputs [28], voice commands [46], eye tracking [47] [48], and cortical motor activity-based control [49]. In [50], a 3D joystick is introduced in a study comparing the 3D joystick with traditional joystick and keyboard inputs for quadriplegics. The 3D joystick was demonstrated to achieve a higher performance index and required a shorter learning curve, while keyboard input was observed to be the least physically demanding.

In this thesis, a hybrid approach is implemented with a haptic device configured as a 3D joystick and keyboard inputs for shifting between modes.

2.2 Sensory feedback in robot-assisted tasks

Humans depend on sensory feedback to gather information from their surroundings. This information enters the neurological circuits through specialized sensory (e.g. vision, hearing) and somatosensory (e.g. touch, proprioception) receptors, and are processed to inform decisions relevant to daily activities. When one or more of these channels are unavailable due to a physical condition or other circumstance, they may be compensated via intervening systems or channels that provide direct or substituted translations of the relevant information [51]. In the remainder of this section, the types of sensory feedback integrated in robotic devices and the purpose served by these types of feedback will be reviewed. The relevance of feedback for situation awareness will also be explored and results of a preliminary survey to establish the relevance of properties selected for this project will be discussed.

Tasks such as preparing coffee, feeding fluids to a patient, and handling chemicals and samples involve a complex exchange of information between the user and their environment. A limitation of using assistive manipulators is that the somatosensory information usually received via direct interactions is not available when an intermediary agent is adopted to perform the task. This gap may be bridged by the effective integration of sensory feedback interfaces.

Robotic devices supporting non-invasive sensory feedback provision has been investigated for a range of applications and feedback types. Auditory feedback has been effective to warn of impending hazards [52] and provide system alerts [53]. Electrical and vibratory feedback are frequented for prostheses [54] [55]. Haptic feedback mechanisms to indicate grasp force [8] [56] [57] [51] and slip [58] aid in robot and prosthetic control. However, approaches aimed at improving situation awareness in daily life activities remain underexplored.

2.2.1 **Feedback for situation awareness and decision making**

Several cognitive science studies of mental simulation have demonstrated that humans have implicit knowledge and mechanisms to rationalize everyday physics with relative ease, which inform their predictions, inferences, and planning [59] [60]. Liquid pouring is one example of a subtle manipulation task that humans learn early and requires continuous monitoring of vessel states such as liquid level and tilt speed to avoid spilling [61].

Feedback needs that are important to maintain situational awareness and influence task-relevant decisions in daily life interactions remain to be addressed for users of assistive robots. Limitation of operator performance by the ability to maintain situation awareness and build mental models of remote environments has been previously identified among the challenges of teleoperation [62]. Sensory deprivation is one factor identified to affect this awareness and the accuracy of mental representations of the environment.

'Situation awareness' is a term that originated in aviation psychology to describe the pilot's understanding in tactical flight operations. Dominguez [63], merges Endsley [11] and Carroll [64] to define situational awareness as the "continuous extraction of environmental information, integration of this information with previous knowledge to form a coherent mental picture, and the use of that picture in directing further perception and anticipating future events." The concept is applicable both in the active awareness that informs decision-making as well as the passive awareness that keeps an operator aware of changes in the environment. Cognitive factors affecting situation awareness include attention, pattern recognition, and working memory [65]. Endsley's model for situational awareness [11] illustrates that cue detection and recognition, followed by situation assessment and prediction are necessary inputs to the human decision-making process. In the executive brain, decisions may arise from external environmental influences (bottom-up processes) and from the motivation and goals of the person (top-down processes) [66]. The bottom-up decision-making processes result from passive situation awareness cues while the top-down processes seek cues actively from the environment.

As illustrated in Chapter 1 of this thesis, recognizing and assessing cues such as weight and temperature can inform both bottom-up (e.g. realize a vessel is empty and throw it out) and top-down (e.g. assess the temperature to ensure that it is safe to drink) decisions in a container manipulation task such as making and drinking a cup of coffee. It is therefore important to identify and integrate feedback that is relevant beyond grip control, particularly for devices such as assistive robot manipulators that are expected to be instrumental in the execution of everyday decisions.

The need for such feedback has been addressed to some extent in interfaces designed for prosthetic arms where the need is clearer due to the more intimate integration with the user. Temperature and tactile feedback are most commonly integrated in these interfaces [67]. In addition to its importance in the daily use of prosthetic devices, situational feedback such as task state and navigational information are also identified to be of high importance in the contexts of visually limited telerobotic applications [10]. In [14] poor perception is identified as having a detrimental effect on situation awareness and consequently on robot teleoperation tasks. Interfaces that provide situational feedback to users of assistive robotic manipulators can thus be expected to advance device utility and effectiveness in the lives of their users.

2.2.1.1 Selected Properties

In this project, we selected vessel temperature, initial weight/amount of liquid, and a binary indicator of liquid level (above or below the grasp point) as a set of properties relevant to enhancing situation awareness to be provided through a multimodal feedback interface developed specifically targeting those properties.

Weight and liquid level correspond to amount of fluid in a container and is perceived via haptic receptors when the task is executed by humans. Initial amount of fluid in a container has been identified as one factor affecting the estimation of tilt angle in pouring [68]. Instead of relying on simple qualitative heuristics, humans rely on the perceived viscosity and fluid volume to make quantitative judgments, including angle of tilt [59]. Liquid level in the container has been identified as a state to be monitored in pouring tasks [61]. In this project, the combined information of weight and the detection liquid at the grasp point was used to allow the user to better judge the required angle of tilt estimate the amount of fluid in the container. The congruence of the two properties has been shown to increase the effectiveness of feedback [69].

Temperature informs external decisions such as whether to drink a hot beverage at a given time, whether to reheat, or to determine proportions of beverages to mix. Thermal feedback protects against scald injuries prior to drinking and can also be useful in other daily functions such as washing. Temperature has been previously integrated as feedback in prosthetic limbs [67]. We provide feedback of the surface temperature of the vessel to mimic direct contact.

2.2.2 User acceptance

Despite the significance and anticipated benefits associated with assistive robotic solutions, there is not a wide acceptance by potential user groups. In a study conducted with the ASIBOT, an intelligent robotic arm, “too remote from life” was identified as one barrier to acceptance [10]. This can be interpreted as a lack of sense of ownership and device embodiment, factors that have been long since investigated for prosthetic devices [12]. Castellini et al. emphasizes the intimate relationship between human factors and technical devices by tracing this lack of embodiment to a few factors including the lack of afferent sensory feedback [70]. The influence of multi-faceted tactile information on the ownership and bodily integration of an external object has also been demonstrated in several studies of illusory rubber hand setups [71]. For assistive robotic manipulators, while the desired extent of device ownership has been demonstrated to be more variable [72], it has been argued that enhancing the sense of embodiment would facilitate use and thereby increase both acceptance and task performance for these devices [73] [71]. Moreover, increasing situational awareness by providing information users of elusive properties, a feedback interface may also serve to increase a user’s sense of ownership and therefore, contribute to facilitating increased use and acceptance of assistive robotic manipulators.

2.3 Multimodal Feedback

This section will review the cognitive premise for providing multimodal feedback and multimodal feedback displays in various applications.

The premise of a multimodal feedback interface is that information can be conveyed more effectively when distributed across modalities. For example, if one is engaged in a visually occupying task such as driving, it would be better to provide route guidance through sound rather than a visual display so as to preserve the visual cognitive resources required for driving [74]. Thus, the intention is to avoid overloading a single perceptual pathway and/or provide additional information that cannot be obtained by a single modality alone. Cognitive models of information processing such as Wickens' multiple resource theory [15] and measured reaction times [75] support this reasoning [76]. A multiple resource framework for workload in robot teleoperation based on Wicken's theory (Figure 2.1) included multimodal displays as a positive solution to workload issues in human-robot interaction [77]. Based on Wicken's theory, performance should be improved when provided cross modal cues (e.g. visual and audio) compared to intra-modal cues (visual and visual) [77]. Further, Ernst's theory of sensory integration, which employs Bayesian decision theory, indicates that the accuracy of perception increases with the number of modalities that present congruent or redundant information [16].

Although multimodal feedback studies with assistive robotic manipulators are limited, investigations spanning a range of other similar applications have been reported. In [78] an interface provides visual, auditory, and tactile feedback from a virtual telepresence robot through the corresponding modalities. In [79], visual, audio, and haptic feedback is provided in redundance for a virtual manipulation task. A multimodal vibrotactile interface provided multiple properties in an upper limb prosthesis [80]. Interfaces have also been studied for collaborative robots to inform users of robot status [76] and independent robot interactions [81]. Multimodal feedback proved useful in poor visual conditions such as low frame rate [82] and 2D display [83] in teleoperation tasks. Several reviews of multimodal displays [13] [14] [84] have concluded that performance is empirically shown to improve with multimodal feedback across a variety of tasks.

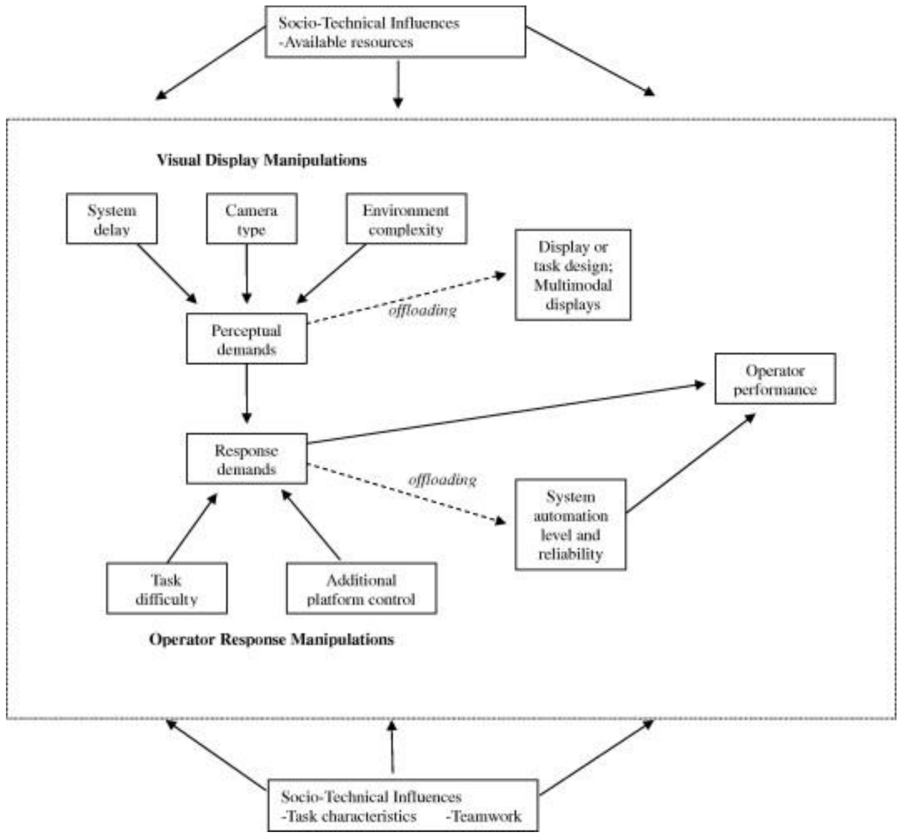

Figure 2.1: A multiple resource framework for workload in robot interaction. Multimodal displays are illustrated as a strategy for offloading perceptual demands.

However, some studies suggest that certain combinations of modalities may instead prove to be cognitively burdensome and an optimal combination may be dependent on the task type [13], individual differences [85] and context [86] [87]. As a result, evaluative studies of multimodal feedback have yielded conflicting results across the literature. In a study comparing uni-, bi-, and tri- modal feedback conditions [88], the bimodal condition of haptic and visual feedback emerged most effective while the remaining bi- and tri-modal combinations were observed to be among the least effective. A user study found that the introduction of vibrotactile and auditory feedback to improve performance time in the operation of an impact wrench, but the addition of force feedback was not observed to improve performance [9]. Results from a multimodal vibrotactile feedback study indicated the need for additional studies to determine whether the combination of certain feedback types may cause sensory confusion [80]. A neural efficiency study found task performance to be highest for a visual only compared to visual and haptic feedback in a virtual robot interaction task [81]. A type of system that yields such variability would benefit from a generalized design approach that is adaptable to their specific applications.

Multimodal feedback interfaces should be designed to make effective use of the human sensory channels and available display modalities while balancing any cognitive burden associated with the interface. Approaches for designing interfaces that achieve this balance have not been discussed extensively. A systematic approach to designing an interface for stationary robot feedback in an industry setting by employing 100 employee responses to an online questionnaire has been proposed previously [76]. However, this approach relies solely on subjective responses and may also not be as easily adapted in applications where the reachable number of users is limited. In the study by Zhang et al. [89] an optimal assignment approach is used to provide multimodal feedback of image properties for a virtual image exploration task. Apart from this, many of the studies discussed so far have been evaluative studies of selected combinations measuring performance time, accuracy, and cognitive load. These findings are arguably possible to adapt into working systems, however, as evident by varying results across the spectrum, they are likely to be most applicable to those specific applications and circumstances.

2.3.1 Cognitive demands of robot-assisted tasks

Cognitive workload has long been of interest for human-computer interaction and has been recognized as an important element of human performance in complex systems [90]. Optimization of cognitive load has been found to reduce human error, improve system safety, and increase productivity and user satisfaction [91] [92] and therefore has a direct influence over a user's ability to perform tasks [88]. Increased cognitive effort has also been tied to reduced ownership and acceptance of prosthetic devices [12] [70].

Remote robot manipulation draws heavily on visual resources as the manual control operation is performed. It uses ambient vision to guide navigation and focal vision to detect critical objects and if applicable, display alerts [77]. It would therefore be expected that perceptual demands will primarily be placed on visual channels as demonstrated by a number of studies evaluating visual cues and displays in teleoperation [77]. The primary manual tasks related to robot control may include subtasks such as mode shifts, button presses, and other input interactions while steering a joystick in a traditionally controlled robot. The set of primary tasks involved require visual and motor attention and may involve other cognitive functions depending on the task. Including multimodal feedback in the user interface adds several (i.e. the number of modalities to be perceived) secondary sub tasks to the task of visually tracking and manually controlling the robot, that may distract from the primary tasks involved. Thus, to design an effective multimodal feedback interface, the perceptual demands of the interface should be balanced with those of the primary tasks. As such, the visual distraction from the primary task and the overall mental load would ideally be minimized while the feedback gap is effectively bridged.

One task that closely resembles these demands of robot operation and has been researched extensively is driving [93] [94] [95]. Driving too involves a set of primary tasks (accelerating, breaking, steering, navigation, etc.), requires visual attention, and is frequently accompanied by secondary tasks (digital navigation, communication, entertainment, etc.) that may distract from the primary tasks [93]. Driver cognitive load is measured using several different tools such as the Lane Change Task or subjective methods such as the NASA TLX assessment or self-evaluation ratings [94]. One popular tool that has also been used in human-computer interaction studies and focuses on cognitive attentional resources is the Detection Response Task (DRT) which we adopted in this project.

2.3.1.1 The Detection Response Task

The detection response task is intended to measure the cognitive attentional resources that are available to drivers when performing secondary tasks [95] [96]. The method consists of a simple task where subjects respond to a frequently repeated stimuli presented at randomized intervals of 3-5s [97]. Hit rate and reaction time are analyzed as measures of cognitive load. Decreased hit rate and increased reaction time correlate to increased cognitive load. For driving experiments, secondary tasks such as visual-manual tasks (typing on the phone, radio tuning, etc.), cognitive auditory tasks such the N-back task, and other cognitive load tasks such as backward counting have been evaluated using DRT measurements [94] [97] [98].

The DRT may be administered in three versions as standardized by the ISO in 2016 [95]. The Head-mounted DRT (HDRT) and Remote DRT (RDRT) involve different placements of the visual stimulus, which is typically a single red LED. During HDRT the visual stimulus is mounted on a head band directly in front of the subject's eye. For RDRT the visual stimulus is placed in a fixed location in the driver's field of view such as the dashboard. A third version is the Tactile DRT (TDRT) that replaces the visual stimulus with a vibrating tactile stimulus.

Of the three methods, the RDRT is a standardized version of a Peripheral Detection Task (PDT) that is primarily used for assessing visual distraction [97]. The nature of the secondary task should also be taken into account when choosing the appropriate DRT such that overlaps are minimized. For example, for interfaces relying primarily on tactile information processing, the TDRT should not be used [94]. In accordance with the considerations for this project, an RDRT was implemented so as to capture effects of visual distraction and minimize overlap with the tactile feedback modalities.

Figure 2.2: Remote DRT in a Driving Experiment [96]

2.3.1.2 Visual Challenges in Robot-assisted Tasks

Remote robot operation can pose a multitude of visual challenges. [99] identifies field of view, orientation of the robot, view point, and depth perception as factor that affect perception and manipulation in teleoperation tasks. [77] identifies depth cues and environment details such as the number of visual objects or visual complexity to be challenges in teleoperation interfaces. These factors may also affect robot tasks that are viewed directly rather than through video or virtual displays.

The tasks of operating a vehicle and operating a robotic manipulator possess the shared attributes of being visual attention demanding and manually controlled operations. The DRT, as discussed above, has been an effective tool in driving experiments [94] [97] [98]. Additionally, it has also been proven effective for assessing workload in human-computer interaction applications such as gaming interfaces [100]. However, the tool is yet to be adopted widely in human-robot interaction studies. In this thesis, we first conducted an experiment (detailed in Chapter 3) to demonstrate the utility of the RDRT in measuring attentional load in robot manipulator operation tasks. Based on those results, we integrated it in the experiments for addressing the main research questions.

This thesis aimed to develop and evaluate an effective multimodal feedback solution specific to the defined application, which strikes a balance between minimized distraction and load and effective conveyance of feedback. The approach developed in this thesis to achieve this goal may also be adapted as an approach for developing multimodal feedback interfaces for other visual-manual tasks with similar cognitive demands such as driving and virtual reality applications.

2.4 Modality-matched and Substituted Sensory Feedback

In this section, strategies for providing somatosensory feedback, including visual and auditory sensory substitution will be introduced and reviewed.

A sensory feedback gap produced as a result of distancing from the task can be bridged in one of two ways. The first strategy is to provide modality-matched feedback by stimulating the sensory receptors in a similar manner to the direct contact case. This type of feedback has been previously demonstrated by providing tactile pressure using a pneumatic pressure mechanism for a prosthetic limb [101]. Likewise, thermal feedback has been provided using thermal elements [102] [103]. Haptic force and stiffness feedback rendered through remote haptic devices or other mechanical solutions is another illustration of modality-matched feedback featured in a number of applications ranging from surgical robotics to virtual reality [104] [105] [106].

The second strategy is to map sensory information that is usually perceived through one sense to a different sense. This is referred to as sensory substitution, a term that commonly describes a technological intervention that performs this translation for its user [107]. As illustrated in [107], a sensory substitution system acquires information that typically corresponds to one sensory modality and maps the information to the selected display actuators through which the information is presented to an alternative human sensory modality.

Sensory substitution is a common strategy to compensate for a blocked or impaired sensory pathway such as with blind or deaf individuals [89] [108] [109] or with tasks executed in the dark [110]. This strategy may also be extended to situations that place a heavy demand on one sensory modality such as in the driving navigation tasks discussed in the previous section, where substitutions may reduce the load on a single modality. Sensory substitution is also employed to reduce technological complexity in virtual reality applications (substituting force and touch feedback with vibrations for example) as well as to reduce encumbrance (the extent to which a user is burdened with wearing various devices to interact with a system) while increasing situation awareness [51] [111]. Further, sensory substitution has also been used to reinforce feedback through a second modality and proven to create more powerful representations of virtual experiences [112] [113]. Stimulation of one sensory channel that produces the illusion of stimulation in another has also been suggested to be powerful in remote teleoperation [114].

2.4.1 Somatosensory Feedback

Somatosensation refers to a set of perceptual processes related to the body and skin, and includes touch, pressure, vibration, pain, thermal sensation and proprioception (limb position) [66]. A variety of receptors including six types of mechanoreceptors, thermoreceptors (temperature), chemoreceptors (chemical stimuli), proprioceptors (limb joints and muscular states), and nociceptors (pain) gather information pertaining to their specific sensations from the skin (cutaneous feedback) and from muscles, joints, and tendons (kinesthetic feedback). This information is transduced into neural signals and carried to the brain where the sensations are integrated to form perceptions and inform both sensorimotor outputs and executive functions [66]. These receptors are more concentrated in the glabrous skin of the hand and surrounding areas.

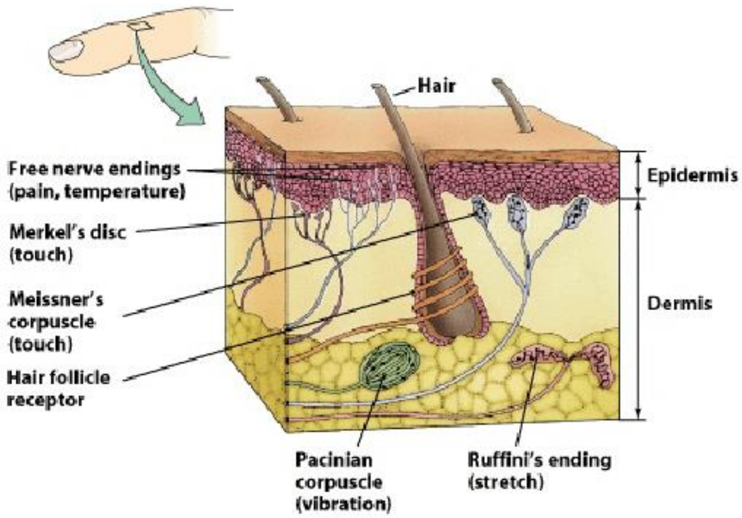

Figure 2.3: A cross section of the skin illustrating sensory receptors [115]

Cutaneous receptors typically collect information about surface characteristics of an external body such as hardness, stiffness, smoothness or friction, vibration, temperature, moisture, and texture. Kinesthetic receptors collect information about external forces, including weight and other forces as well as information that aid proprioception. In this project, we focused on vibration, thermal, and force feedback as candidate modalities through which temperature, weight, and liquid level feedback may be provided because these modalities could be integrated with little encumbrance and have been tested extensively as providers of sensory feedback as discussed in the sub sections that follow.

In this thesis, both direct and substituted modalities will be evaluated for providing selected somatosensory feedback properties that are deprived during remote robot pouring tasks. In particular, these somatosensory feedback channels may be substituted by distinctly different channels such as visual or auditory modalities as well as by other somatosensory channels including haptic, vibrotactile, or thermal modalities, as elaborated below.

2.4.1.1 Vibration

Vibrotactile stimulation involves an actuator vibrating against the skin. The mechanoreceptors primarily involved in the perception of vibrations are the Pacinian corpuscles located in the dermis. Typically, frequencies are chosen to maximize Pacinian FA II receptor sensitivity which is highest near 250 Hz [107].

Vibrotactile stimulation has been used to substituted information in a variety of applications. [115] demonstrates force and deformation for a forearm prosthesis conveyed via amplitude modulation of a tactor array. [116] encodes material stiffness information in vibrations using signals generated by tapping a material for upper limb prostheses. Virtual reality and human-computer interaction applications have frequently used vibrations for binary or modulated representations of instantaneous touch or force [117] [118] [119]. Texture stroking signals are also communicated through vibration in [118]. In [120] voice coil actuators generate asymmetrically normal to the ground to generate the sensation of weight for virtual reality applications. [51] introduces a vibrotactile glove for providing tactile, force, and haptic feedback in teleoperation tasks, where homogeneous linear mapping to frequency and inhomogeneous radiating patterns are investigated. In [89], vibration frequency is linearly mapped to several image features such as intensity, texture, and shape for blind users.

In this project, vibration frequency was mapped linearly from the tactor device range to constrained ranges of each of the identified properties and delivered through C2 tactors (Figure 2.4).

Figure 2.4: A C2 Tactor

2.4.1.2 Kinesthetic Force Feedback

Force feedback displays are primarily aimed at accessing the kinesthetic haptic channel. The main source that drives external force perception are afferent discharges from Golgi tendon organs that signal intramuscular forces [121].

Haptic devices have been a central tool in the provision of force feedback in a number of applications. These devices are available commercially [122] [123] [124] and are capable of providing a range of force feedback to a handheld stylus in applications that allow the integration of a stylus. A large portion of these applications have focused on providing modality-matched, rather than substituted, feedback of force and stiffness as discussed above. Additionally, [125] provides friction and gravitational acceleration information in exploratory tasks through a haptic device. In [89], image features such as intensity and texture are mapped to corresponding force feedback for blind users (Figure 2.5).

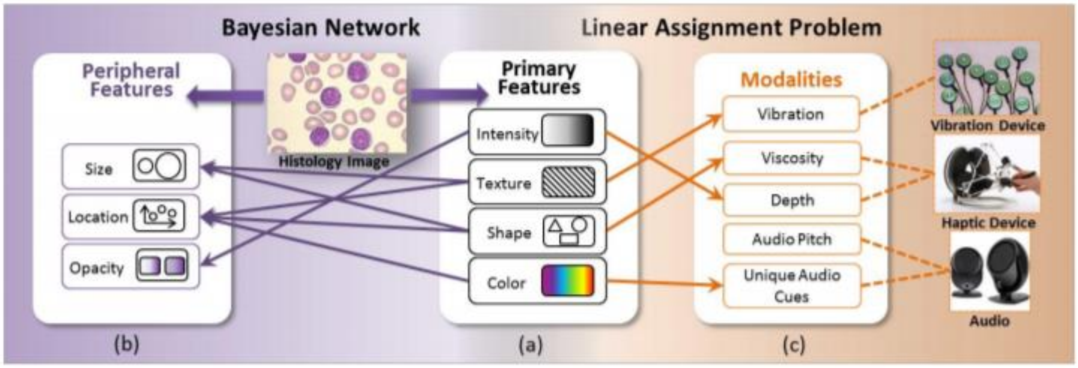

Figure 2.5: Image feature representation through multimodal feedback *[89]*

In this project, haptic feedback was provided as modality-matched feedback for weight (i.e. a downward force/weight bearing on the joystick stylus) and as a binary indicator of liquid level as above or below the grasp point.

2.4.1.3 Thermal Feedback

In thermal displays, heat is directed toward or away from the skin. Thermal perception depends on two different kinds of receptors known as cold and warm receptors, of which cold receptors outnumber warm receptors up to 30:1 [126]. Cold receptors respond to decreases in temperature while warm receptors respond to increases in temperature. No thermal sensation is noted in the range of 30–36°C although both types of receptors exhibit spontaneous firing, and outside this range, continuous discharge is primarily limited to one type of thermoreceptor [126].

Thermal perception and the ability to discriminate between changes depends on a variety of factors including the site of stimulation, the amplitude of the temperature change, the rate of heat transfer, and the baseline temperature of the skin [126]. It must be noted that thermal receptors do not perform as effectively as thermometers due to perceptual changes associated with altering stimulation duration (adaptation) or the spatial extent (spatial summation) [126]. Temperature perception on external skin differs from oral temperature perception due to heat transfer with environment. In the case of oral temperature perception, particularly of fluids, ~32-34°C is perceived as neutral, while above this range is typically perceived as warm and below as cold [127].

Thermal displays may be implemented using Peltier cells, which can be electronically controlled to pump heat toward or away from an area of skin that it is in contact with [107] [121]

[128]. Improving energy efficiency and response time have been identified as challenges in previous development efforts [129] [102].

In this project, a Peltier device was implemented (Chapter 3) to provide modality-matched feedback for temperature, with an oral to skin perception association to be learned by users.

2.4.2 **Visual and Audio Substitution**

In the interface developed for this project, visual and audio modalities were included as substitution modalities for the somatosensory feedback due to the ease with which humans interact with visual and audio displays.

2.4.2.1 Visual substitution

Visual displays allow the use of various visual information representations including color, semantic or numerical text, and graphical objects. In manual tasks, visual attentional requirements may interfere with the task and should be considered. Visual attentional requirements of robot-assisted tasks will be discussed in section 2.5 of this thesis.

Visual substitution of haptic or somatosensory feedback has been explored to some extent in teleoperation and virtual reality applications. In [130] a graphic display of colored bars were used to display force levels in surgical suture knots using a da Vinci robot. In [131] an arrow representing force magnitude and direction is used for endoscopic surgery training. [132] demonstrates using visual feedback in the form of a bar to augment haptic feedback of grip force in teleoperated suturing while [133] demonstrates bar graphs of force feedback for a virtual reality glove. In [134] collision forces are presented in the form of a bar graph to augment haptic and auditory feedback for telepresent manual assembly tasks.

However, humans and animals tend to discretize continuous information into categories for decision making [135]. This phenomenon is termed ‘categorical perception’ [136] and was first revealed in human speech perception research [137]. Thus, while bar graphs may be effective in monitoring force levels, information that requires less precision and is aimed at aiding decision making as in this project may be better conveyed through a more intuitive mode of communication such as semantic text identifying discrete categories.

Unlike force, temperature has a more intimate association with color. Cooler temperatures are often associated with blues and warmer temperatures with reds, and reds and blues are often referred to as warm or cool colors in photography and art. This is often leveraged in engineering designs of human-machine interfaces and other thermal communications to users. This is demonstrated in [138] background color changes indicating temperature is demonstrated in an optimized design of an human-machine interface (HMI). Thermochromic straws [139] and cups [140] are other examples of thermal color representations to users.

In this project semantic text and background color gradients was used as a substituted modality for all three selected properties.

2.4.2.2 Auditory substitution

Audio feedback may be displayed as pitch or amplitude varied sounds or tones or speech cues. However, conversational requirements may disrupt or be disrupted by audio cues, and applications that require collaboration may benefit from brief indicator cues rather than continuous ones.

Audio substitution of haptic and somatosensory cues have been integrated in teleoperation and virtual reality applications. In [130] a single tone was used to indicate that the suture tension had reached the applied tension for teleoperated robotic suturing. In [134] a metallic sound was used to indicate collision in telepresent manual assembly tasks. The sonification device in [141] includes provision of thermal information through frequency modulated sounds.

Audio-visual substitution has been investigated more extensively. In [89] both audio speech cues and pitch varied tones are investigated to substitute image features for visually impaired individuals. [132] uses a more complex auditory encoding to deliver visual depth information. Auditory speech cues are also commonly used in navigation tasks [142] [143].

Following the concept of categorical perception, in this project semantic auditory cues will be provided as a substituted modality to identify levels of all three selected properties.

In this project, we used a categorical approach to defining levels for testing perception of the three identified properties. Further, as noted above, the visual and audio cues was provided as category labels in addition to color changes accompanying the visual feedback for further resolution.

2.5 The Linear Assignment Problem

In this section, the linear assignment problem that was used to generate the optimal solution of feedback modalities in this project will be introduced. Algorithms for generating solutions and types of application are also reviewed.

The assignment problem is a fundamental combinatorial optimization problem that deals with the question of assigning a given number of tasks to a given number of agents such that the total cost is minimized. The problem was first called an 'assignment problem' in 1952 by Votaw and Orden [144]. Assignment problems consist of two components: the underlying combinatorial structure that defines the assignment and an objective function that models the cost of assignment [145].

If the total cost of the assignment for all tasks is equal to the sum of the costs for each agent, then the problem is called linear assignment. The Linear Assignment Problem (LAP) is one of the simplest forms of assignment problems [146]. The objective of the LAP can be described using graph theory as being to generate the minimum cost mapping of n tasks to n agents in a weighted bi-partite graph.

A bi-partite graph (Figure 2.6) contains two independent sets of vertices, U and V and may be denoted as H= (U, V; E) where H denotes the graph, U and V represent the sets of vertices, and E denotes the set of edges. The problem constrains the mapping such that the edges E may only connect one vertex in U to one vertex in V, and may not connect any vertices within a set. In a weighted bi-partite graph, each edge carries a weight or a cost of being mapped from a given vertex in U to one in V.

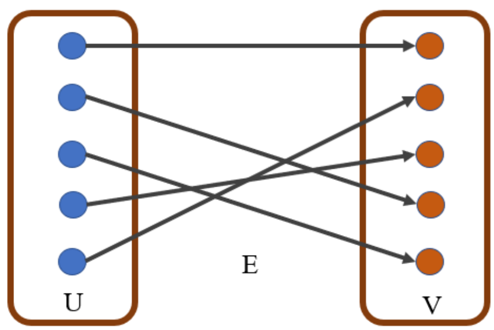

Figure 2.6: The bi-partite graph

Thus, given n tasks in U and n agents in V and a set of costs, the LAP can be formulated and solved to find the minimum cost combination of mappings. If a problem is unbalanced, that is if the number of tasks and agents are not equal, one approach to solve is to add a 'dummy' task (or agent) with a radically high cost such that balance is regained.

To construct a mathematical model for the problem, a n x n cost matrix, C=(c_{ij}), is defined where row i corresponds to U_i and column j represents V_j, and c_{ij} is the cost of assigning U_i to V_j.

Thus, the LAP can be defined as follows:

For a binary matrix X=(x_{ij}) such that

$$x_{ij} = \begin{cases} 1 \text{ if there is an assignment of i to j} \\ 0 \text{ otherwise} \end{cases} \quad (2.1),$$

The minimum cost linear assignment is

$$\min \sum_{i=1}^{n} \sum_{j=1}^{n} c_{ij} x_{ij} \quad (2.2)$$

where

$$\sum_{i=1}^{n} x_{ij} = 1 \quad (2.3)$$

and

$$\sum_{j=1}^{n} x_{ij} = 1 \quad (2.4)$$

Beginning with Easterfield in 1947 [147], many sequential and parallel algorithms have been proposed to solve the LAP in polynomial time. These algorithms can be classified into three main classes: Linear programming-based algorithms, Primal-dual algorithms, and Dual algorithms [145] [148]. Due to their polynomial worst-case complexity, the primal-dual algorithms such as the famous Hungarian algorithm [149] and Dual algorithms such as the shortest path algorithms [150] generally outperform the simplex-based linear programming algorithms such as the primal simplex algorithm [151] [148]. The theoretical time complexity of the most efficient primal-dual or shortest path algorithms is $O(n^3)$, where n is the number of resources or tasks [148]. The first computer program for solving the LAP [152] was based on the Munkres' algorithm [146].

Apart from straightforward applications such as personnel assignment in operations, the LAP has been applied in a number of settings. These include generating efficient communication routes in earth-satellite systems with TDMA protocols [152], tracking objects in space [153], multi-object tracking [154], optimal engine scheduling in railway systems, vehicle routing problems to de-densify transportation terminals, and vehicle and crew scheduling [145]. Further details on these applications can be found in [145]. Additionally, the LAP occurs frequently as sub problems in other combinatorial problems such as the quadratic assignment problem and travelling salesman problem [145].

In this thesis, the LAP was used to compute an optimal mapping of properties to feedback modalities. The cost function modeling the problem will integrate measures of feedback perception accuracy and resolution as well as visual load and subjective user preference metrics to for which the solution was optimized.

3. METHODOLOGY

This chapter describes the system developed for controlling the robot and providing feedback and the methodology used to generate the feedback solution using the linear assignment problem. The developed system includes robot control, feedback modalities and corresponding property-to-feedback translation strategies and sensing. The methodology to generate the optimal mapping includes the selection of metrics, problem and cost function definition, methodology for weighting the cost metrics, and the algorithm used to generate the final solution. The final solution generated with data from the first set of experiments will be presented in Chapter 4 following the experimental results discussion.

3.1 System

This section details the overall architecture, robot control modalities, and feedback configurations of the system developed for this project.

3.1.1 Overall Architecture

The overall architecture for the system robot control and user feedback system is summarized in Figure 3.1 below. The blue arrows represent information flowing into the system from the user, while the green arrows represent information flowing out of the system to the user as feedback.

A Gen2 6DOF JACO arm (Kinova®) [18] was used without the manufacturer-provided joystick. Control inputs to guide the robot is provided through a Force Dimension® Omega 7 haptic device [124] joystick and keyboard presses. Sensors were mounted on the robot gripper including a capacitance-based non-contact liquid sensor for liquid level (SEN0204 by DFRobot®)

and an infra-red thermal sensor for temperature (MLX90614 by Melexis®). Property information acquired from the robot end are provided through multiple feedback modalities including kinesthetic force feedback through the same haptic device, visual feedback through a 7” LCD monitor, vibration feedback through an Engineering Acoustics® tactor device [155], audio speech cues through the computer speakers, and thermal feedback through an Arduino-controlled Peltier device. Serial communication was established between all devices and integrated in a multithreaded console application on a Windows™ desktop computer.

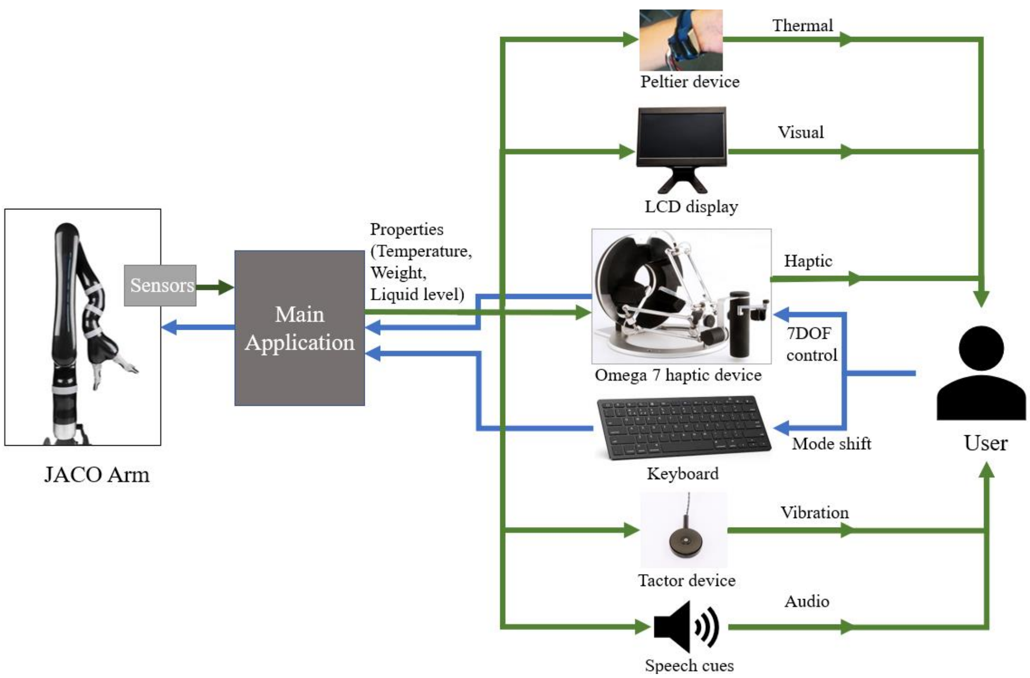

Figure 3.1: Overall interface architecture

In this thesis, the research problems focused on the user interaction aspect of robot manipulator control. Therefore, control input modality and individual feedback configurations are discussed in more detail in the following subsections.

3.1.2 JACO Robot Hybrid Control

The hybrid control model implemented in this system was based on previous research as well as user feedback during testing prior to experiments. Following the results and tradeoffs discussed by Jiang et al. in [50] in a comparison of multiple input modalities including the haptic device 3D joystick, a hybrid approach integrating a haptic device joystick and keyboard inputs was implemented in this system. The haptic device served as the motion control input method to guide the robot while keyboard inputs were used for shifting between modes and to carry out other built in single-command motions.

The input configuration included seven possible modes. Three modes shifted between X, Y, and Z axis translations while three shifted between rotational axes. Only one rotational mode, that is robot wrist rotation, was introduced to subjects and used in this experiment. The seventh mode was to open and close the gripper. While mode shifts were initiated through keyboard inputs, the translation was performed using the joystick. In all cases, the position of the joystick was mapped to the velocity of the robot translation allowing for easier and more precise control of both robot speed and positioning. For intuitive controllability, the translation axes were mapped to the same axes on the haptic device when viewed from the user's perspective, as were the rotational degrees of freedom. For example, to move the robot end effector left or right (in the x axis), the user had to move the stylus of the haptic device left or right. To rotate the wrist to pour, the user had to rotate their own wrist (and the corresponding degree of freedom on the haptic device) to pour. Because the position was mapped to robot velocity, the user had to move the stylus in the desired direction and hold it in one place for the robot to continue moving the in the same direction at a constant velocity. If desired, the user could move the robot faster initially and then decelerate when approaching the target in the same motion of the stylus. The rotational axes were configured the same way, with angular velocity mapped to angular displacement on the haptic device. An origin of +/- 0.01m in all directions was defined where no motion would occur. To open and close the gripper, the forward/backward (y axis) translation of the haptic device was used where pulling the stylus backwards mapped to closing the gripper (similar to closing a drawstring pouch). Some mapping included multiplication coefficients, fine-tuned through empirical testing to achieve enough resolution at a reasonable speed.

The set of equations mapping the controller to the robot can thus be defined as:

$$\dot{x_r} = 1.2x_j \qquad (3.1)$$

$$\dot{y_r} = 1.2y_j \qquad (3.2)$$

$$\dot{z_r} = 1.2z_j \qquad (3.3)$$

$$\dot{w_r} = w_j \qquad (3.4)$$

$$g = 1000y_j \qquad (3.5)$$

where x represents the left to right motion form the user's perspective, y represents forward and backward and z represents up and down for both the robot and the haptic device, $\dot{x_r}$, $\dot{y_r}$, $\dot{z_r}$ are the linear velocities (m/s) of the robot, x_j, y_j, z_j are the positions (m) of the haptic device joystick, $\dot{w_r}$ is the angular velocity (rad/s) of the robot joints, w_j is the angular positions (rad) of corresponding joints of the joystick stylus (counterclockwise positive for both), and g is the set of angular finger positions (0 at fully closed to 60 degrees at fully open) of the robot.

Table 3.1 below summarized the control mappings between the input modalities and the robot used in the experiments.

Table 3.1: Summary of robot control modality configurations

Robot Motion	Keyboard	Haptic device joystick
Move in X axis (left/right)	X	Move stylus in X (left/right)
Move in Y axis (forward/backward)	Y	Move stylus in Y (forward/backward)
Move in Z axis (up/down)	Z	Move stylus in Z (up/down)
Rotate wrist	P (Pour)	Rotate wrist to rotate stylus
Open/ close gripper	G	Push/ pull stylus
Send robot to home position	H	-
Emergency control release	R	-

Built in keyboard press motions in the system included sending the robot to home position and severing the connection between the joystick and the robot for an emergency stop. Keyboard presses could also be used to toggle the feedback properties on and off by the user as an additional feature. However, this feature was not used by subjects in the experiments.

3.1.3 Feedback Devices and Configurations

Five feedback modalities were selected as potential options for delivering feedback in this project. This section details modality-matched or substituted feedback configurations implemented based on work reviewed in section 2.4 and device and human limitations. Modalities that did not have previous work to demonstrate effectiveness of delivering a property or did not have a simple heuristic solution were not assigned to the properties in question.

3.1.3.1 Haptic Feedback

Haptic force feedback was configured to provide the weight and liquid level properties in this system. Haptic to weight feedback was a direct mapping of modality-matched feedback. The true weight (N) of the object was provided as a downward (negative Z direction) force (N) on the Omega 7 haptic device stylus (Figure 3.2), felt as a weight bearing down on the operating hand.

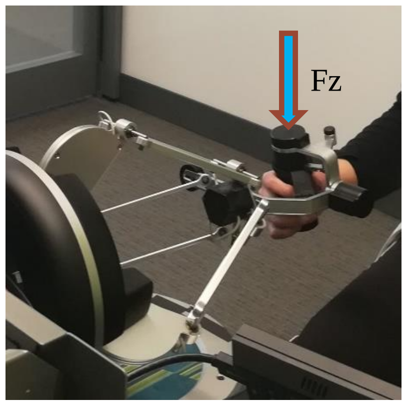

Figure 3.2: Downward force on stylus

For the binary liquid level feedback, if liquid was detected in front of the sensor (i.e. if liquid was above the grasp level), a downward force of 2N was exerted on the device stylus, and if liquid was below level, no force was exerted. This configuration provided a simple yet effective mapping to learn and perceive.

3.1.3.2 Vibration Feedback

The vibration modality was a substitution modality for all the properties selected for this problem. In all three cases, frequency was mapped linearly from the expected range of feedback to the maximum range afforded by the tactor device.

The tactor device [155] comprises C-2 tactors, considered the "gold standard" for vibrotactile research. The C-2 is a linear actuator with a moving magnet design. Its mechanical resonance is in the 200-300 Hz range, coinciding with the peak sensitivity of the Pacinian corpuscle at 250Hz [107]. For this system, two C2 tactors were placed on the right wrist of the subject (Figure 3.3).

Figure 3.3: Tactor placement

The C2 tactors on this device have a frequency range from 30 to 349 Hz which corresponds to a range of 319 frequencies. Expected ranges of weight and temperature were mapped to this full range to achieve maximum resolution. The mapping equation thus took the form:

$$f(x) = 319\frac{(x-x_{min})}{(x_{max}-x_{min})} + 30 \qquad (3.6)$$

Where f(x) was the mapped frequency as a function of x, x was the weight or temperature being mapped, x_{min} and x_{max} were the minimum and maximum of the expected weight or temperature ranges. For weight, the expected range was defined as between 0 and 10N, such that up to a 1kg mass object could be supported and the expected temperature range was set between 60° F to 150° F. If the range was exceeded, the maximum frequency vibration would be continued. A sinusoidal wave with the mapped frequency was the output feedback for vibration.

For the binary liquid level property, a frequency of 300Hz indicated that liquid was detected, while if no liquid was detected, 0Hz (no feedback) was provided.

3.1.3.3 Thermal Feedback

The thermal feedback modality in this system was implemented through a wrist-mounted Peltier device. The device was developed with two Peltier elements placed back-to-back. Each element served to heat or cool the wrist-side surface, and a TMP36 temperature sensor was placed on the wrist side for closed-loop control of the temperature. Two PID controllers were implemented for the heating and cooling functions such that the placement of the cooling element behind the heating element may be accounted for through the PID coefficients. A heat sink absorbed the opposite surface heat from the cooling element during cooling. The device was placed on the wrist (Figure 3.4) because of its sensitivity to temperature (e.g. we often use the wrist to test formula in feeding bottles or cooked liquids), proximity to the palm where a high concentration of thermal receptors are found, and practical positioning in the robot control task.

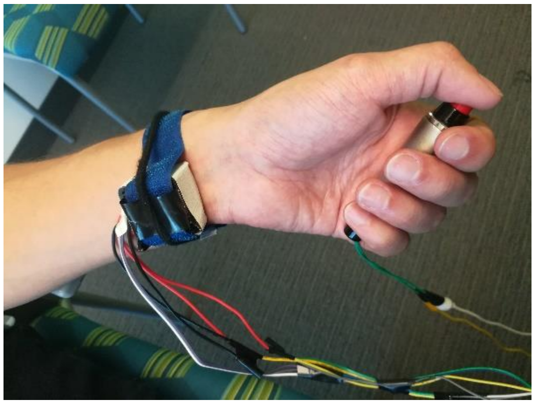

Figure 3.4: Thermal feedback device

The thermal feedback was only configured to provide direct modality-matched feedback of temperature. No conversions were made to map ranges. Similar to weight, the actual temperature was provided as input to this device.

3.1.3.4 Visual Feedback

The visual feedback modality provided information through text and color displayed on a 7” LCD monitor placed in front of the user (Figure 3.5). Feedback properties were categorized to provide text outputs of categories (e.g. ‘Hot’, ‘Very Hot’), and background color was used to differentiate between higher and lower values within categories.

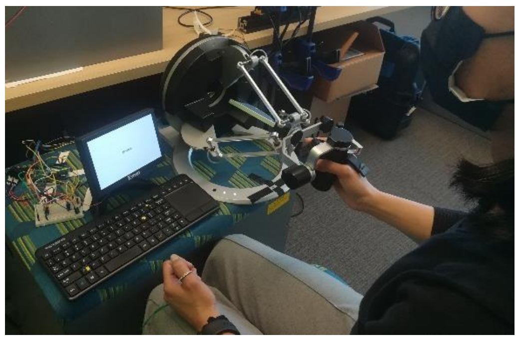

Figure 3.5: Visual display

Seven categories were defined for temperature based on oral temperature perception of beverages. A ‘Neutral’ range was defined between 90-95F [127] in white (R,G,B=1,1,1). Temperatures higher than this (‘Warm’ 95° F-105° F, ‘Hot’ 105° F-115° F, ‘Very Hot’ >115° F) were progressively deeper red in color, and lower temperatures (‘Cool’ 80° F-90° F, ‘Cold’ 70° F-80° F, ‘Very Cold’ <70° F) became progressively deeper blue in color. The set of equations 3.7 defines the mapping of R,G,B values for warm temperatures while 3.8 represents the mapping for cool temperatures.

$$R = 1, \ G = 0.25 - \frac{(T)}{(92.5)}, \ B = 0.25 - \frac{(T)}{(92.5)} \qquad (3.7)$$

$$R = 0.25 - \frac{(T)}{(92.5)}, \ G = 0.25 - \frac{(T)}{(92.5)} \ \ B = 1 \qquad (3.8)$$

where T represents the temperature to be mapped.

Five categories were defined for weight, dividing the weight of water in the vessel to be used in experiments into ‘Less than one quarter full’(0g-187.5g), ‘One quarter to one half full’ (187.5g-375g), ‘One half to three quarters full’(375g-562.5g), and ‘Three quarters to full’ (562.5g-750g). Background color changes for weight ranged from white at 0N to progressively greener. The set of equations 3.9 represents the R,G,B mapping for weight.

$$R = 0.25 - \frac{(W)}{(10)},\ G = 1\ \ B = 0.25 - \frac{(W)}{(10)} \qquad (3.9)$$

where W is the weight to be mapped.

For the binary categories in liquid level, text was displayed as ‘Liquid is ABOVE level’ on a yellow background or ‘Liquid is BELOW level’ on a black background for eye-catching contrast.

3.1.3.5 Audio Feedback

Audio feedback was provided as speech cues describing the categories for each of the properties. The same categories as described above were implemented here. Speech files generated from a text to speech converter were used with equal playback speed, volume, and pitch across all modalities. The audio cues were provided through the speakers installed on the LCD monitor in close proximity to the user.

3.2 Feedback Modality Assignment Problem

The theoretical core of this research lies in the feedback modality assignment problem and the associated framework to generate an optimal solution based on a set of experimental data. Optimization approaches have been used previously combining perception or recognition accuracy and psycho-physiological measures for haptic image rendering [89] and gesture-based interaction studies [156]. In this thesis, we use the structure of the Linear Assignment Problem (LAP) (described in section 2.5), to find an effective mapping of each of the three identified properties to one of five available feedback modalities with feedback perception accuracy and cognitive load metrics taken into account.

The overall solution framework followed to achieve this goal (Aim 01) is summarized in Figure 3.6 below. First, a set of metrics were identified to measure the factors of interest. Data corresponding to these metrics were then collected from a set of screening experiments, along with subjective ratings to define the weight of each metric in the cost computation. Results from these experiments were then used to filter out the relevant metrics based on significance, and the weights re-scaled to reflect the new filtered set of metrics. The means of those metrics were then input into the LAP, and the optimum mapping (as identified by this experiment) was generated as the final solution. A validation experiment was run subsequently (Aim 02) with three use cases to evaluate the effectiveness of the feedback interface when compared to no feedback.

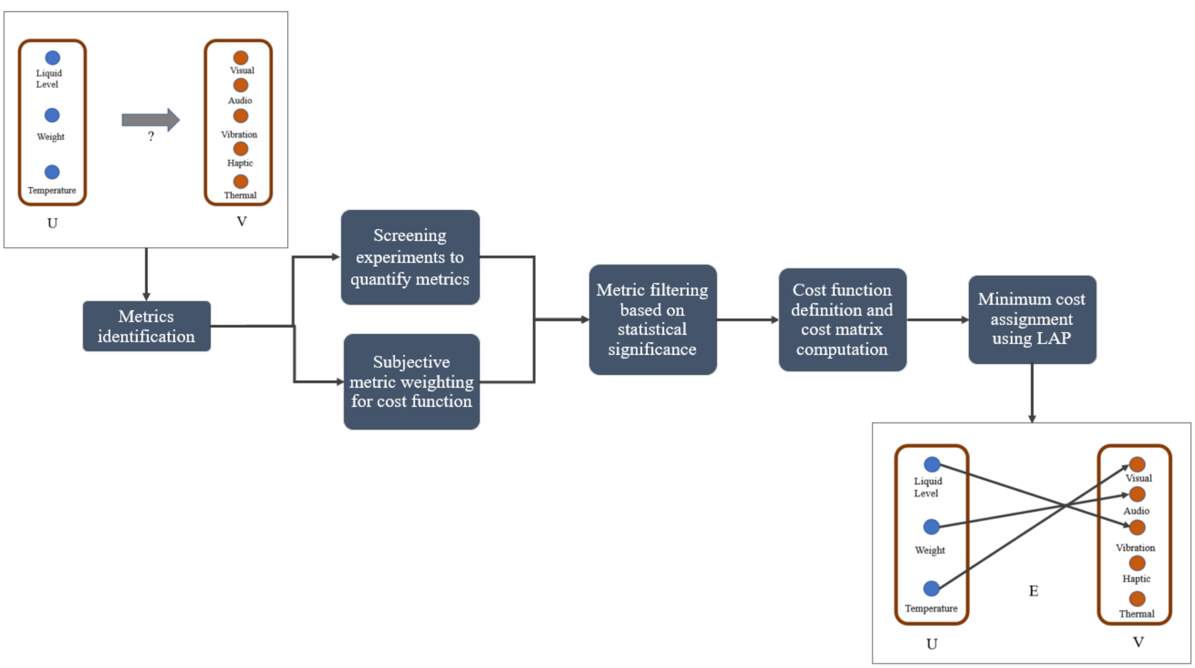

Figure 3.6: Solution framework. U, E, and V represent the set of properties, edges, and modalities respectively in the bi-partite graph.

The subsections below detail the methodology followed in each of the steps identified in the solution framework above. The selected metrics are detailed first in section 3.2.1 with brief description of their utility in the screening experiments. The screening experiments and results as well as the procedure for metric filtering are detailed further in Chapter 4. Section 3.2.2 introduces the assignment problem definition and is followed by definitions of the cost function, cost weighting (the procedure for which was conducted parallel to screening experiments), and the solution algorithm used to solve the LAP.

3.2.1 Metric Selection

Several metrics were identified for which the feedback interface was to be optimized. These included feedback perception metrics, cognitive load metrics, and subjective preference metrics detailed further in the remainder of this section.

3.2.1.1 Perception Accuracy and Change

The purpose of a feedback interface is to provide information to the user. Increasing the content of the information content of presented cues has been identified as the key to increasing information transfer [157]. Thus, for the identified feedback, it would be desired that both the perception accuracy of the delivered feedback and sensitivity to changes be optimized. To that end, two metrics representative of feedback perception accuracy and response to change were included in the screening experiments.

Given the categories (or levels) into which the range of one property was divided, perception accuracy was defined as the closeness of the perceived category to the actual category [158]. Sensitivity to change was defined as the ability to differentiate whether a change (increase or decrease) has occurred and in which direction [126] [158]. This included changes within the same category division as well as changes across categories.

Equations used to quantify these metrics in the screening experiments are provided in chapter 4.

3.2.1.2 Attentional Load Metrics from the DRT

Hit rate and mean reaction time measurements of the DRT has been used as an objective attentional load metric in driving and human-computer interaction tasks [94] [97] [100]. Hit rate refers to the number of stimuli responded to as a percentage of total number of stimuli presented within a trial. Mean reaction time is the average of the times elapsed between the stimuli and the response for the stimuli that were responded to within a trial.

To capture the visual attentional load, we selected the remote DRT with a visual stimulus for the robot-assisted pouring task in this project. Since previous work with robotic manipulators was limited, a preliminary experiment was conducted (described under the preliminary work sections of Chapter 4 and 5) to demonstrate the utility of the DRT in capturing the visual attentional challenges of robot operation.

3.2.1.3 Subjective Preference Rating

Subjective feedback has been an integral method of assessing user acceptance and identifying additional requirements in assistive robot manipulator surveys [10] along with design processes for many human-centric products including user interfaces [159], consumer products [160] and in the apparel industries [161]. Subjective preference ratings can capture a number of factors that are subtle and/or difficult to quantify including perceptions of physical comfort, psychological comfort, and integrated sensory impressions [161]. Subjective preference ratings may also capture effects of subjective workload which may reflect effects of resources such as memory [162] and task differences [91].

To capture a combined measure of these other factors that may affect the efficacy of a multimodal feedback interface, a subjective preference rating was introduced as a metric to inform the assignment cost. A multi-attribute preference weighting technique known as the Analytic Hierarchy Process (AHP) [163] [164] was used to determine subjective preference ratings. In this method, pairwise comparisons of attributes are used to make evaluate preferences over available alternatives when multiple conflicting attributes are available. This process was applied by collecting pairwise preference indications of the feedback modalities (e.g. Visual vs. Vibration, Audio vs. Visual, etc.) from the subject after each property set in the screening experiments. These ratings were then used to compute scores per modality by adding the total number of times a modality was selected from a pair and dividing by the maximum possible score (where the maximum score was 3).

The metrics introduced in this section served to quantify the costs in the LAP cost matrix. As illustrated in Figure 3.6, these metrics were quantified through screening experiments and statistically significant metrics were filtered out as described in Chapter 4. The definition of the LAP, cost function, and solution algorithm are discussed in the next sections.

3.2.2 Modality Assignment Problem Definition

Five possible sensory modalities (vibration, visual, haptic, audio speech cues, and thermal) were selected to convey three selected properties of interest in this study. Each property was rendered in different formats through each of the modalities as detailed in section 3.1. Under the constraint that only one modality can be used to represent one property, the mapping of properties to modalities was modeled as a linear assignment problem. A cost computed from the metrics identified in the previous section will be assigned to each property-modality mapping. The optimum mapping combination of 30 possible combinations can thus be generated by finding the combination of mappings that yields the minimum total cost.

In this problem, not all modalities were included as candidates for each property. Only modality renderings that have been demonstrated in previous work or renderings that had straightforward translations for the property were used. The remaining mappings were treated as initial conditions with costs set to infinity. Table 3.2 presents the cost matrix to be filled and identifies candidate modalities (white cells) for each property.

Table 3.2: Cost matrix indicating candidate modalities. Black cells indicate maximum cost initial conditions. Each column i corresponds to a property and each column j corresponds to a modality.

i

j

	Weight	Temperature	Liquid Level
Haptic			
Visual			
Vibratory			
Audio			
Thermal			

Thus, this assignment problem can be formally defined as follows:

Given two sets of vertices, P representing a set of properties (size 3) and M representing a set of modalities (size 5) with a cost function C: P x M →Q, find a bijection function h:F→ M that minimizes the total cost. Thus, for the matrix presented in Table 3.2, find the minimum cost linear assignment is:

$$\min \sum_{i\in P} \sum_{j\in M} C_{ij} x_{ij} \qquad (3.10)$$

where:

$$\sum_{j \in M} x_{ij} = 1 \quad \text{for } i \in P \qquad (3.11)$$

and

$$\sum_{i \in P} x_{ij} = 1 \quad \text{for } j \in M \qquad (3.12)$$

with

$$x_{ij} = \begin{cases} 1 \text{ if there is an assignment of i to j} \\ 0 \text{ otherwise} \end{cases} \qquad (3.13)$$

and the cost of no assignment (dark cells in Table 3.2) are set to infinity.

3.2.3 **Cost Function and Weighting**

The objective cost function to compute the costs of each cell in the cost matrix was defined as a weighted sum of the metric measures identified in section 3.2.1 and generated through the screening experiments.

Human subjects were recruited to perform the same task with feedback modality varied for each property. The selected metrics were evaluated as response variables. Thus, defining the set of metrics y of size k as response variables from the screening experiments and a set of corresponding weights w of size k to define the contribution of a given metric to the cost, the cost function was defined as:

$$C_{ij} = \sum_k w_k y_k \qquad (3.14)$$

where y is the set of metric means normalized to between 0 and 1, that may include measures of perception accuracy and change, DRT load measures, and the subjective preference rating. The set of weights, w, were subjectively generated by the participants in the screening experiments and are detailed in the subsection below.

3.2.3.1 User-generated Cost Weighting

The multi-attribute decision making technique known as the Analytic Hierarchy Process (AHP) [163] [164] discussed in section 3.2.1 was used to determine subjective metric weightings. To do this a hypothetical scenario was constructed where the robotic manipulator would be used to make and drink a cup of coffee or tea. Subjects were asked to provide a pairwise comparison rating of which attribute they perceived to be more important in this task. The metrics in question were presented as relevant to the task and the feedback properties (e.g. the initial temperature, weight, or level of liquid, the change in temperature, weight, or level of liquid, your attention on controlling the robot to perform the tasks, etc.; See Appendix C). These ratings were collected after the subject had trained on the robot such that they had a clear idea of the demands of manipulating the robot, but before the screening experiments and introduction to feedback modalities such that responses would not be biased by the idea of feedback availability. These ratings were then used to compute scores per metric by adding the total number of times a metric was selected from a pair. Final weights were generated by taking the mean scores and dividing by the sum of means such that total weights summed to 1. Thus, the weight computations for a set of metrics size k may be summarized as:

$$w_k = \frac{mean(m_k)}{\sum_k mean(m_k)} \qquad (3.15)$$

where means were taken over the responses of s subjects and:

$$m_k = \sum N \qquad (3.16)$$

with

$$N = \begin{cases} 1 \; if \; metric \; was \; chosen \\ 0 \quad otherwise \end{cases} \qquad (3.17)$$

These weights were rescaled after metrics filtering step using the same formula (with k reduced to reflect the new set of metrics).

Using the problem definition, cost function definition, and weighting strategies discussed thus far, the LAP was solved to generate and optimal mapping. The solution algorithm used to solve the problem is discussed in the next section.

3.2.4 **Solution Algorithm**

Because the sizes of the property and modality sets are different, an extension of the Hungarian Algorithm for a rectangular cost matrix [165] is used to solve this problem. To address this, columns of zero elements are added to the matrix to produce a square matrix. The sequence of steps to solve the problem with the resulting matrix is as follows:

A preliminary procedure precedes the main algorithm. We begin by defining k to be the minimum of number of rows and columns such that:

$$k = \min(n, m) \qquad (3.18)$$

where n and m represent the number of rows and columns respectively. If $n > m$, then for each column, subtract the smallest element in the column from every element in that column. Else, if $m > n$, subtract the smallest element in each row from every item in that row. Once the procedure above is completed, the following steps should be followed to execute the main algorithm:

1) Sweeping the resulting matrix from left to right and up to down, identify and mark zeros with a star (*) if no zero in its row or column has yet been marked. Repeat this procedure for all zeroes.

2) Cover every column that contains a marked zero. If k columns are covered, an optimal assignment exists among the marked zeroes and the algorithm stops. If not, the following steps should be followed.

3) Choose an uncovered zero and mark it with a prime (‘). If no zero is starred in its row, a sequence of changing between starred and primed zeroes described in step 4 should be repeated until all zeroes are covered before proceeding to step 5.

4) Define Z_0 as an uncovered primed zero, Z_1 as the starred zeros in the same column as Z_0, and Z_2 as the primed zeroes in the same row as Z_1. Look for uncovered primed zeroes Z_0 until one with no corresponding Z_1 is found. In this manner, unmark every starred zero and star the primed zeroes. Delete all primes and uncovered lines. Return to step 2.

5) Add the minimum uncovered element in the matrix to every covered row. Subtract the minimum uncovered element from every uncovered column. Return to step 3.

This chapter detailed the system and solution framework used to solve the identified problem. The screening experiments that yielded the values for the cost function and validation experiments that evaluated the solution are detailed in subsequent chapters.

4. SURVEY AND EXPERIMENTAL DESIGN

This chapter describes the survey conducted to establish a basis for selecting properties, preliminary experiments, the screening experiments that yielded the results to be input into the cost function, and the validation experiments that were conducted to evaluate the efficacy of the generated solution. Section 4.1 describes the survey and preliminary DRT experiment. The screening experimental design including three use cases, the control treatment, the arbitrary mapping, and response variables are detailed in section 4.2. The experimental design for the validation experiment including experiment set-up and response variables is detailed in section 4.3.

4.1 Preliminary Work

4.1.1 Survey

To establish a preliminary basis for the selected properties as relevant feedback in pouring tasks, a survey was conducted to determine the pertinence of non-visual information for users of robotic manipulators. The survey was designed in the form of a thought experiment, and guided respondents through a task of pouring milk into and drinking a cup of coffee using an assistive robot manipulator without the aid of somatosensory feedback that is present during direct manual contact. Images of each stage of the task from the perspective of the user were provided to ensure visual access was retained. Figure 4.1 depicts three of the key stages presented (see Appendix A for full survey).

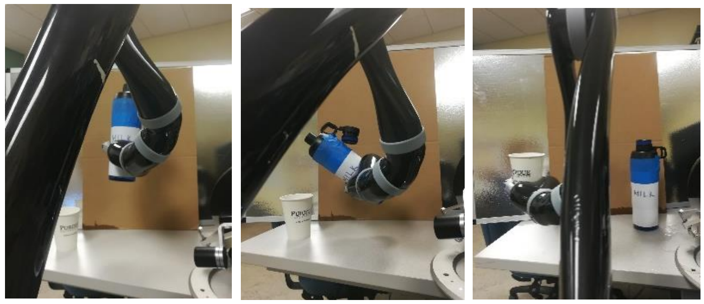

Figure 4.1: Images presented in survey to illustrate visual access to holding the server vessel before pouring (left), tilting (center), and holding the receiver vessel after pouring (right) from the perspective of a wheelchair user operating an assistive robotic manipulator mounted to the wheelchair.

Responses were collected from 102 participants (median age between 35-50) from a survey distributed to target populations for assistive devices through the University of Pittsburgh Human Engineering Research Laboratories (HERL) database, the Rehabilitation Hospital of Indiana, and Easterseals Crossroads, a non-profit organization for disability services in Indiana, in addition to the general distribution through social media. 67 of the respondents were individuals with ADL-impairing disabilities including spinal cord injury, multiple sclerosis, traumatic brain injury, and stroke. 59 respondents were users of assistive devices such as wheelchairs, prosthetic limbs, quadjoy mouse or mouth joystick, and reaching and grabbing tools. The full report of survey responses can be found in Appendix A.

Questions were posed at each stage where awareness of one of the selected properties was expected to inform a decision. These included deciding to pour after picking up the milk (stage 1), deciding the initial tilt angle (stage 2), and deciding to drink after picking up the coffee cup (stage 3) as illustrated in Figure 2.1. At each stage respondents were asked what they would do next for which all possible options (proceed with the task, throw the empty vessel, wait to cool before drinking, etc.) were provided including ‘I would need more information’ and ‘Other’ (to be specified). This question was followed by rating of the importance of each of the selected properties for making the decision, once again with the option to specify other properties that may be useful. Next, the subjects were asked to specify whether a combination of properties would aid the decision and then to identify how they would proceed without the information, including any alternative strategies they may employ to obtain the necessary information. Results from the survey are presented in the next chapter.

4.1.2 Preliminary DRT Experiment

Although frequently used for driving experiments and having been used previously in human-computer interaction, no previous work could be found that demonstrated the use of a DRT in robot manipulator operation tasks. Therefore, we conducted a preliminary experiment to establish its relevance as a measure for optimization during robot operation. This section summarizes the experiment and its results.

The same experimental set-up detailed in Chapter 4 of this thesis and the robot control configuration detailed in section 3.1.2 was used for this experiment (Figure 4.2, left). The visual stimulus was a red LED as per the ISO standard [95] mounted on the bowl in the visual field of operation, to which the user responded with a hand-held button. The visual stimuli were presented at the recommended randomized intervals of 3-5 seconds. Nine subjects were recruited for this experiment.

A within-subjects design was used, and the DRT hit rate and mean reaction time was recorded for each of three tasks performed by the subjects. The first task was the baseline task in which subjects only responded to the DRT stimulus without a robot operation task. Each subject performed the task for 2 minutes, responding to ~20 stimuli. In the second task, subjects completed a robot-assisted pouring task into a wide-rimmed bowl (Figure 4.2, center). This task involved grasping the vessel, moving the end effector towards the bowl, positioning, lowering, tilting to pour, straightening, and releasing the grip. To demonstrate a case of visual attentional demand in robot-assisted pouring tasks, a third depth perception task was included in the experiment. The subjects performed a pouring task into a narrower cup (Figure 4.2, right). The narrower receiving vessel was designed to pose a visual positioning challenge related to depth perception when pouring. It was hypothesized to show greater visual demand than the wide-rimmed bowl and result in poorer DRT performance. Tasks 01 and 02 included the additional task of responding to the DRT simultaneously, and the experiment was preceded by robot training where participants familiarized themselves with control modes and by two practice trials each of tasks 01 and 02.

Figure 4.2: Experimental set-up for robot-assisted pouring task 01 (left), task 02 (center), and task 03 (right).

4.2 Screening Experiment Design

In this set of experiments, a within-subjects design was employed where each subject tested all the individual property-modality assignments with the same task. For the properties selected in this application, a robot-assisted pouring task was chosen. Experiments were divided into three sets representing each property (temperature, weight, liquid level) completed on separate days, each of which contained four modality assignments. To compensate for possible learning effects tied to participants becoming more comfortable with controlling the robot, the three sets were ordered from the easiest to the hardest property set (liquid level, weight, temperature) and within each set from easiest to hardest feedback rendering (visual, audio, vibration, haptic/thermal). Each subject performed three trials of the pouring task for each assignment pair, for four modalities assigned to each of the three properties, totaling $3 \times 4 \times 3 = 36$ trials per subject. Nine subjects (4 male, 5 female) were recruited for this experiment, yielding a data set with a total of 324 trials with n=27 trials per each individual assignment.

4.2.1 Experimental Set-up and Execution

This section describes the experimental set-up, task performed by a subject in each trial, and training and post-experimental procedures preceding each set.

Set-up

The experimental set-up for this experiment was similar to the preliminary DRT experiment set-up described above, but with inclusion of the different feedback modalities. The system with the JACO robot, haptic device, sensing, and feedback modalities as described in section 3.1 was setup for a robot-assisted pouring task as illustrated in Figure 4.3 below. Black 26oz plastic tumblers (6.62 in. tall, 3.5 in. diameter opening) were used as the sample vessels from which to pour, while a large bowl was used as the receiving vessel. The robot was mounted in a fixed position on the table and the bowl position remained fixed. The robot end effector was returned to the same 'home' position before each trial. A control console placed between the subject and the table supported the haptic device, keyboard for mode shifts, and LCD display with speaker. The vibrating tactor elements were placed on the subject's right wrist as illustrated in the figure, and the thermal feedback device was worn on the left wrist. The DRT stimulus was mounted on the bowl similar to the preliminary experiment, with the button held in the participant's left hand.

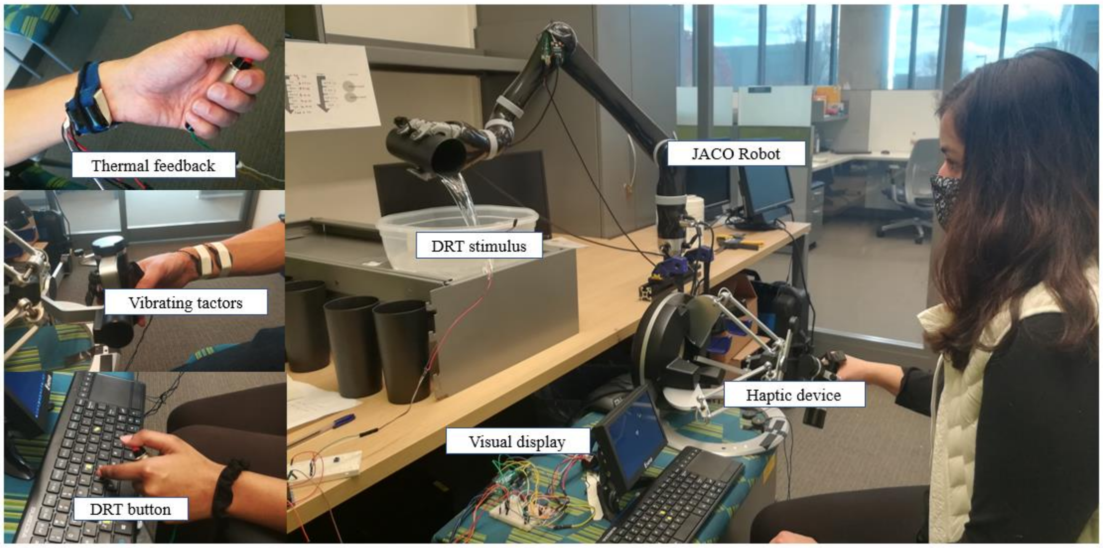

Figure 4.3: The experimental set-up with robot, joystick-haptic device, feedback devices, and pouring task apparatus. Tumbler used as sample vessels is also pictured in robot grip.

<u>Task</u>

Figure 4.3 also illustrates the pouring task carried out by participants in each trial. In each trial, the subject was required to grasp the vessel handed to the robot while at home position, move the robot end effector towards the receiving vessel, lower the end effector, and tilt the robot wrist to pour out water. The wrist was then straightened and the grip on the vessel released (vessel received by the experimenter). During each trial, the subject also responded to the DRT stimulus (rendered in the same manner as in the preliminary experiment to ISO standards) which was initiated prior to grasping and ended after the vessel was released.

During each trial, the subject was also required to assess feedback (e.g. temperature is in 'cold' category or liquid is above level) and change (i.e. property is higher than, lower than, or the same as the previous trial) as perceived through the relevant modality. The feedback perception assessments were provided three times when asked by the experimenter at three different stages (during transfer towards the receiving vessel, lowering, and initial tilting) to improve the feedback modality effect on the Detection Response Task. Change assessment was provided once at the beginning of the trial since it was a comparison to the previous trial.

These steps were followed across all trials by all participants such that the task attributes and length remained consistent independent of the feedback modality and property variations. This trial was repeated across all modalities three times, and after each 12 trial set, the participant provided a pairwise comparison rating of subjective preference of modalities for that particular property (See section 3.2 and 4.1.2 for further details and Appendix C for comparison table provided to subjects).

Samples

Water was used as the liquid contained in the pouring vessel across all the trials. The property variations of water within each set was randomized while holding the remaining properties constant. For example, in the temperature set, the temperature category of the sample in each trial was selected randomly (of all possible categories) while the amount of water was held constant at half full. For constant temperature trials, room temperature water was used.

Training

Prior to the full experiment, each subject followed the same training procedure to become familiarized with the robot control. Once the control instructions were explained, subjects had the opportunity to try moving the robot in each degree of freedom until they felt comfortable with the control aspects. They were then required to perform three dummy trials with the pouring task (but with no feedback or DRT), two with empty vessels and one with a full vessel.

Prior to each assignment set of three trials, subjects also received training on the feedback modality. In this training procedure, the subject was walked through the feedback categories as rendered by the given modality in ascending and descending order twice with category borders repeated twice (e.g. ‘warm’, ‘warm’, ‘hot’, again-‘warm’, ‘hot’-, ’hot’, ‘hot’ etc.) by equal increments and then given ten random renderings to assess. Up to three additional random renderings were provided for subjects who opted for it. The feedback training preceded each individual feedback assignment set.

4.2.2 **Response Variables**

Metrics identified to be optimized in section 3.2.1 were the response variables of interest in in this set of experiments. These included feedback perception metrics, cognitive load metrics, and subjective preference metrics as detailed in section 3.2.1.

Perception accuracy

Perception accuracy was intended to quantify the closeness of the perceived stimulus to the actual stimulus. Thus, in the screening experiments, it was defined as:

$$Acc = 1 - \frac{|C_a - C_p|}{n} \qquad (4.1)$$

where C_a is the actual category of stimulus, C_p is the perceived category of stimulus, and n is the number of possible categories for the property. The perceived category was the first feedback assessment provided by subjects during each trial.

Change response

To gain a measure of sensitivity to change in the screening experiments, responses were recorded of whether the perceived feedback was higher than, lower, than, or the same as the previous trial. If the response was correct (i.e. matched the actual), a score of 1 was given, and if incorrect, a score of 0 was given.

DRT hit rate and reaction time

The DRT was used to obtain a measure of attentional load as described in the preliminary experiment detailed in Chapter 3. The same set-up was used with the feedback modalities added to the task and hits and reaction times to hits per trial were captured. Hit rate and mean reaction times (RT) were computed as follows:

$$Hit\ rate = \frac{Hits}{Hits+Misses} \qquad (4.2)$$

$$Mean\ RT = \frac{\sum RT\ for\ Hits\ only}{No.of\ Hits} \qquad (4.3)$$

where Hits indicate the number of times a stimulus was responded to and Misses indicate the number of times a stimulus was missed. Reaction times were normalized between 0 and 1 after data collection for the purpose of computing costs in the cost function.

<u>Subjective preference score</u>

The subjective preference scores were computed using the analytic hierarchy process described in the previous chapter. After each set in the screening experiment (e.g. after all trials for all modalities in the temperature set) subjects were required to complete a pairwise preference comparison of all possible modality pairs (Appendix C) totaling six comparisons per property. One modality could be selected a maximum of three times. Preference scores for each modality were thus computed as follows:

$$Pref.Score = \frac{\sum M}{3} \qquad (4.4)$$

where

$$M = \begin{cases} 1\ if\ modality\ was\ preferred \\ 0\ \ otherwise \end{cases} \qquad (4.5)$$

4.3 Validation Experiment Design

The primary objective of the validation experiments was to determine whether the generated mapping provided feedback in an effective manner. To address this, the solution feedback treatment was assessed against a control treatment of no feedback. To further evaluate whether the generated solution was better than another solution, it was assessed against a third treatment of a randomly mapped feedback solution. Three separate use cases targeting different properties were defined to test each of the treatments.

A within-subjects design was used where each subject tested each treatment with each use case. The same set-up and robot-assisted pouring task used in the screening experiments was adapted for these experiments. Instead of assessing perceived feedback categories, in this experiment participants were tasked with making decisions relevant to the use cases. These decision tasks were informed by the feedback provided, and in the control treatment, inferred using alternative exploratory strategies detailed further below. Decision success, response time, and subjective mental demand ratings were collected as response variables. The control treatment was tested first to eliminate biases that may arise from knowing that feedback could be available.

Each subject performed two trials of the pouring task per treatment for each use case. Twelve subjects (6 female, 6 male) were recruited to test the control vs solution, totaling (2x12) 24 trials per use case per treatment, (24x3) 72 trials total per treatment, and 144 total trials for both treatments. Seven subjects (4 male, 3 female) tested all three treatments, yielding (2x7) 14 trials per use case per treatment, (14x3) 42 trials total per treatment, and a total of 126 trials for all three treatments.

<u>Samples</u>

Black plastic 26oz tumblers were used in this experiment. Unlike in the previous experiment, in these experiments samples were enclosed containers with black coffee lids covering the top (Figure 4.4). Water was used as the liquid contained in the pouring vessel across all the trials. The specific samples used in each use case are described in each case below.

Figure 4.4: The sample vessel (26oz, 6.62in. x 3.5in.)

Training

The same training procedures used in the previous experiment were followed prior to the feedback treatments in these experiments. Training was provided separately for each individual property. Additionally, during the robot training, participants also completed practice trials of the motions for the alternative strategies in the control experiment.

Arbitrary Mapping

The mapping used in the third treatment in this experiment was selected randomly. This solution mapped liquid level to the visual display, weight to the haptic device/joystick, and temperature to the vibration modality.

The next subsection describes the tasks in detail for each use case, how success was defined, and the alternative strategies used in the control experiment.

4.3.1 **Use Cases and Control Alternatives**

Three distinct decision tasks were defined as use cases, each expected to leverage one or more of the properties provided as feedback. Conditions were defined to mark success or failure of the decision, and participants were made aware of those defining conditions. All three feedback modalities were simultaneously activated for the duration of each trial. For each of these cases, an alternative strategy to obtain the necessary information in the absence of feedback was identified for the control treatment and are described at the end of this section.

<u>Case 01: Temperature Decision Task</u>

The first use case was a temperature decision task. For each trial in the experiment, subjects were tasked with making the decision to pour based on the perceived temperature. If the sample was in the desired 'Hot' range (105° F-115° F), the decision should be to continue with the pouring task. If the sample was above this range, subjects should wait till the sample reached the correct range and then decide to pour. Success (1) and failure (0) was recorded based on the decision. The decision was marked as a failure if:

The sample was at the desired temperature, but the participant chose to wait

- The sample was too hot but, the participant chose to continue
- The participant did not wait long enough for the temperature to reduce to the desired range
- The participant waited too long and the temperature fell below the desired range

The temperature of the water was measured at the end of the trials where participants waited for the temperature to reduce to identify whether the wait time was long enough. Participants were instructed to inform their decision to wait or pour as it was made, and wait times were recorded to be subtracted from the total task time to yield response times that were comparable (see response variables). At the end of the trial, a subjective mental demand rating was provided on a 0-100 scale.

Two fixed sample levels were defined for this experiment. The first was at110° F (the desired) and the second was at 145° F (too hot). The sample type was selected randomly with replacement for each trial so that the second trial could not be guessed based on the first trial.

<u>Case 02: Empty Vessel Identification</u>

The second use case required the participant to identify whether the vessel was empty or not empty. For each trial in the experiment, subjects were tasked with identifying whether the vessel was empty or not. Success (1) and failure (0) was recorded based on the decision. The decision was marked as a failure if:

- The sample was empty, but the participant identified it as not empty
- The sample was note empty, but the participant identified it to be empty

Participants were instructed to inform of their decision as it was made, and to keep the task time at a comparable length to when not empty, they were instructed to continue with the pouring motion even if the vessel was perceived to be empty. At the end of the trial, a subjective mental demand rating was provided on a 0-100 scale.

Two fixed sample levels were defined for this experiment. The first was an empty sample the second was a half full sample. The sample type was selected randomly with replacement for each trial so that the second trial could not be guessed based on the first trial.

<u>Case 03: Tilt Angle Estimation</u>

In the third use case the participant was tasked with estimating the angle of tilt to bring the top of the liquid stream to a desired region in the vessel. Prior to the experiment, the subjects were shown the marked target range in the vessel (Figure 4.4, left) which covered an area of 0.75 inches below the rim of the cup without spilling.

For each trial in the experiment, subjects were tasked with tilting the vessel to an estimated angle to bring the meniscus of the liquid to the target range based on the perceived amount of liquid in the vessel. The decision was marked as a failure (0) if:

- The liquid spilled out of the opening in the coffee lid
- The liquid was below the level of the targeted range

For this use case, a third middle level was introduced because of the occurrence of a special case. If the liquid did not spill out of the opening, but spilled when the lid was removed for assessment, the trial was marked with a 0.5. Outside of this, if the liquid was within the target range, the trial was marked a success (1). A successful tilt is shown in below (Figure 4.5, right).

Figure 4.5: Target tilt marking (left) and successful tilt (right)

Participants were instructed to release the robot controller using the ‘release’ command (see Chapter 3) to hold the position stationary once their decision was made. The lid was removed, and the liquid meniscus was observed to mark the trial as a success or failure. At the end of the trial, a subjective mental demand rating was provided on a 0-100 scale.

Two fixed sample levels were defined for this experiment. The first was a quarter full sample the second was a three quarters full sample. The sample type was selected randomly with replacement for each trial so that the second trial could not be guessed based on the first trial.

Alternative Strategies

In the control treatment, since feedback was not available to make the relevant decisions, alternative strategies were identified for each use case. These strategies were informed by responses to the survey discussed in section 4.1. The alternative strategies used in each of the use cases are summarized in Table 4.1 and illustrated in Figure 4.6 below.

Table 4.1: Alternative strategies for control treatment

Case	Alternative Strategy
01: Temperature Decision Task	Transfer the vessel towards themselves and touch the outer surface to determine temperature
02: Empty Vessel Detection Task	Tap the vessel on the table surface to perceive fill level from the hollowness of sound
03: Tilt Angle Estimation	Tap the vessel on the table surface to perceive fill level from the hollowness of sound

Figure 4.6: Alternative strategies: touch (left) and tap (right)

Prior to the trials for each case in the control treatments, the participants were familiarized with how the samples presented in these alternative strategies in the following manner:

Case 01 (Temperature): Prior to the experiment, subjects were given a sample heated to 110° F to hold. They were told that this was the desired temperature in the temperature decision task that followed. A sample heated to 145° F was also given to hold, and subjects were told that this was an example of a hotter sample for their reference.

Case 02 (Empty vessel): Prior to the experiment, an empty vessel and a half full vessel were tapped on the table to demonstrate the difference between the tapping sounds. The empty vessel sounded hollower and consequently higher in pitch.

Case 03 (Tilt angle): Prior to the experiment, vessels representing the two types of samples were tapped on the table to demonstrate the difference between the tapping sounds. The less filled vessel sounded hollower and consequently higher in pitch.

All participants used the same alternative strategies to minimize effects from strategy variations in the results.

4.3.2 Response Variables

Three response variables were selected for study during this experiment. **Task success** was marked between 0-1 following the conditions described in each of the use cases above. Thus,

$$Success = \begin{cases} 0 & if\ a\ failure\ condition\ is\ met \\ 0.5 & if\ an\ applicable\ conditions\ is\ met \\ 1 & otherwise \end{cases} \qquad (4.6)$$

Because the alternative strategies resulted in tasks of varying lengths, the DRT was not used to quantify load in this experiment. Instead, a **subjective mental demand** rating on a 0-100 scale (presented as a number line; see Appendix C) was collected at the end of each trial. This was supplemented by the **response time** variable which, in addition to capturing additional load imposed by alternative strategies and perception through more complex modalities, also represents a convenience measure for real life situations. Configurations that significantly reduce the time investment into performing a robot-assisted task can lead to improved task efficiency and improved usability.

Response time captured the time taken to make the decision and complete the pouring task. For the temperature trials where some trials were compounded by a wait time, response time was computed as:

$$Response\ time = Total\ task\ time - Wait\ time \qquad (4.7)$$

One-way ANOVA was performed to analyze results using a linear mixed model that factored in the treatment and sample as main effects and the subject as a random effect.

5. RESULTS AND DISCUSSION

This chapter details the results of the survey and experiments described in the previous chapter. The results of the survey and preliminary DRT experiment are presented in section 5.1. Section 5.2 presents the results of the screening experiment and discusses their implications. Section 5.3 describes the final cost function and minimum cost assignment solution resulting from these experiments. Section 5.4 presents the results of the validation experiment and discusses their implications.

5.1 Results from Preliminary Work

5.1.1 Survey Results

The results of this survey served to establish an initial basis for the selection of situation enhancing properties in this project. Further, the alternative strategies identified by respondents were also used in the control case of no feedback for the evaluation experiment set. As elaborated in the previous chapter, the survey guided respondents through a task of pouring milk into and drinking a cup of coffee using an assistive robot manipulator. Questions were posed at three key stages: deciding to pour after picking up the milk (stage 1), deciding the initial tilt angle (stage 2), and deciding to drink after picking up the coffee cup (stage 3).

5.1.1.1 Results

As observed in Figure 5.1, 58% responded that more information would be needed at stage (1), 54% at stage (2), and 51% at stage (3). The remaining responses were distributed over the remaining response options in each stage, the highest of which involved 33% opting to proceed with the task in stages (1) and (3) and 33% selecting to tilt a little in stage (2).

Mean ratings for the selected properties on a rating scale of 0-5 (Figure 5.2) were as follows: 3.63 (weight), 3.84 (liquid level), 3.33 (temperature) in stage (1), 3.88 (weight), 4.40 (liquid level), 2.87 (temperature) in stage (2), and 3.02 (weight), 4.59 (liquid level), 4.28 (temperature) in stage (3). Only a small percentage (<10%) of respondents opted 'Other' for this question.

When asked how they would proceed without the feedback, proceeding with the task to the best of their ability was indicated by 66% in stage (1), 74% in stage (2), and 64% in stage (3) (Figure 5.3).

Alternative strategies were identified by a number of participants, mainly involving exploratory and testing procedures such as shaking or swirling the vessel, tipping slowly to try and gain visual access, bringing the cup to the lips or taking small sips to assess temperature, or simply leaving it for a while to cool.

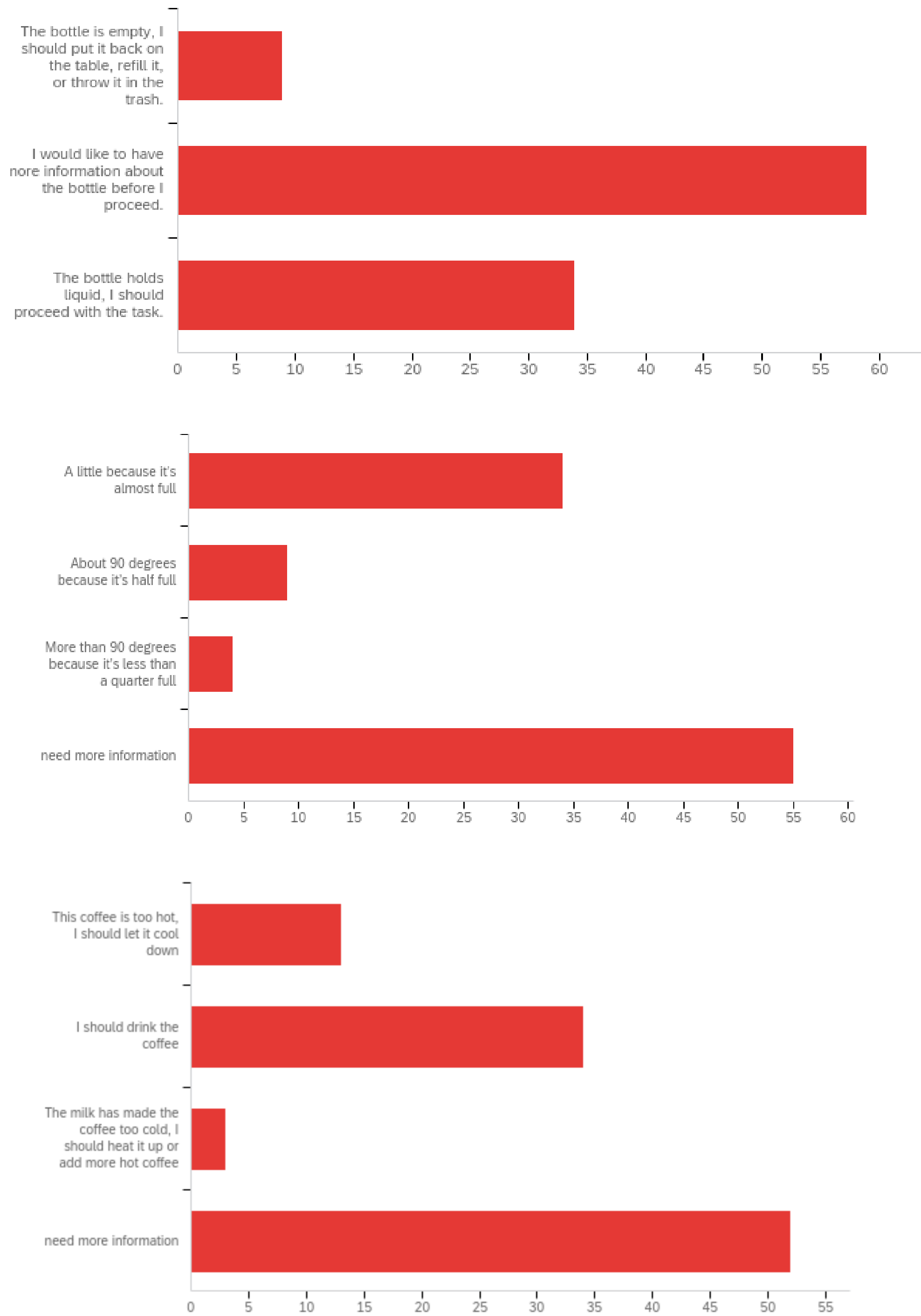

Figure 5.1: Responses to ‘what would you do next?’ in stages (1) (top), (2) (center), and (3) (bottom)

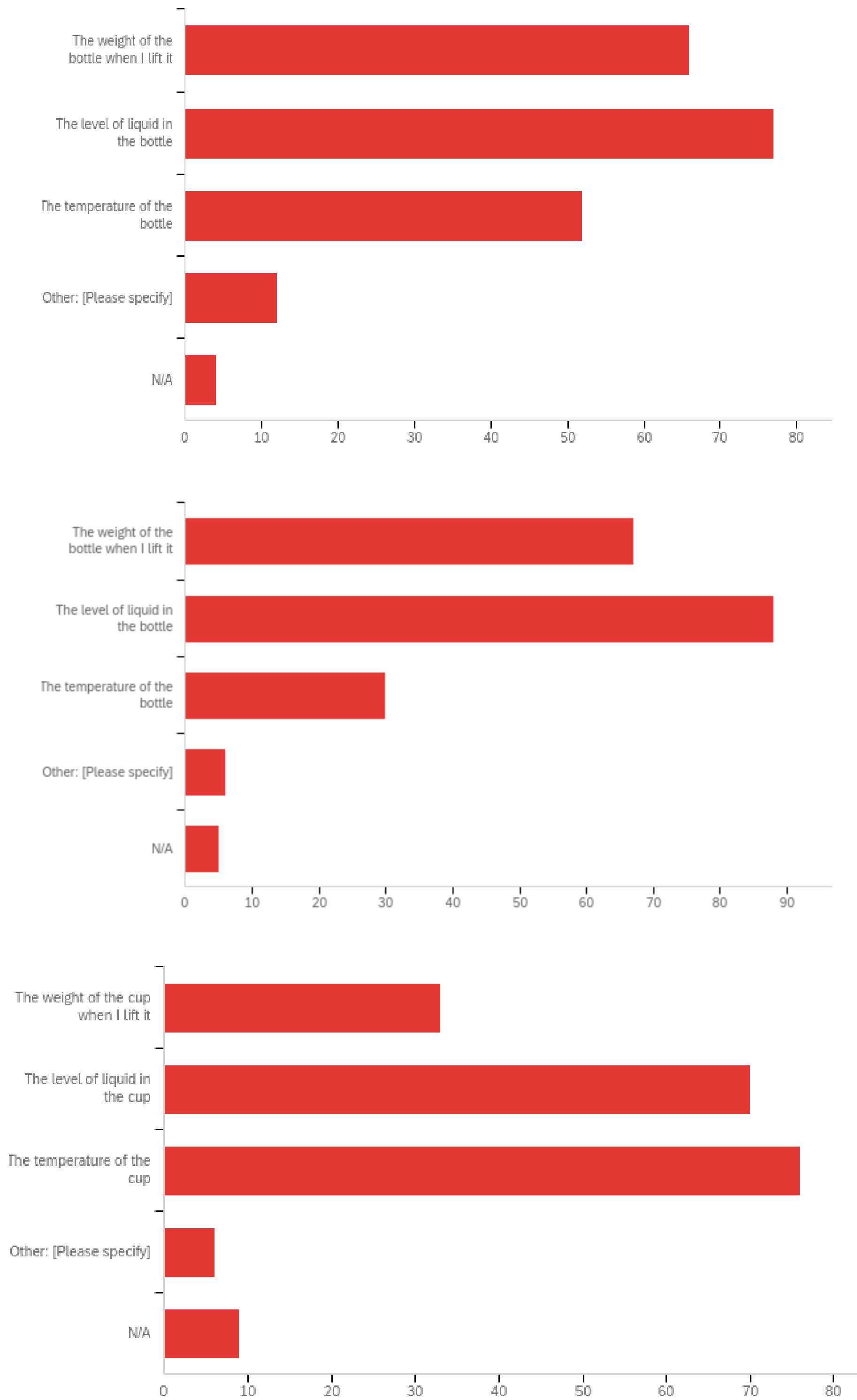

Figure 5.2: Mean importance ratings for properties in stages (1) (top), (2) (center), and (3) (bottom)

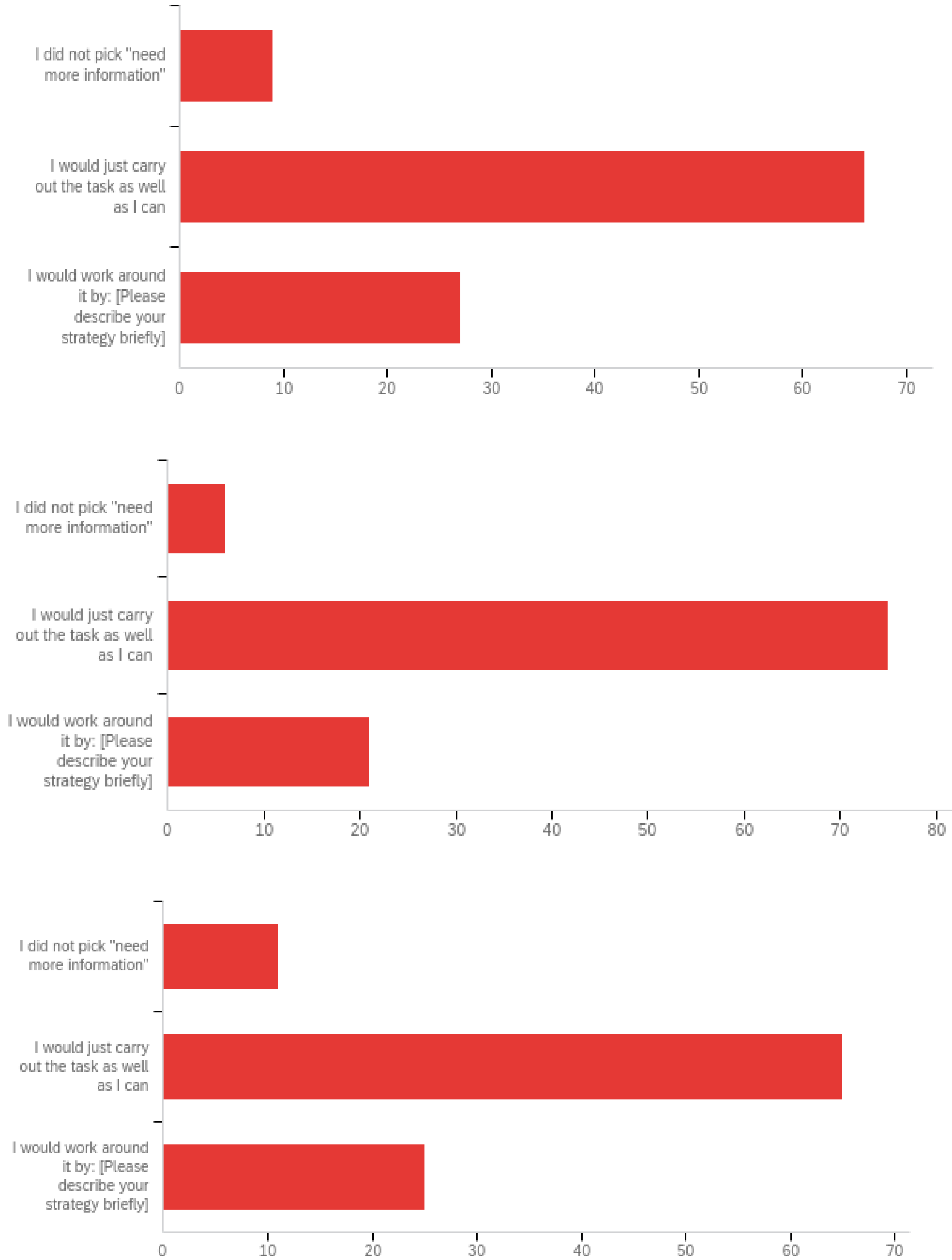

Figure 5.3: Responses to 'how would you proceed without feedback?' in stages (1) (top), (2) (center, and (3) (bottom)

5.1.2 **Discussion**

The clear majority indicating that more information was necessary in all stages demonstrated that there was a lack of information to inform these decisions that would have been made with ease in a direct interaction setting (Figure 5.1). This lack of information is evident even with visual access to the scene and before respondents are introduced to the possibility of sensory feedback. This observation solidifies the importance of sensory feedback for decision making in robot control tasks in addition to demonstrating the relevance of the feedback properties selected for this study. The results in Figure 5.2 support the selection of these properties as critical to situation awareness. Weight and liquid level take prominence in stages (1) and (2) (assessing whether there is liquid in the vessel prior to pouring and estimating tilt angle) and temperature in stage (3) (deciding whether to drink) as expected. All three properties may have been deemed important at each stage beyond the specific decision that was targeted, eliciting ratings better than 50% for all three properties in each stage. Additionally, weight and liquid level were identified as a desired *combination* in stages (1) and (2) by a majority of respondents while temperature and liquid level were identified as a desired combination is stage (3). This indicates that the congruence of these two properties were perceived by respondents to be helpful together in making the relevant decisions. Responses to how respondents may proceed without feedback illustrated in Figure 5.3 suggest that without feedback, users may choose to either continue with the task at the expense of time and/or at risk of safety, or spend time maneuvering the robot to perform heuristic tests. This once again underscores the utility of multisensory feedback in improving user experience.

5.1.3 **Results from Preliminary DRT Experiment**

This experiment demonstrated the relevance of cognitive attention load in robot-assisted pouring tasks and established the utility of the DRT as an effective measure of visual demand in robot operation tasks. A similar set-up and methodology to this experiment was followed in the incorporation of the DRT as in the screening experiments.

5.1.2.1 Results

The mean DRT hit rates and mean reaction times produced in each task are illustrated in Figure 5.4 below. One-way ANOVA (α=0.05) performed on the data (with subject as a random effect) revealed highly significant differences for both hit rate ($F=21.38$, $p<0.0001$) and reaction time ($F=14.55$, $p<0.0001$). Post-hoc Tukey tests identified the significant differences in hit rate to be between the bowl vs cup and cup vs baseline at $p<0.05$, while the difference observed between baseline and bowl (Figure 5.4) were found to be insignificant. Post-hoc Tukey tests performed on reaction times for the hits found a significant difference between the robot manipulation tasks and the baseline at $p<0.05$ while differences between the two depth perception tasks were found to be insignificant. However, it must be noted that one data point was treated as missing in the cup set because one subject had zero hits during their cup trial (and reaction times are only computed for hits).

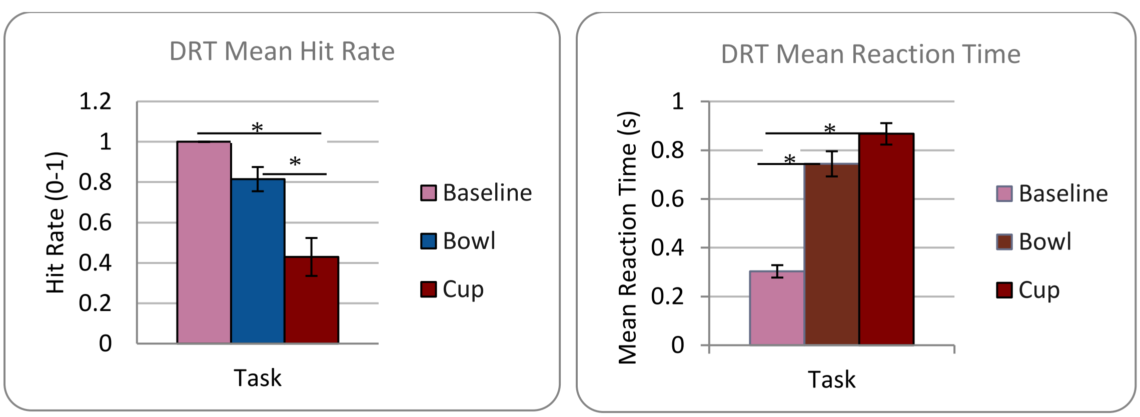

Figure 5.4: Mean hit rate (left) and mean reaction time (right) for each task. Error bars represent standard error. Decreasing hit rate and increasing reaction times point to increasing load across tasks. * indicates significantly different pairs (p<0.05).

5.1.4 Discussion

The combined trends of increasing reaction time with decreasing hit rate observed in these results indicate increasing load. The similarity of the trends across the metrics establishes this result without contradiction. This supports the expectation of increased load (depicted by increasing reaction times and decreasing hit rates) for the robot manipulation tasks relative to the baseline, as well as for the more visually challenging manipulation task (Cup) between the two robot tasks. Overall, given the large difference in hit rate and reaction time, it can be concluded that the robot manipulation tasks required more cognitive attentional resources compared to the baseline, and that this requirement increased with increasing visual challenges in the manipulation task. Further, the differences in hit rate between the bowl vs cup and cup vs baseline indicated increased visual demand when the target vessel was narrowed. These results demonstrated that the DRT was successful in capturing the relevant demands of robot manipulation tasks, and therefore supported the selection of DRT cognitive load measures as a cost metric for the interface assignment problem.

5.2 Screening Experiment Results

This section discusses the results of each response variable for the different properties and modalities. Means of responses and One-way ANOVA results (α=0.05) are presented for each response variable separately and interpretations and implications are discussed in this section. The experiments, results, and procedures detailed in this section led to a final feedback property to modality assignment combination solution as solved for using the linear assignment problem (section 5.3). The solution was then evaluated in a set of validation experiments detailed in section 5.4 of this thesis.

5.2.1 **Perception Accuracy**

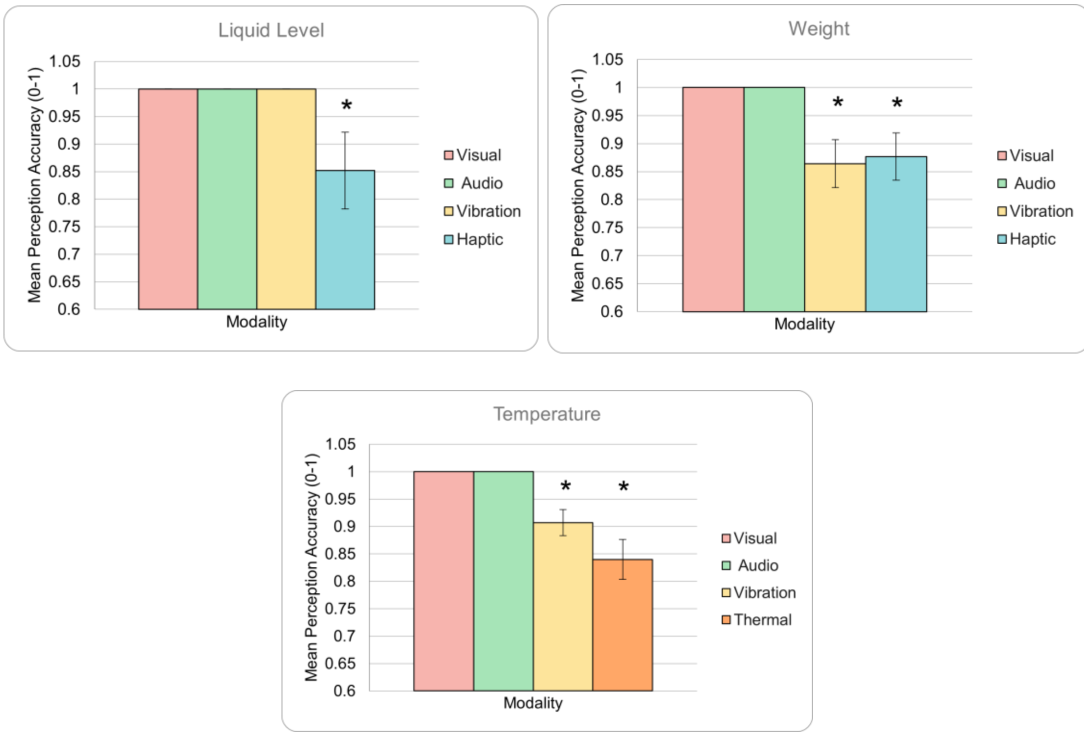

Figure 5.5: Means of perception accuracy for each property and modality. Error bars represent standard error. * indicates modalities significantly different from visual display ($p<0.05$).

One-way ANOVA results for perception accuracy show significant differences between modalities for all three properties with $F=4.52$, $p=0.0051$ for liquid level, $F=8.46$, $p= 4.427e(-05)$ for weight, and $F =17.32$, $p=3.389e(-09)$ for temperature. The significant results for perception accuracy confirm that it is an important and relevant metric to be included in the cost function for identifying an appropriate mapping.

5.2.2 **Change Response**

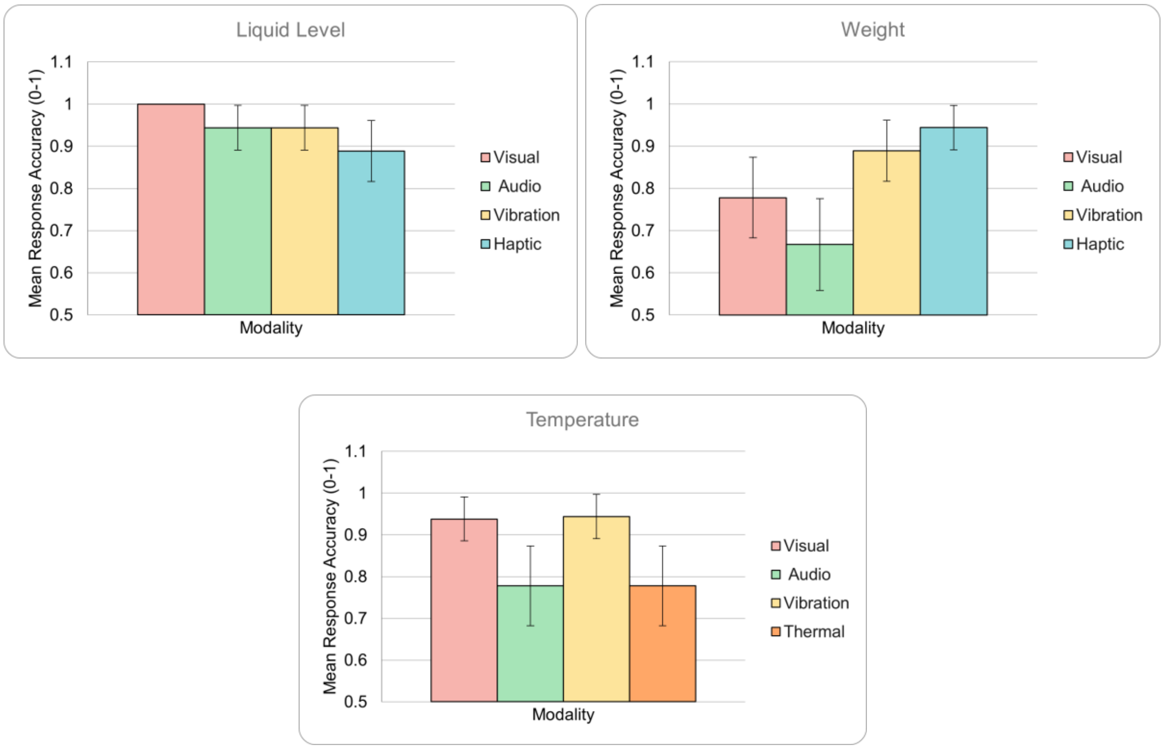

Figure 5.6: Means of change response accuracy for each property and modality. Error bars represent standard error. * indicates modalities significantly different from visual display (p<0.05).

Despite the differences in means observed on Figure 5.6, the ANOVA results for change response accuracy yielded $F=0.69$, $p=0.5632$ for liquid level, $F=1.89$, $p= 0.1397$ for weight, and $F =1.4$, $p=0.2512$ for temperature. The insignificance of results for this metric indicates that it may not be a critical metric to be included in the cost function.

5.2.3 DRT Hit Rate and Reaction Time

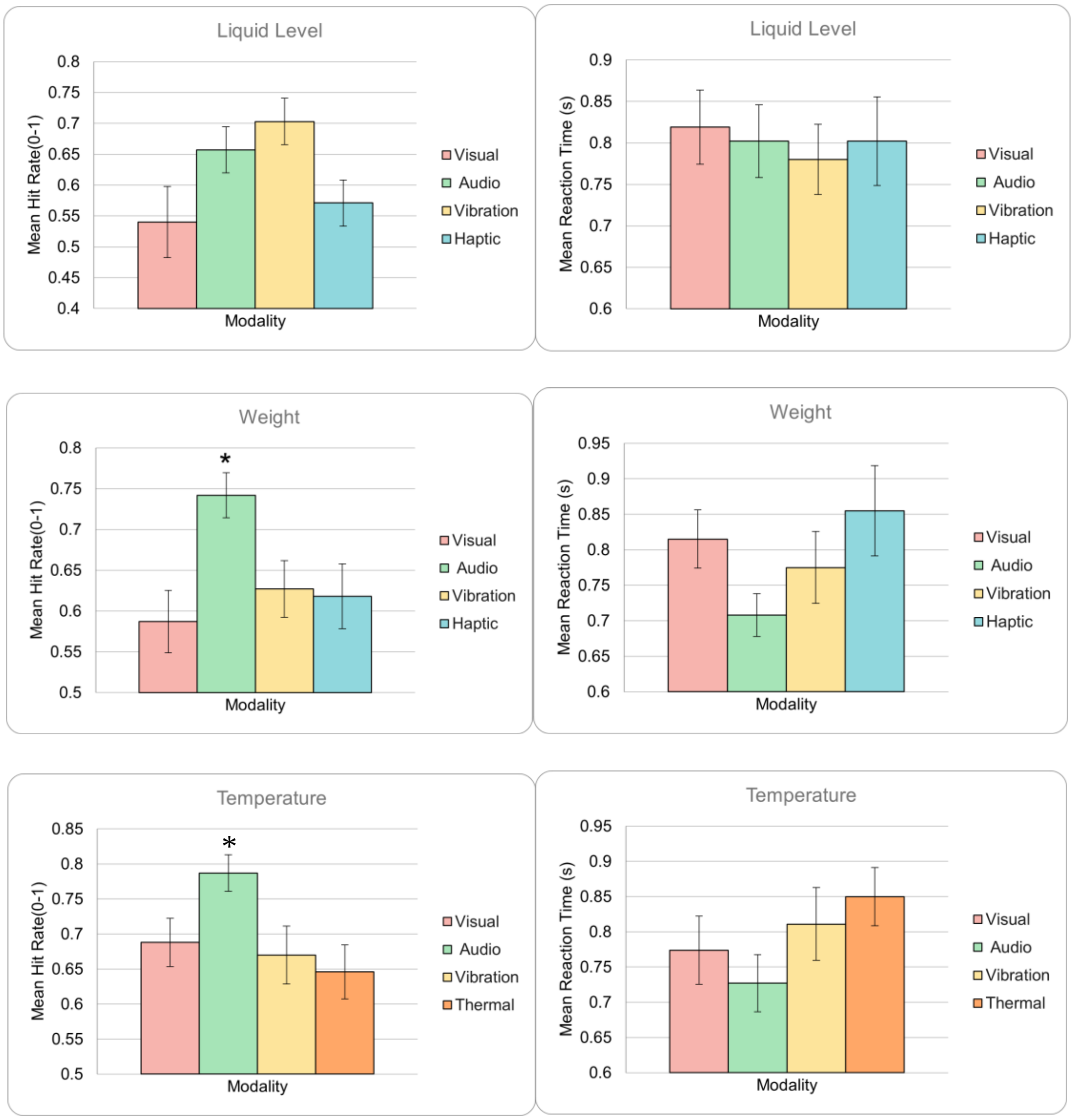

Figure 5.7: Means of DRT hit rate (left) and reaction time (right) for each property and modality. Error bars represent standard error. * indicates modalities significantly different from visual display (p<0.05).

For the hit rate means observed in the left graphs in Figure 5.7, the ANOVA results found $F=2.01$, $p=0.1166$ for liquid level, $F=4.47$, $p= 0.0054$ for weight, and $F =3.0$, $p=0.0338$ for temperature. While liquid level was found to be insignificant, the results for weight and temperature categories are observed to be significant for the DRT hit rate. Since liquid level is the simplest of the properties, and the more complex properties were significant, we can interpret these results to indicate that DRT hit rate is a valid inclusion in the cost function for optimization.

Although differences in means are observed on Figure 5.7, the ANOVA results for DRT reaction time produced $F=0.12$, $p=0.9486$ for liquid level, $F=1.8$, $p= 0.1509$ for weight, and $F =1.22$, $p=0.2704$ for temperature. The insignificance of results for this metric indicates that it may not be a critical metric to be included in the cost function.

5.2.4 Subjective Preference Score

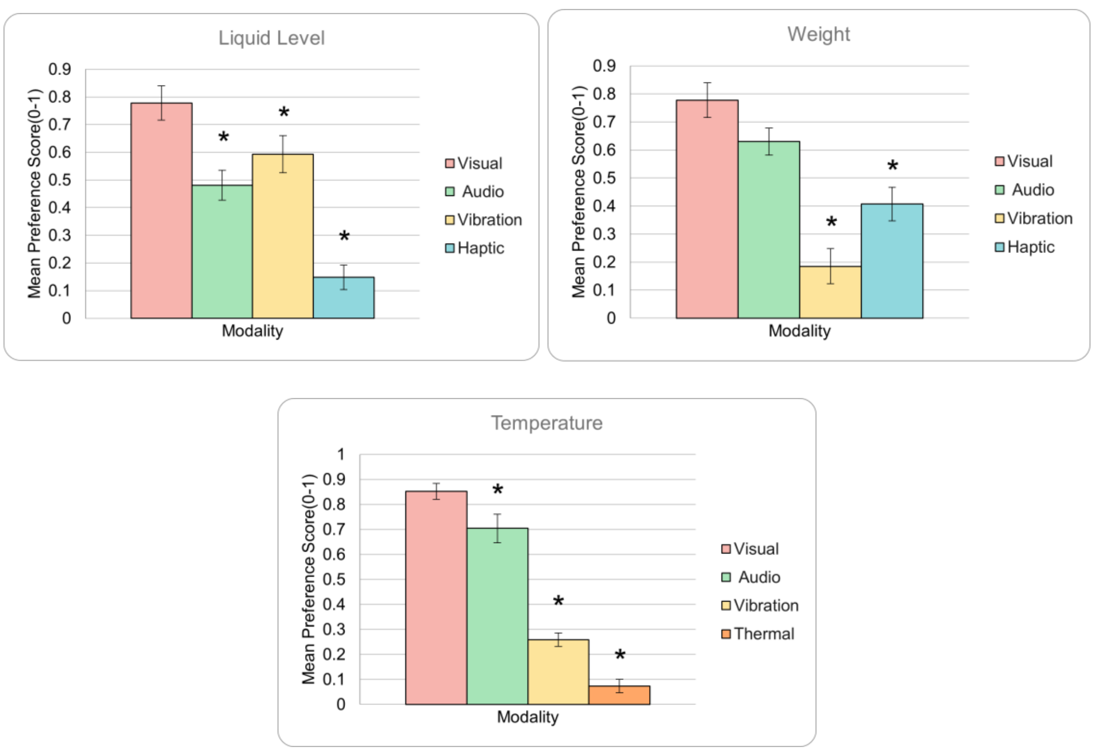

Figure 5.8: Means of subjective preference for each property and modality. Error bars represent standard error. * indicates modalities significantly different from visual display ($p<0.05$).

ANOVA results for subjective preference comparisons (Figure 5.8) were found to be highly significant with $F=21.05$, $p=9.861e(-11)$ for liquid level, $F=19.75$, $p= 3.289e(-10)$ for weight, and $F =92.26$, $p=3.439e(-29)$ for temperature. The significance of results confirms that it is an important and relevant metric to be included in the cost function for identifying the minimum cost assignment.

5.2.5 Discussion

From the results across all metrics in the previous sections, we observed that perception accuracy, DRT hit rate, and subjective preference yielded significant differences between two or more modalities, while change response accuracy and DRT reaction time differences were not found to be significant. For the purposes of our optimization cost function, we divided our approach into two parallel paths from this point forward: we computed cost weights and matrices and finally generated solutions with (1) only the significant metrics and with (2) all the metrics. In the remainder of this section, we will discuss the results obtained from each metric separately.

Perception Accuracy

From Figure 5.5 it can be observed that the visual and audio modalities provided the best perception accuracy consistently across all properties while vibration (with the exception of liquid level where the two levels are perceived with 100% accuracy), haptic, and thermal modalities were less effective. This is not surprising as humans tend to favor visual and audio channels as general means for communication and learning [66]. For literate individuals, text, color, and speech cues are simple to learn and interpret, and can provide clear labels and representations of distinctions needed to be made. Information processed through mechanoreceptors such as vibration and haptic perception, on the other hand, do not provide the same resolution and are not as intuitive, especially when used as a substituted modality. Thermal perception is even lower in resolution due to the relatively sparse spread of thermoreceptors in the skin and is affected by the participant’s basal body temperature which can have an effect on the heat transfer rate and thus the perception of thermal cues [126]. Further, since thermal perception responds primarily to heat transfer rather than temperature (e.g. a room temperature table may feel cold to a warm hand and warm to a cold hand), perception is affected by initial skin temperature and the rate of change of temperature at the time of each trial. However, it should be noted that all modalities yielded over 80% mean accuracy, supporting the choice of selected modalities and corresponding feedback rendering configurations (as discussed in Chapter 3.1) across the three properties despite the relative drawbacks of some of them.

Another trend to note is the decrease in significance between liquid level and the remaining two properties. This trend is observed across most of the metrics here and can be explained by the simpler binary distinction to be made for the liquid level detection compared to the more involved multi-level distinctions to be drawn in the other two properties. Defining properties and category distinctions that would best suit the target tasks can therefore be identified as an important aspect when using this method to develop a multimodal feedback interface.

Change Response

In Figure 5.6 we observe that where the haptic and vibration modalities provide better perception of change, especially relative to the audio feedback, and in the case of weight, also visual feedback. Since audio speech cues did not provide a method to draw distinctions within categories compared to the linearly scaled vibration and haptic feedback, this result captures when samples provided were in the same category in consecutive trials. Because this is a relatively low occurrence for randomized samples, it may be necessary to increase the number of trials or to perform an experiment with fixed samples to observe this trade-off with better significance. However, the low occurrence with randomization can be taken to represent the frequency of occurrence in real-life situations. Therefore, the lack of significance can be treated as capturing the importance of this metric.

Additionally, the same decreasing significance trend between liquid level and the remaining two properties is observed as in the previous section and can be explained again by the property level differences.

DRT Measures

Looking at Figure 5.7, the DRT results show that hit rate was lower for the visual modality compared to audio across all properties with higher corresponding reaction times, as well as compared to vibration and haptic in liquid level and weight indicating higher attentional load. In temperature, the combination of lowest hit rate and highest reaction time for the thermal feedback indicated it to be the highest load modality. Overall, audio feedback is seen to impose the lowest load for the robot-assisted pouring task. This aligns with the expected visual attentional load trade-off despite easier perception in the visual modality. Further, its better performance relative to the tactile, haptic, and thermal modalities may have been due to kinesthetic involvement in controlling the joystick. In the case of the haptic feedback, which was rendered through the joystick, there may have been an added distraction to the *control* aspect rather than the visual attention aspect that may have been captured in these results. This would also be a relevant factor to be incorporated for a robot-assisted task with given control and input modalities.

While the significances of the DRT hit rate and mean reaction times are different, it should be noted that the reaction time is computed only from hits while hit rate is a measure relative to the total of hits and misses. Improved significances may be observed for reaction time with a higher number of subjects. Despite this lack of significance, it is important to observe that the hit rate load increases are corroborated by the reaction time results without contradictions (i.e. lower hit rate and lower reaction time together) and can therefore be safely relied on to represent cognitive load.

Additionally, once again the lower significance of liquid level relative to the remaining two properties is observed as in previous metrics. Since liquid level is only a binary property, lower cognitive demands are likely required.

<u>Subjective Preference</u>

The subjective preference score metric is by far the most distinct measure between modalities. While the preference scores indicate that the visual modality was preferred consistently across all modalities, it is interesting to observe that for the remaining modalities, preferences vary depending on the property. The visual modality preference can be explained by our natural affinity for processing visual information, the ease of understanding text and color representations, as well as attributes such as low memory and effort requirements to retain the different category levels. These may have been factored into the subjective preference indications by participants. While the audio feedback can have similar advantages, one repeated comment during experiments was that the repetitive vocalization of the category was irritating. Thus, for liquid level it may have been viewed as an unnecessary inconvenience compared to the visual and vibration modalities while for the other properties the ease of understanding exceeded its irritation. Between the vibration and haptic properties, in liquid level the higher preference for vibration may indicate that the control distraction imposed by the haptic device was less desirable, while in weight, the direct modality-matched feedback of weight was more intuitive than learning an association to vibration. The low preference score for thermal feedback, although modality-matched, may have resulted from confusions arising from perceiving temperature changes from one trial to the next and from initial to target temperature, as well as learning the association between skin temperature perception and oral temperature perception, which for some of the mid categories may have been counter-intuitive.

Overall, the subjective preference metric can be seen to have captured a number of different factors that would be useful to consider, and also presents the most variation between modalities.

5.2.6 **Metric Weighting and Filtering**

Metric weights were generated through a subjective pairwise comparison (detailed in section 3.2.3) completed by the nine participants after robot training and before the experiments. The resulting weights (summing to 1) for all the metrics are displayed in Figure 5.9. Here, 'attention' represents the importance of their visual attention on the control task and is intended to isolate only DRT hit rate while 'overall demand' captures DRT reaction time.

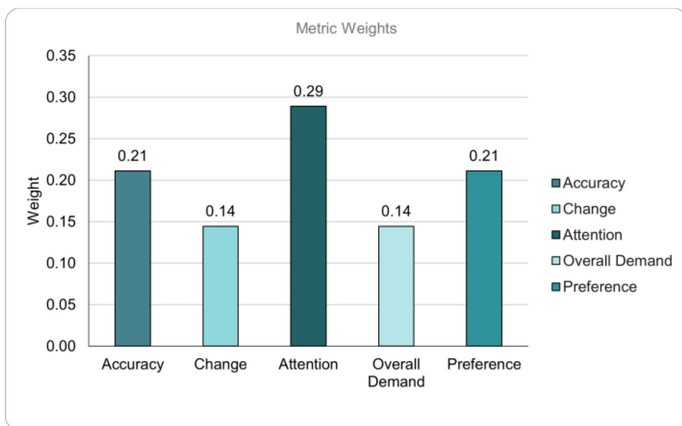

Figure 5.9: Weights for all metrics

However, since some metrics were found to not be significant in the screening experiment results, a second set of weights were generated with those metrics filtered out. The weights were adjusted to include only the significant metrics (summing to 1) and are represented in Figure 5.10 below.

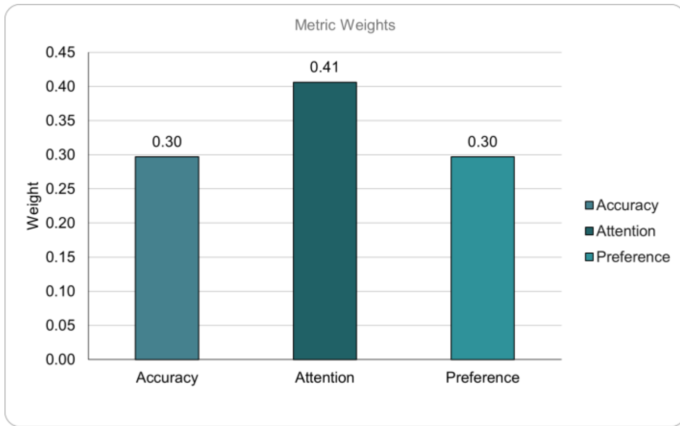

Figure 5.10: Adjusted weights for significant metrics

An interesting observation to note here is that the weights that were removed were not only the metrics that were insignificant in the experiments, but also the metrics that were perceived to be least important and weighted the lowest in the subjective weighting. Since the weighting was completed prior to the introduction of the feedback interface, the experiments, and the perception tasks, the responses were not biased by knowledge of what was measured during the experiment. The significance results and the metric weighting results were thus mutually supportive of their relevance and provide further validation of the process.

5.3 Assignment Solution

The final step in the solution strategy is to define a cost function, generate a cost matrix, and solve for the final solution using the linear assignment problem solution algorithm.

5.3.1 **Cost function**

Since some metrics were found to be insignificant and two sets of weights were found, cost matrices were generated for two cases, both with and without the insignificant metrics. Equation 5.1 defines the cost function for significant metrics only to be:

$$C_{ij} = w_1(1 - Acc) + w_3(1 - HR) + w_5(1 - Pref) \qquad (5.1)$$

Where Acc, HR, and $Pref$ are the means of perception accuracy, hit rate, and preference score respectively, and $1 - Acc$, $1 - HR$, and $1 - Pref$ translate to error, miss rate, and disfavor of the modality, all of which would increase the cost.

For the case with all the metrics, this equation would be modified to be:

$$C_{ij} = w_1(1 - Acc) + w_2(1 - Ch) + w_3(1 - HR) + w_4(RT) + w_5(1 - Pref) \qquad (5.2)$$

Where Ch and RT are change response accuracy and DRT reaction time respectively and $1 - Ch$ is the change response error. w_k represents each respective weight identified in section 5.2.5. Computing costs in this manner yield the cost matrices corresponding to Equation 5.1 and Equation 5.2 respectively. These cost matrices are shown in Figure 5.11 below.

	Liquid	ight	Temperature	C34	C35
Visual	0.25497	0.23603	0.17226	Inf	Inf
Audio	0.29607	0.20545	0.17627	Inf	Inf
Vibration	0.25678	0.42775	0.38514	Inf	Inf
Haptic	0.47599	0.37125	Inf	Inf	Inf
Thermal	Inf	Inf	0.47091	Inf	Inf

	Liquid Level	Weight	Temperature	C4	C5
Visual	0.2585	0.24447	0.23769	Inf	Inf
Audio	0.29309	0.23056	0.25687	Inf	Inf
Vibration	0.26341	0.36008	0.39188	Inf	Inf
Haptic	0.42702	0.3185	Inf	Inf	Inf
Thermal	Inf	Inf	0.48085	Inf	Inf

Figure 5.11: Cost matrices for significant metrics only (top) and all metrics (bottom).

5.3.2 **Mapping Solution**

Using the algorithm described in Chapter 3, minimum cost solutions were generated from both matrices. Both versions generated the same mapping solution illustrated in the bipartite graph in Figure 5.12 below. This outcome makes sense since the weights were lower for the metrics that were insignificant and contributed least to the cost even in the version that used all the metrics.

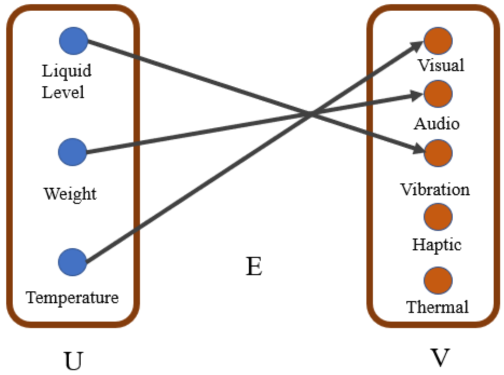

Figure 5.12: Bi-partite graph for solution mapping assignment

It is interesting to note that in this outcome, both modality matched feedback assignments (weight to haptic and temperature to thermal) were outperformed by the audio and visual modalities respectively.

5.4 Validation Experiment Results and Discussion

This section discusses the results of the validation experiment to evaluate the performance of the optimal solution against a control treatment of no feedback and an arbitrary design. First, the results comparing the optimal solution vs. the control strategies (12 subjects) are presented. These are followed by the results comparing the optimal solution with both the arbitrary design and the control (7 subjects). Means of response variables and One-way ANOVA for a linear mixed model and Tukey test results (α=0.05) are presented for each use case and implications are discussed in this section.

5.4.1 **Solution vs. Control**

The results comparing the solution mapping to the control experiments from the three use cases (the temperature decision task, empty vessel identification, and tilt angle estimation) are provided in Figure 5.13 below.

From the means it can be observed that results are as expected across all the test cases with the solution performing consistently better with higher success rate, lower response times, and lower mental demand. ANOVA results are presented case by case below.

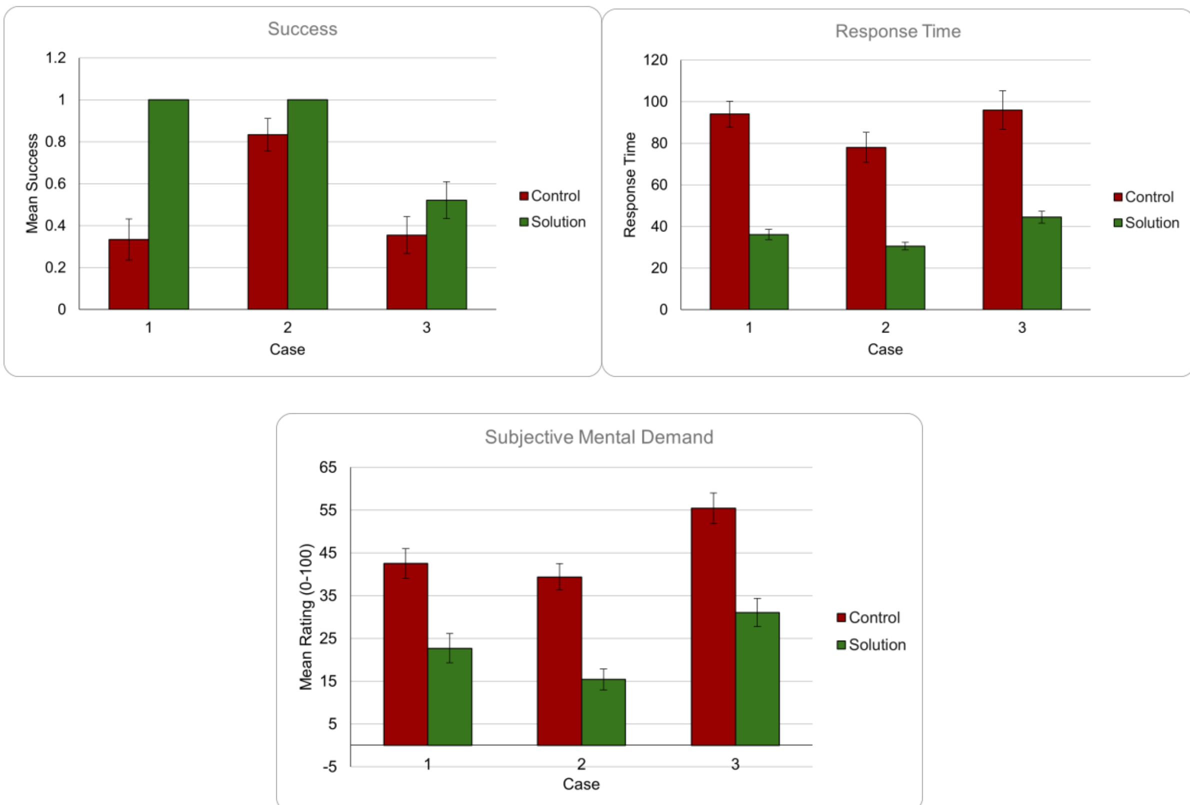

Figure 5.13: Solution vs control means for success (top left), response time (top right), and subjective mental demand (bottom). Error bars represent standard error.

Case 01 (Temperature): Results from all three response variables are observed to be highly significant with $F=56.87$, $p<0.0001$ for success, $F=96.44$, $p<0.0001$ for response time, and $F=33.32$, $p<0.0001$ for mental demand. These results indicate that the feedback interface performed much better than the control strategies by providing significantly more reliable information to inform the decision, significantly reducing the time taken to execute the task, and offering a significant reduction on the cognitive demand of the task. Further, a secondary analysis on success of only initial temperature perception (i.e. wait time-related failures excluded), the difference was still significant with $F=6.54$, $p=0.0159$. This helps refute any concern that the significance may have been affected by subjects simply growing impatient during the waiting period.

Case 02 (Empty vessel): Significant differences are observed across all three variables once again for the second use case with $F=4.52$, $p=0.0419$ for success, $F=45.62$, $p<0.0001$ for response time, and $F=110.83$, $p<0.0001$ for mental demand. The feedback interface is seen to have performed much better than the control strategies in feedback delivery, task time, and cognitive demand in this use case.

Case 03 (Tilt angle): Results are observed to be highly significant for response time $F=41.42$, $p<0.0001$ and mental demand $F=116.82$, $p<0.0001$, indicating that the feedback interface was successful in reducing task time and cognitive effort associated with this task. Despite the difference observed in Figure 5.13, however, success is not statistically significant with $F=1.63$, $p=0.2116$. This is likely due to the more complex nature of the task relative to the other use cases, on which the impact of the feedback interface may be more subtle. Testing this case with more subjects may produce significant results. However, considering all three variables overall, we can conclude that the solution feedback is a better option for this use case as well compared to the control.

5.4.2 **Solution vs. Arbitrary Mapping and Control**

Figure 5.14 illustrates the results comparing the solution mapping to an arbitrary mapping and the control in each of the three cases in this experiment. These results help determine whether the solution mapping was better than providing any arbitrary mapping of feedback.

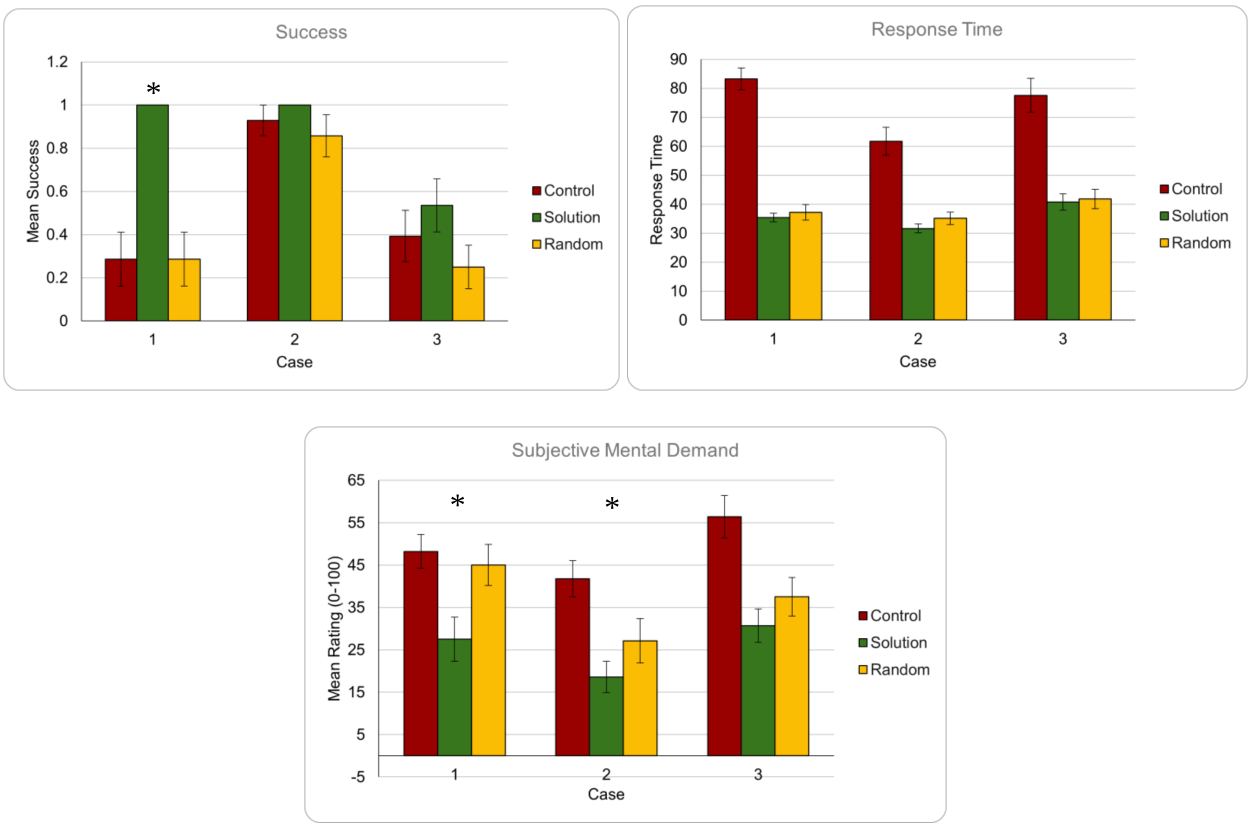

Figure 5.14: Solution vs arbitrary and control means for success (top left), response time (top right), and subjective mental demand (bottom). Error bars represent standard error. * indicates optimal solution significantly different from arbitrary design.

Overall, consistent patterns are observed across the use cases, reflecting reliable experimental design and conditions and consequently reliable results. Results from One-Way ANOVA and post-hoc Tukey tests are presented case by case below.

Case 01 (Temperature): Results from all three response variables are observed to be highly significant with $F=18.42$, $p<0.0001$ for success, $F=124.08$, $p<0.0001$ for response time, and

F=8.13, p=0.0018 for mental demand. Post-hoc Tukey tests indicated that the differences in success were significant between the solution and control and the solution and arbitrary treatments, indicating that the solution is capable of significantly better feedback delivery than both the arbitrary mapping and control. For response time there was no significant difference detected between the solution and arbitrary mapping as predicted upon observation of means. For subjective load the Tukey tests detected significant differences between the solution and control and the solution and arbitrary treatments, indicating that the solution significantly reduced cognitive load relative to the arbitrary mapping in addition to the control. Overall, considering all variables, these results indicate that the solution mapping performs better than the control for this use case.

Case 02 (Empty vessel): Significant differences are observed with *F=26.68, p<0.0001* for response time, and *F=22.98, p<0.0001* for mental demand, while the observed differences are found to be insignificant for success with *F=1.6, p=0.2202*. Given that the significance observed for solution vs control with twelve subjects in the previous analysis is not observed here, a significant difference may be detected with the arbitrary mapping if a larger number of subjects were used to test this case. Tukey tests revealed that for response time there was no significant difference detected between the solution and arbitrary mapping similar to the previous case. For subjective load the Tukey tests detected significant differences between the solution and both the control and arbitrary treatments, indicating that the solution significantly reduced cognitive load relative to the arbitrary mapping as well as the control.

Case 03 (Tilt angle): Results are observed to be significant for response time *F=33.76, p<0.0001* and mental demand *F=15.86, p<0.0001*, while success is not statistically significant with *F=0.5, p=0.6096*. This is not surprising following insignificant results from the previous analysis and can be interpreted in the same way. Testing this case with more subjects may produce significant results. Similar to the previous cases, Tukey tests did not detect significant differences between the solution and arbitrary mapping for response time, although both treatments were significantly better than the control. The same was true for subjective mental load despite the differences in means observed in the graph. While none of the variables could differentiate between the arbitrary mapping and the solution in this use case, means indicate that the solution has an overall advantage in success and mental load.

5.4.3 Discussion

In this set of experiments, we evaluated the solution mapping against a control treatment with alternative strategies and no feedback, and a third treatment with an arbitrary design. The treatments were tested with three use cases where subjects performed decision making tasks including assessing temperature, detecting an empty vessel, and estimating initial tilt angle. Task success, response time, and subjective mental demand ratings were assessed to evaluate the generated solution.

Considering the first set of results (solution vs. control in Figure 5.13) we can conclude that the optimal solution is significantly more effective than the control treatment. This was true for all three metrics in the first and second use cases, and response time and subjective demand metrics in the tilt angle use case. The insignificance observed for tilt angle success may be attributed to the complexity of that task and may perhaps be observed more distinctly with a larger sample size. Overall, higher success rates, lower reaction times, and lower subjective load results demonstrated a clear and significant benefit from the presence of the feedback interface to aid in these tasks.

To determine whether the optimization approach yielded a near optimal solution, we compared the solution against an arbitrary design (Figure 5.14). Based on these means, the overall results observed were as expected across all the test cases with the solution performing with higher success rate and lower mental demand compared to the arbitrary mapping. While the arbitrary mapping was seen to improve response time and mental demand relative to the control, it performed as badly or worse than the control in task success. This is arguably the most important performance metric for the interface because it reflects effective delivery of feedback and indicates that the optimization approach guarded against highly unreliable solutions. This observation underscores the value of the optimization approach used to produce the solution mapping.

Despite these promising observations in the means, only three of the comparisons (success for temperature task, subjective demand for temperature task, subjective demand for empty vessel task) resulted in statistical significance in the differences. In all these comparisons that were significant, the optimal solution performed better than the arbitrary solution. In the remaining comparisons, the optimal solution performed better in means. This indicates that it had a considerable overall advantage over the arbitrary solution.

In order to further investigate those results that were statistically insignificant, we considered the costs generated for each of these mappings from the first set of screening experiments in the interpretation of these results. The total cost for the optimal solution was computed to be 0.634 while that of the arbitrary mapping was 1.011. However, there were a number of mappings that will result in even higher costs, the highest of which is 1.375 (mapping liquid level-haptic, weight-vibration, temperature-thermal). The difference between this worst mapping and the optimal (0.741) is almost double the difference of cost between the arbitrary solution (0.377) and the optimal. Therefore, we can expect the optimal solution to perform even better against a worse mapping and are likely to see increasing significance of results as the mapping cost increases. We can thus infer from these results that an effective solution has been generated from the optimization strategy, and that it has effectively guarded against unreliable solutions that, as observed, may perform even worse than no feedback. Thus, we prove both of our hypotheses to be true by concluding that (1) we were able to generate an effective mapping using the proposed approach and (2) the solution we produced has higher efficacy and provides a better user experience compared to no feedback and compared to an arbitrary design.

Through closer inspection of the trends observed in these results, we can draw further inferences beyond the main investigations of this project. In Figure 5.13 we see that while the differences between the control and solution are similar for response time and mental demand across the use cases, the differences vary in success accuracy. This may be attributed to the varying alternative strategy variations between the cases, i.e., the perception of hollowness may have been a better predictor of amount of liquid than touching the surface of the vessel was for temperature. In Figure 5.14 we observed that for response time, there was no significant difference between the solution and arbitrary mappings (although the response time was very slightly but consistently higher for the arbitrary treatment across the cases). This was not surprising because response time was mainly affected by the alternative strategies required to gain the same information in the absence of feedback. Thus, it may be that simply providing the feedback, regardless of the specific modality, improves task execution time.

The results reported above are for only three of many possible use cases that could be constructed for this feedback. The solution feedback was determined to perform distinctly better than the control strategies based on the first analysis. Considering the complete set of results from the second analysis, the solution mapping was observed to have an advantage over the arbitrary mapping as evident in two of the three use cases and the trends in means. This visible advantage supports the use of the optimization approach in producing a sensory feedback interface. Further evaluation with more use cases, more elaborate versions of these use cases, and/or more subjects may also solidify these findings further.

6. CONCLUSIONS AND FUTURE WORK

In this thesis, an optimization approach is taken to develop a multimodal sensory feedback interface for robot-assisted tasks. Feedback perception accuracy, cognitive load, and subjective preference measures are selected as optimization metrics to produce a solution that balances effective feedback delivery with added attentional load requirements to those of controlling a robot. A robot-assisted pouring task is chosen as the functional task to be investigated. Three selected properties, temperature, weight, and liquid level are configured to be conveyed through five available sensory feedback modalities including visual, audio, haptic, vibration, and thermal. A set of screening experiments are conducted to quantify the selected metrics. A subjective pairwise comparisons test is used to produce weighting coefficients for each of the metrics. The optimization problem is formulated and solved as a linear assignment problem to generate the minimum cost property-to-modality assignment mapping. In a set of validation experiments with three selected use cases, the solution mapping is evaluated against a control treatment with alternative strategies and no feedback, and a third treatment with a randomly mapped solution. Task success, response time, and subjective mental demand ratings are analyzed the evaluate the generated solution. Overall results indicate that the solution is significantly more effective than the control treatment and has considerable advantage over the arbitrary mapping solution. The proposed approach can therefore be concluded to have produced an effective solution for delivering feedback for robot-assisted tasks.

This approach addresses the contradicting requirements of providing effective sensory feedback to bridge the disconnection between the user and the task environment and minimizing the compounded cognitive load on robot operation which is by itself an attention-demanding function. It produces a solution that delivers information effectively, reduces the time taken to execute the task and improves user satisfaction and perceived mental effort. Bridging the multi-sensory feedback gap can expand the scope of robot-assisted tasks, increasing efficiency of the functions and processes that they are a part of, and advancing the utility of robots in the field and/or in the lives of users. Additionally, the ability to provide information through multiple modalities effectively can open doors to studying the provision of additional information that is not generally available to the human, in order to enhance the task execution experience and improve task outcomes and efficiency further.

6.1 Considerations for Future Work

The work detailed in this thesis shows promise for further investigations both to refine these findings and branch out in different directions. This section introduces possible directions in which this research can be expanded going forward, and experimental improvements that may further refine the results of this work.

6.1.1 Formulating with Other Combinatorial Assignment Problems

While the linear assignment approach used in this thesis proved to be an effective model for formulating problems, other approaches can be taken to formulate and solve for minimum cost assignments with varying degrees of complexity. One way to reformulate this problem is to apply other combinatorial optimization problems such as the weapon target assignment problem [166] and the quadratic assignment problem [167].

Reformulating as the weapon target assignment problem removes the condition that one property (weapon) can only be mapped to one modality (target), opening the problem to possibilities of mapping multiple properties to a single modality. This may lead to a more comprehensive investigation and could be especially useful if the number of properties desired to be conveyed exceeds the number of available modalities. One factor to consider with this approach is the potential for sensory overload through one modality, which should be quantified and incorporated in the cost function.

The quadratic assignment problem is defined to map a set of facilities to a set of locations, given the distances between locations and the flow between facilities. Redefining our problem as a quadratic assignment problem would map the properties (facilities) to modalities (locations), taking into account any relationships between the properties (flow) and relationships between the modalities (distances). This may allow taking into consideration factors such as physiological interactions between sensory receptors involved, quantitative and physical relationships between properties (if any), and the characterization of cognitive load interactions between modalities. While this approach may require pre-screening experiments to characterize these relationships, it may lead to a more accurate model from which to generate a solution.

6.1.2 **Alternative Methods for Metric Weighting**

For metric weighting this work used a subjective pairwise comparison weighting method known as the Analytic Hierarchy Process (AHP). Other subjective or objective methods for generating the metric weights can be investigated and compared to identify if other methods may lead to different or improved outcomes. Weighting procedures can be developed to employ statistical methods such as correlation analysis or principal component analysis [163]. However, this must be considered carefully especially if social indices are involved since if any control over the weighting procedure is removed from the analysis, it may result in an illusion of mathematical objectivity that is practically difficult to achieve [163]. A subjective approach known as Conjoint Analysis (CA) is a multi-attribute approach similar to AHP that works in the opposite direction by disaggregating preferences [163]. Studying both approaches side by side to ensure mutual agreement could further validate the resulting weights. Scaling methods such as the Unfolding Approach [163] where individual rankings are used to determine a common joint ranking scale may also be adopted to provide weightings. Empirical studies to establish whether one method may be better than another will contribute to refining this approach further.

6.1.3 Considerations for Future Experiments

Improvements to the experiments can also improve the reliability of the resulting solution and evaluation. In the screening experiments, designing the experiments to include effects of dynamic changes of the properties during a trial could provide a better estimation of the metrics for situations where properties may change dynamically and quickly. Further, integrating task complexity variations such as depth positioning challenges (demonstrated in Chapter 3) or pouring from different types of vessels with different grip configurations (bowls, bottles, jugs) can capture effects of varying challenge levels compounding the feedback perception. Expanding these experiments may also involve introducing additional or alternative metrics such as supplementing the DRT load data with subjective ratings and comparing results. Expansions specific to the pouring task discussed in this thesis can include the incorporation of liquids with different viscosities and other similar properties that could affect weight, pouring rate, and how the temperature affects the liquid. These considerations can lead to richer data sets and improve the accuracy of the solution generated. However, integrating these factors should be done systematically to avoid confounding of variables.

For the validation experiments, evaluating the resulting solution with more use cases can improve the reliability of the results. These use cases should be constructed to target one or more of the available properties and effectively capture the distinctions between treatments. Further, the use cases identified in this thesis could be expanded to include more sample variations (beyond the two levels used here) to ensure generalizability. The validation experiments can also be expanded to include more sub-optimal mappings so that the utility of the optimization approach can be verified further. Evaluating the interface with targeted user groups in application-specific tasks may also provide insights into how domain knowledge and experience influence the utility of the provided feedback.

6.1.4 Considerations for Expanding the Feedback Interface

One clear direction for expansion is simply expanding the number of properties and modalities included in the interface and the assignment problem. This may include additional properties within the focus task (such as viscosity for the pouring task) or properties that are added as a result of expanding the pool of focus tasks. Considerations in expanding the number of available modalities can involve not only using other distinct sensory modalities such as smell and taste, but also leveraging multiple degrees of freedom of a single modality to generate sub-modalities. For example, the audio modality can deliver combined speech, pitch, and volume modulated cues and the haptic modality can provide force outputs in multiple directions while the vibration modality can deliver modulations in frequency and amplitude. Physical locations for providing the sensory feedback can also be leveraged if skin is the sensory organ of interest. The effect of such combinations on property perception should be taken into account if pursuing this direction.

If the number of properties and modalities expand into a large matrix that is experimentally intensive, solution algorithms used to solve sparse matrices can be used to find a solution with only some of the matrix costs computed. The sparse algorithm in [168] is one example of how this may be solved as a linear assignment problem. Another approach is presented in [169] where a neural network architecture and solution algorithm are proposed to solving a sparse matrix problem.

6.1.5 **Considerations for Human-Robot Interaction**

The methodology used in this thesis may be extended to multimodal sensory feedback provision in the general human-robot interaction space. This may include multimodal feedback provided in human-robot collaboration environments [170] or for studies of effective communication or associated distractions with social robots [171] as well as in teleoperated control studies [172].

In addition to providing a methodology for developing multimodal sensory feedback interfaces for robot operation tasks, the preliminary work presented in this thesis also established a basis for the utility of the Detection Response Task for visual attentional load measures in robot operation. The use of the DRT can therefore be expanded to be included in robot interaction studies that do not involve sensory feedback but are evaluating attention challenges in robot control such as in the preliminary experiment detailed in Chapter 2 of this thesis, or to identify and quantify distractions in collaborative environments. For example, the DRT can be extended to studies such as [173] which focuses on optimizing learning by minimizing distraction in human-robot interaction tasks and [174] where operator attention during multi-robot control is investigated.

6.1.6 **Multimodal Feedback for Other Applications**

In addition to developing multimodal feedback interfaces for robot control applications, this methodology can be extended to optimizing the provision of multimodal feedback in other similar visual-manual tasks. One such task where the use of the DRT is already established in driving [95]. As vehicles evolve to integrate technological features such as navigation and media, it is necessary to identify solutions to providing this additional information effectively without compromising the task and putting the driver in danger. This can also be extended to studies of external sensory cues targeted at drivers, such as car horns, sirens, and road signs.

This methodology may also be extended to human-computer interaction technologies that usually require some form of manual input such as keyboard or mouse clicks and sensory feedback through tactile, visual, and audio interfaces in applications such as education and gaming. Specifically, this methodology may best transfer to the simulation gaming domain including technologies such as the Nintendo Wii [175] and other virtual or augmented reality applications that involve manual tasks such as training simulators for operating tooling machines [176], performing telepresent assembly tasks [134], practicing or performing remotely assisted surgical procedures [177] [178], or undergoing rehabilitation therapy [177].

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APPENDIX A. SURVEY

This appendix includes the survey and responses report that acted as a basis for the properties selected for the interface. Appendix A1 consists of the survey questions presented to participants through a Qualtrics survey while appendix A2 presents a report of the responses to the survey. Purdue Internal Review Board (IRB) approval for the survey was obtained for the survey under number IRB-2020-1563.

A1: SURVEY

Assistive Robot Interface: Predevelopment Survey

Thank you for participating in this study. Please answer all questions to the best of your ability. The first three questions of this survey are intended to capturebackground information relevant to the study.

If you do not have a physical disability that significantly restricts your ability to navigate general daily activities such as eating, drinking, preparing meals, etc. without help, please respond N/A to the following questions.

Do you have any physical disabilities linked to the following conditions? (Please select)

0 Spinal cord injury (SCI)

0 Multiple Sclerosis (MS)

0 Traumatic Brain Injury (TBI)

0 Stroke

0 Other [Please Specify]

N/A

Do you currently use any assistive devices to aid your daily life activities?

0 Yes (Please Specify)

0 No

0 N/A

Which age category do you belong to?

0 18-20

0 20-35

0 35-50

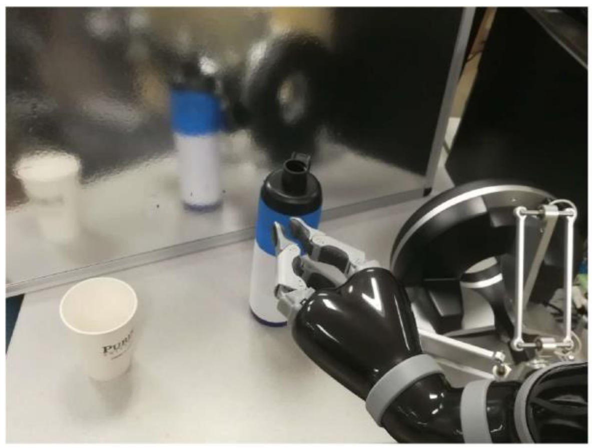
0 50-70

0 >70

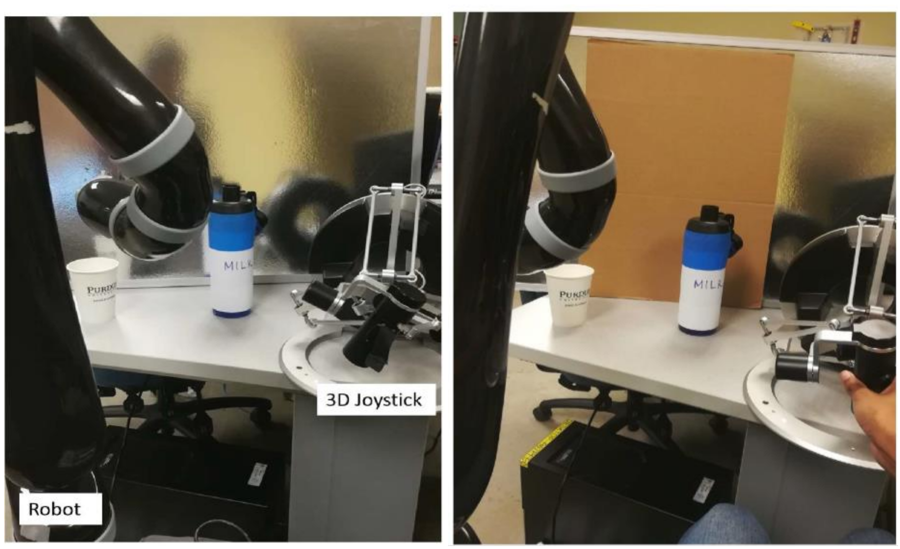
The remainder of this survey is conducted in a thought experiment format. Visual aids will be provided to aid questioninterpretation. Please answer to the best of your ability with thegiven information.

You are seated on a wheelchair, controlling a robotic arm via a 3D joystick (see images below). You have visual access to the workspace of the arm as seen from your chair, however, your movements on the chair are constrained: you are not able to lean forward,or move the other arm that is not controlling the joystick.

Aerial view:



Your view:



In the image on the right, the hand is placed on the 30 joystickthat controls the robot.

There is an opaque plastic bottle labeled 'milk' and a cup of hot coffee on the table infront of you. You have interacted with both vessels many times before.

You would like to drink some coffee, so you use the robotic arm to pick up the bottle.

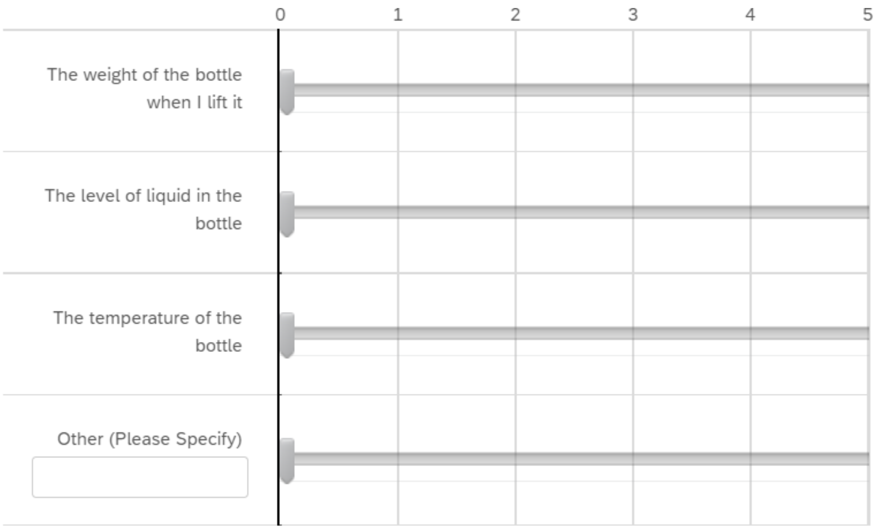
What should you do next?

0 The bottle is empty, I should put it back on the table, refill it, orthrow it in the trash.

0 The bottle holds liquid, I should proceed with the task.

0 I would like to have more information about the bottle before Iproceed.

Please rank how important the following additional information would be to help you make this decision. 0 represents not at all important, 5 represents extremely important.



If you think a combination of information would be more helpful than one type, pleaseselect which ones you would prefer a combination of.

- ☐ The weight of the bottle when I lift it
- ☐ The level of liquid in the bottle
- ☐ The temperature of the bottle
- ☐ Other: [Please specify]
- ☐ N/A

Since you don't have access to any additional information, how would you navigate this situation?

0 I did not pick "need more information"

0 I would just carry out the task as well as I can

0 I would work around it by: [Please describe your strategy briefly]

You were just informed that the bottle is not empty. Using the robotic arm, you carry the bottle carefully over to the cup. The task ahead of you is to pour milk into the cup withoutspilling. Your view of the cup and the robot is from your chair, as shown below.

First, you position the robot. How confident are you that you would not spill milk?

0 Extremely confident

0 Somewhat confident, and I think that's enough

0 Somewhat confident, but I would like to be more confident

0 Not very confident

I
f you answered (c) or (d), would access to an aerial view (shown below) help increaseyour confidence?

0 Yes, that would help a lot

0 Yes, that would help a little

0 Yes, that would help a little, but something else would help more[Please specify]

0 That wouldn't be very helpful, but something else would [Pleasespecify]

0 That wouldn't be very helpful but I can't think of something thatwould

Now that you are positioned over the cup to the best of your ability, you tilt the uprightbottle,

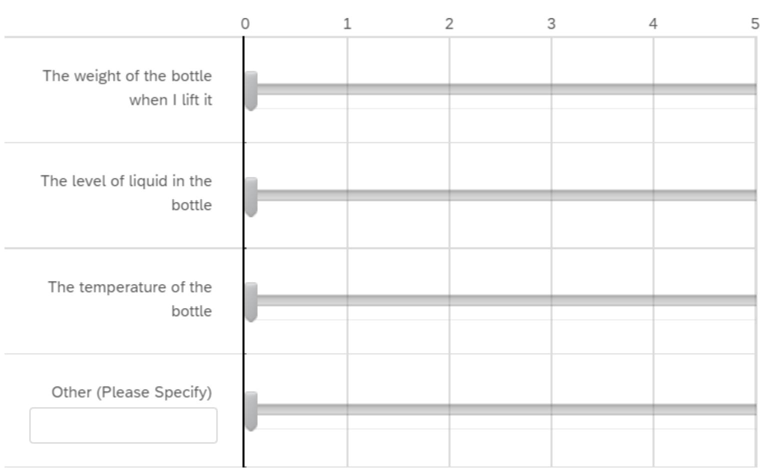
0 A little because it's almost full

0 About 90 degrees because it's half full

0 More than 90 degrees because it's less than a quarter full

0 I need more information

Please rank how important the following additional information would be to help you make this decision. 0 represents not at all important, 5 represents extremely important.



If you think a combination of information would be more helpful than one type, please you would prefer a combination of.

0 The weight of the bottle when I lift it

0 The level of liquid in the bottle

0 The temperature of the bottle

0 Other: [Please specify]

0 N/A

Since you don't have access to any additional information, how would you navigate this situation?

0 I did not pick "need more information"

0 I would just carry out the task as well as I can

0 I would work around it by: [Please describe your strategy briefly]

You tilt the bottle and pour some milk into the cup anyway. Then you place the bottleback on the table, stir the coffee, and pick up the cup using the robotic arm.

What will you do next?

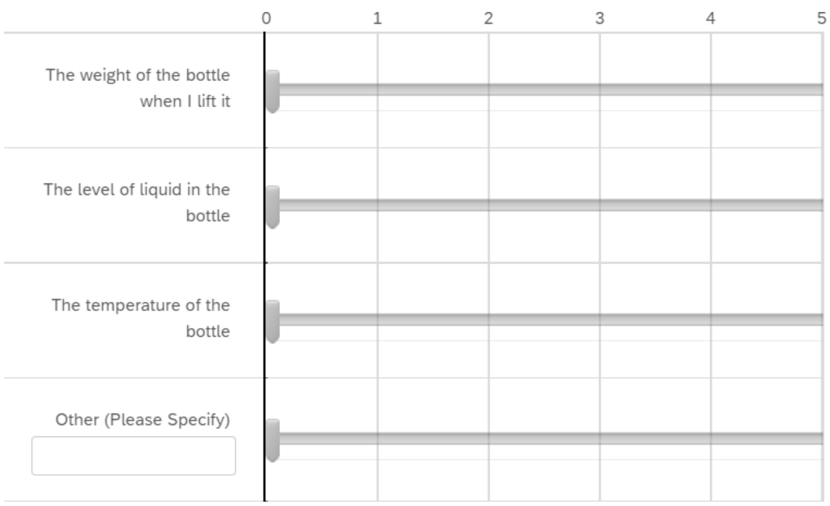
0 This coffee is too hot, I should let it cool down

0 I should drink the coffee

0 The milk has made the coffee too cold, I should heat it up or addmore hot coffee

0 I need more information

Please rank how important the following additional information would be to help you make this decision. 0 represents not at all important, 5 represents extremely important.



If you think a combination of information would be more helpful than one type, please select which ones you would prefer a combination of.

0 The weight of the bottle when I lift it

0 The level of liquid in the bottle

0 The temperature of the bottle

0 Other: [Please specify]

0 N/A

Since you don't have access to any additional information, how would you navigate this situation?

0 I did not pick "need more information"

0 I would just carry out the task as well as I can

0 I would work around it by: [Please describe your strategy briefly]

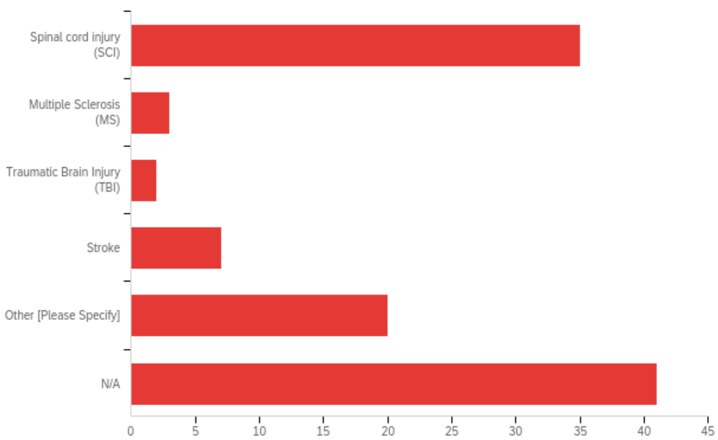
A2: SURVEY REPORT

Assistive report

Assistive Robot Interface: Predevelopment Survey

July 2nd 2021, 9:01 am MDT

Q1 - If you do not have a physical disability that significantly restricts your ability to navigate general daily activities such as eating, drinking, preparing meals, etc. without help, please respond N/A to the following questions. Do you have any physical disabilities linked to the following conditions? (Please select)



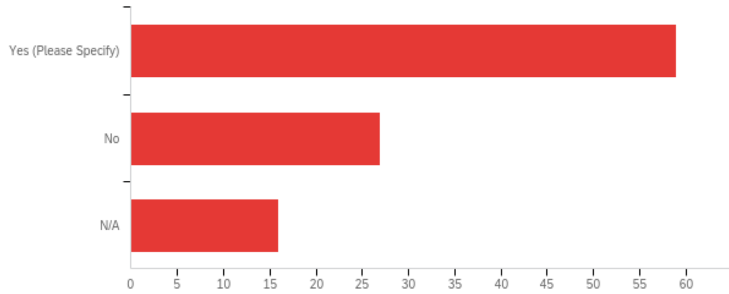
#	Answer	%	Count
1	Spinal cord injury (SCI)	32.41%	35
2	Multiple Sclerosis (MS)	2.78%	3
3	Traumatic Brain Injury (TBI)	1.85%	2
4	Stroke	6.48%	7
5	Other [Please Specify]	18.52%	20
6	N/A	37.96%	41
	Total	100%	108

Q1_5_TEXT - Other [Please Specify]

Other [Please Specify] - Text

Arthrogryposis Multiplex Congenita
nueropathy fibromyalgia
Ehlers-Danlos Syndrome, hypermobility type
Spina bifidia
Post Polio Syndrome
Spina Bifida
Muscular Dystrophy
Spina Bifida
Duchenne Muscular Dystrophy
Stroke at birth. Diagnosed with Cerebral Palsy.
Central Auditor Processing Disorder and Fibromyalgia
CP
SMA TYPE 3
Primary Lateral Sclerosis
spina bifida
chronic migraine, rheumatoid arthritis, fibromyalgia
spinal surgery that inhibits some LE movement
Beckers Muscular Dystrophy
SPINA BIFIDA
Carpel tunnel

Q2 - Do you currently use any assistive devices to aid your daily life activities?



#	Answer	%	Count
1	Yes (Please Specify)	57.84%	59
2	No	26.47%	27
3	N/A	15.69%	16
	Total	100%	102

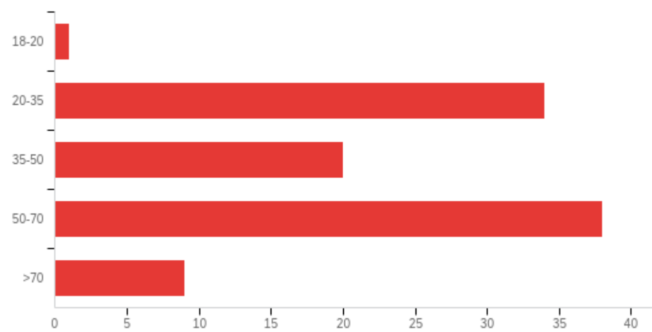
Q2_1_TEXT - Yes (Please Specify)

Yes (Please Specify) - Text
power wheelchair
Power wheelchair, shower bench, a reacher
Wheelchair
moterized wheelchair
wheelchair; scooter; crutches; cane; stool in kitchen; some assistive kitchen tech (strap wrench to open jars, fat-handled knives for chopping, dishwasher)
Wheel chair
Cane
Wheelchair
quadjoy mouse
wheelchair Tenodesis Splint
jouse
Power wheelchair and many small assistive handles and devices

4 prong cane
Wheelchair
Power & Manual Wheelchair, Hearing Aids & Glasses
Electric Wheelchair
power chair, transfer board, reachers
Forearm crutches
hearing aids
Permobil F5 power wheelchair
prosthetic, crutches, wheelchair, cane
Cane
wheelchair
Wheelchair, forearm crutches
Manual wheelchair
wheelchair
Wheelchair
power wheelchair, eye tracker, computer
power wheelchair
wheelchair
Power & manual wheelchairs, assorted reaching tools
Leg braces, canes, wheelchair
Power Wheelchair
Manual and power wheelchair, communication device
Wheelchair, Grabbers
Manual wheelchair
power wheelchairs
My tablet
wheelchair, van hand controls, slide board, magnet grab stick
Communication device and a computer

wheelchair
Manual wheelchair, 3 ft grabber
power wheelchair
Power wheelchair
Maanual wheelchair inside house, and power wheelchair otherwise.
Power chair
Wheelchair,speech recognition, utensils
Hand controls for my car and 2 prosthetic legs
Power Chair
compression gloves and socks, ear plugs, cane
quad canes, rollator, electric scooter
Power wheel chair, handicapped van, handicapped bathroom
Alexa, wheelchair, handsplint
Manual wheelchair
power wheelchair with joystick mouthstick for computer
eyeglasses

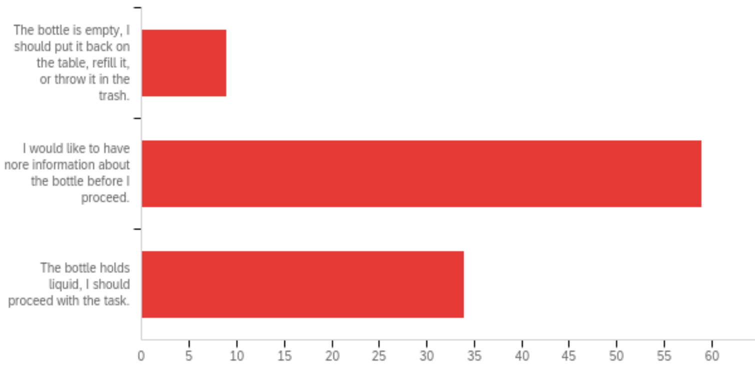
Q3 - Which age category do you belong to?



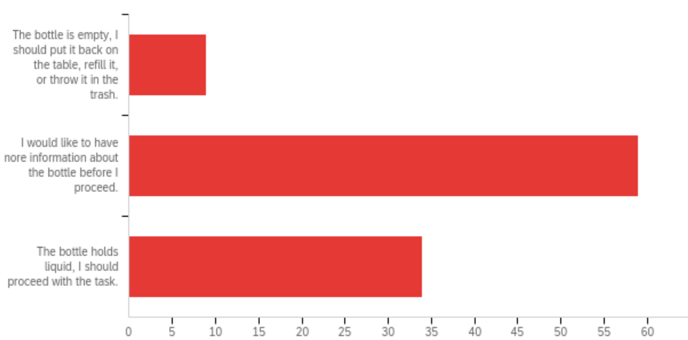
#	Answer	%	Count
1	18-20	0.98%	1
2	20-35	33.33%	34
3	35-50	19.61%	20

4	50-70	37.25%	38
5	>70	8.82%	9
	Total	100%	102

Q6 - There is an opaque plastic bottle labeled ‘milk’ and a cup of hot coffee on the table in front of you. You have interacted with both vessels many times before. You would like to drink some coffee, so you use the robotic arm to pick up the bottle. What should you do next?



#	Answer	%	Count
1	The bottle is empty, I should put it back on the table, refill it, or throw it in the trash.	8.82%	9
2	I would like to have more information about the bottle before I proceed.	57.84%	59
6	The bottle holds liquid, I should proceed with the task.	33.33%	34
	Total	100%	102



Q7 - Please rank how important the following additional information would be to help you make this decision. 0 represents not at all important, 5 represents extremely important.

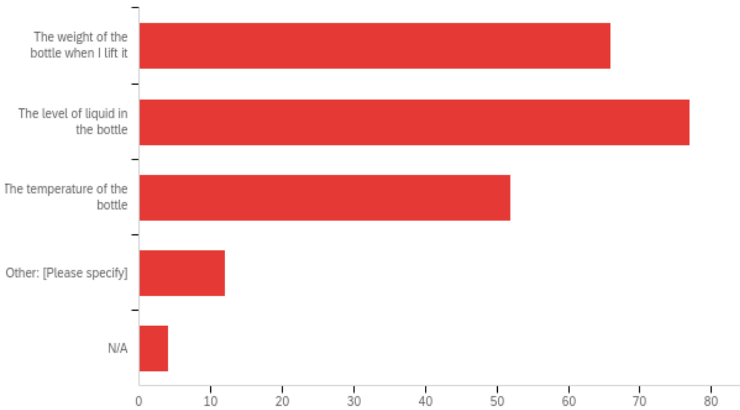
#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
1	The weight of the bottle when I lift it	0.00	5.00	3.63	1.35	1.81	90
2	The level of liquid in the bottle	0.00	5.00	3.84	1.28	1.63	98
3	The temperature of the bottle	0.00	5.00	3.33	1.56	2.43	88
4	Other (Please Specify)	0.00	5.00	2.74	2.05	4.19	19

Q7_4_TEXT - Other (Please Specify)

Other (Please Specify) - Text
whether the bottle "sloshes" i.e. obviously has liquid in it
Angles or Distance
safety and surety that the robotic arm will not spill it.
What is in the bottle?
Shape/contours and material (easy to grip or slippery)
How the bottle pours
HOW MUCH I POUR FROM IT IS IMPORTANT
weight capacity of the arm
Weight is ONLY useful if empty weight is known
Can I open it?
labeled milk. i want coffee
movement/shifting of liquid inside the bottle
Do I really know id it hold milk? Was I already told?
N/A
Confirmation it is milk and it is fresh and not off!

Colour - to check if actually coffee or milk
An ability to tilt the bottle and see the content as it is opaque
Bottle should be transparent. To identify flavor of milk
Viscosity of Liquid

Q8 - If you think a combination of information would be more helpful than one type, please select which ones you would prefer a combination of.



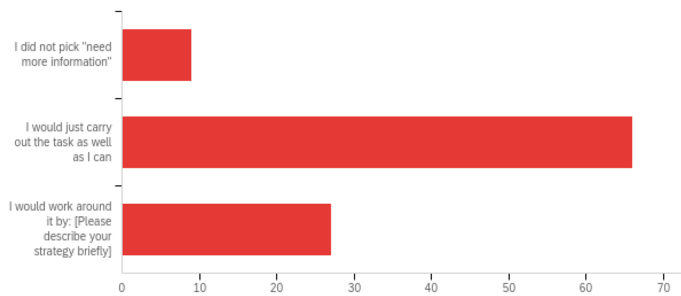
#	Answer	%	Count
1	The weight of the bottle when I lift it	31.28%	66
2	The level of liquid in the bottle	36.49%	77
3	The temperature of the bottle	24.64%	52
4	Other: [Please specify]	5.69%	12
5	N/A	1.90%	4
	Total	100%	211

Q8_4_TEXT - Other: [Please specify]

Other: [Please specify] - Text
If the milk is expired or if there is actually milk in the bottle. Checking before adding to coffee is safe.
content

Shape/contours and material (easy to grip or slippery)
POURING THE MILK AMOUNT
wt. arm can lift
the weight of the bottle - tare value of empty bottle
A good tight lid
The feeling of the liquid moving
All of the above.
What others have told me
Confirm it is drinkable milk
Colour

Q9 - Since you don't have access to any additional information, how would you navigate this situation?



#	Answer	%	Count
1	I did not pick "need more information"	8.82%	9
2	I would just carry out the task as well as I can	64.71%	66
3	I would work around it by: [Please describe your strategy briefly]	26.47%	27
	Total	100%	102

Q9_3_TEXT - I would work around it by: [Please describe your strategy briefly]

I would work around it by: [Please describe your strategy briefly] - Text

Checking the contents of the bottle by opening it and using sight, taste, and smell to decide before using the contents.

Jostle the bottle to slosh the liquid inside and estimate the amount based on the sound. If the milk is empty, or nearly so, then I would dispose of it, otherwise I would refrigerate it before moving on to the coffee task.

I would carefully give the bottle a gentle nudge with the robotic arm to try to get a sense of its weight.

I would first check what is in the milk cup first. Then check temp and weight of the coffee to see how much coffee is there. I would try and complete my task

Trying to pour milk into the cup and giving up and tossing the bottle if no milk comes out of the bottle.

Tip the bottle gently over the cup to see if there is any liquid in it

Since I have interacted with this situation before, I would carefully continue picking up the container in case it is very full.

I would attempt to pour a tiny bit onto a plate so that I can see it and gauge how full the bottle is so that I don't ruin the coffee unexpectedly.

Move my chair close to the bottle and examine it. Get a feel for the speed and flexibility of the arm and approximate what the move would look like proceed with attention and focus

I’d test things out. Not having more information would make me concerned for my physical safety though

I would drink the coffee without adding milk.

attempting to pour milk into coffee - if I get milk, great if not, bottle is empty

Confirm container is milk by visual inspection

i would start over and pick coffee

I would shake or swish bottle and listen for contents.

slowly and carefully moving the bottle upright, assuming that it is full of liquid

Bring it close and have a look how full it is and check visually and by smell that it is drinkable milk.

Trial and error. Try to pour it. If there’s nothing, throw it in the trash.

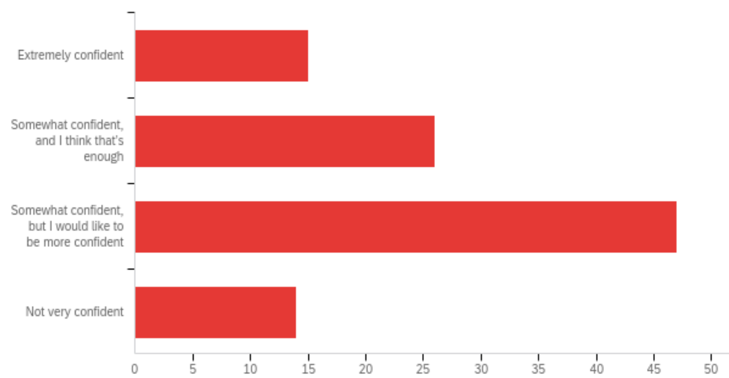
Open and tilt towards me to see inside

Trying to tilt and peek into the content of the bottle. Provided, I see some quantity of milk in it, I'll proceed with my task

If I can't see through the bottle or feel the weight, I'd like to slowly start pouring the milk into the coffee assuming it was full.

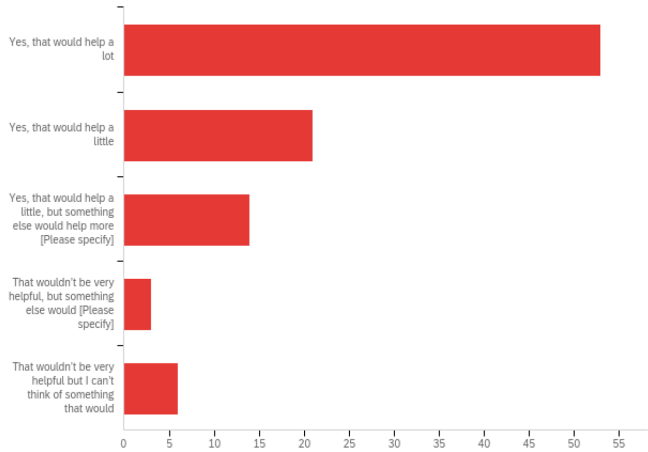
I know it's milk. I'm assuming the bottle is a flask so I know the milk will be warm. Then carry out task as usual. Or I would call for assistance
Trying with minimal force to figure out how heavy or empty the vessel is
I would carefully and very slowly start angling the bottle in anticipation of the liquid to start spilling out at every degree, until it finally does. Will try to gauge the temperature from the smoke that's released once the liquid is in the cup.
I would first assume that the bottle is near empty. This is because the heavier it is the more force you would put in the initial stage and if it was truly almost empty, you might use too much force and it flies out of your grip. After the initial minimum force, I would continue steadily increasing force until I lift it. Since I have interacted with the bottle many times I should be able to judge by the weight (proportional to the amount of force I'm using) approximately how much liquid is in it.

Q10 - You were just informed that the bottle is not empty. Using the robotic arm, you carry the bottle carefully over to the cup. The task ahead of you is to pour milk into the cup without spilling. Your view of the cup and the robot is from your chair, as shown below. First, you position the robot. How confident are you that you would not spill milk?



#	Answer	%	Count
1	Extremely confident	14.71%	15
2	Somewhat confident, and I think that's enough	25.49%	26
3	Somewhat confident, but I would like to be more confident	46.08%	47
4	Not very confident	13.73%	14
	Total	100%	102

Q11 - If you answered (c) or (d), would access to an aerial view (shown below) help increase your confidence?



#	Answer	%	Count
1	Yes, that would help a lot	54.64%	53
2	Yes, that would help a little	21.65%	21
3	Yes, that would help a little, but something else would help more [Please specify]	14.43%	14
4	That wouldn’t be very helpful, but something else would [Please specify]	3.09%	3
5	That wouldn’t be very helpful but I can’t think of something that would	6.19%	6
	Total	100%	97

Q11_3_TEXT - Yes, that would help a little, but something else would help more [Please s...

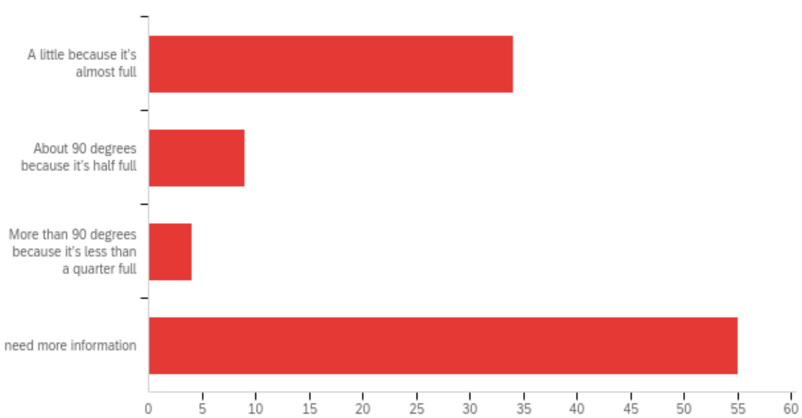
Yes, that would help a little, but something else would help more [Please specify] - Text
The level of milk is still unknown.
Close-up side view
a sturdier looking cup
Knowing how quick the rotation of the robot hand and how quickly the liquid will pour out is important to keep liquid from dribbling down the side of the bottle if the poor is too slow. If the hand rotated downward past 0° that would also help with the potential problem of spills
The level of the coffee in the cup, and thus the amount of room for milk, as well as how fast the movements of the hand are
How does that lid work. Is it getting in the way?

HOW MUCH I POUR
A spout on the bottle to direct the flow or funnel on arm that can direct the flow of liquid.
Aerial view from an angle in line with the mouth of the bottle from the side (a view line intersecting with mine at a 90 degree angle)
Laser pointer guide
I think I would lower the milk to the level of the cup.
A projectile diagram
A view from something like the edge of the handrest? Basically a view from the base of the robot but offset a little bit so that the robot arm doesn't occlude it. (Imagine a camera at the end of the arm rest of the robot arm was at the base of the armrest)

Q11_4_TEXT - That wouldn’t be very helpful, but something else would [Please specify]

That wouldn’t be very helpful, but something else would [Please specify] - Text
Since there is a cap on the bottle, opening it would be helpful
smaller container to pour from, different type of cap
Speed of the pour and about when to pull back

Q12 - Now that you are positioned over the cup to the best of your ability, you tilt the upright bottle,



#	Answer	%	Count
1	A little because it’s almost full	33.33%	34

2	About 90 degrees because it’s half full	8.82%	9
3	More than 90 degrees because it’s less than a quarter full	3.92%	4
4	I need more information	53.92%	55
	Total	100%	102

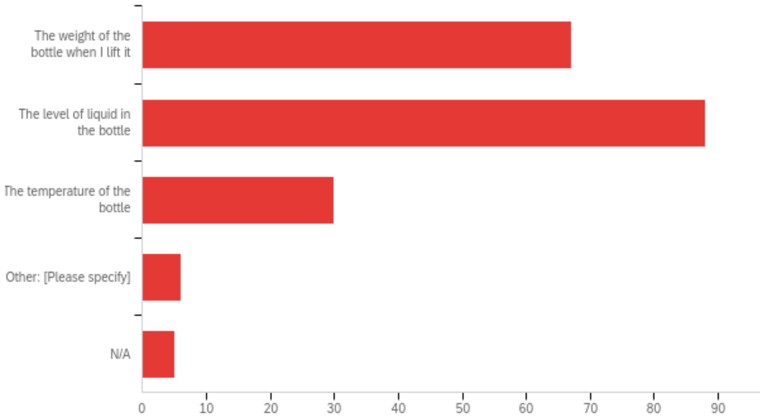
Q13 - Please rank how important the following additional information would be to help you make this decision. 0 represents not at all important, 5 represents extremely important.

#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
1	The weight of the bottle when I lift it	1.00	5.00	3.88	1.14	1.29	86
2	The level of liquid in the bottle	1.00	5.00	4.40	0.90	0.82	97
3	The temperature of the bottle	0.00	5.00	2.87	1.64	2.70	68
4	Other (Please Specify)	0.00	5.00	3.38	1.58	2.48	8

Q13_4_TEXT - Other (Please Specify)

Other (Please Specify) - Text
the weight of liquid the bottle can hold
how much the bottle "sloshes" as a way to determine liquid level
Angle or Distance
I would pour and decide amount
Robot gripping hand wrist Rotary range and speed
The speed of the movements
HOW MUCH AMOUNT OF MILK
total weight - empty weight = weight liquid

Q14 - If you think a combination of information would be more helpful than one type, please select which ones you would prefer a combination of.

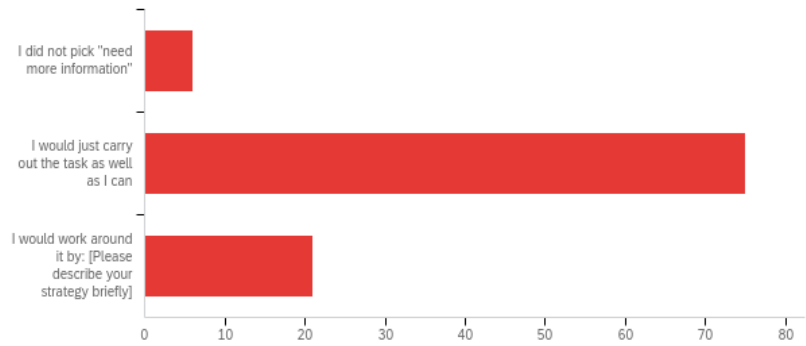


#	Answer	%	Count
1	The weight of the bottle when I lift it	34.18%	67
2	The level of liquid in the bottle	44.90%	88
3	The temperature of the bottle	15.31%	30
4	Other: [Please specify]	3.06%	6
5	N/A	2.55%	5
	Total	100%	196

Q14_4_TEXT - Other: [Please specify]

Other: [Please specify] - Text
The weight of the bottle when full
content of bottle
Robot gripping hand wrist Rotary range and speed
The speed of the movements of the hand and arm, to know how fast it will pour
AMOUNT WANTED OR REQUIRED
any method that allows determining liquid level

Q15 - Since you don’t have access to any additional information, how would you navigate this situation?



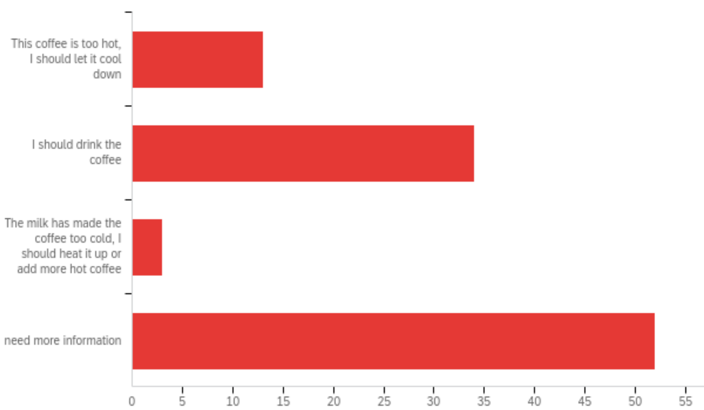
#	Answer	%	Count
1	I did not pick "need more information"	5.88%	6
2	I would just carry out the task as well as I can	73.53%	75
3	I would work around it by: [Please describe your strategy briefly]	20.59%	21
	Total	100%	102

Q15_3_TEXT - I would work around it by: [Please describe your strategy briefly]

I would work around it by: [Please describe your strategy briefly] - Text
Emptying liquid little by little, cautiously
Jostle the bottle to slosh the liquid inside and use the sound of the liquid to estimate the height of the liquid. Hold it up to a light bulb and candle it like an egg.
Lift the bottle to check the weight then slowly tilt the bottle and pour the bottle
pouring starting at a low angle and slowly increasing until milk flows
Slowly tilt the bottle till liquid begins to pour out.
I would tilt slowly to determine the level of liquid in the bottle
I would figure out how to empty the contents of the bottle
I the last picture it looks like the cap has been removed. I would carefully tip the bottle.
I would pour a tiny bit of liquid onto a plate or easy to clean surface to examine the contents and assess the volume of liquid.
Test the robot gripping hand wrist Rotary range and speed

Not knowing how full the bottle is, I would begin to tilt the bottle slowly.
slowly increasing tilt of bottle until I get liquid out.
Tilt bottle a little. Gradually until I see liquid poring.
Pouring slowly
beginning to pour at a slight angle, assuming it is mostly full. IF this does not work I would increase the angle slowly and gently until the fluid flows, increase angle as needed to finish the task
First tilt a little, and if no liquid or not enough liquid comes out, tilt a little more
I would try to pour it by tilting it a little. It is is full, it will pour and I'd not I'd have to tilt more. Heat of Liquid may be apparent on initial pour.
Start from lowest tilt and slowly increase
Same as mentioned previously.
Start by tilting a little to ensure its not full. Keep tilting until liquid starts pouring out. Tilt just enough so that you can control the flow of the amount of liquid pouring out

Q16 - You tilt the bottle and pour some milk into the cup anyway. Then you place the bottle back on the table, stir the coffee, and pick up the cup using the robotic arm. What will you do next?



#	Answer	%	Count
1	This coffee is too hot, I should let it cool down	12.75%	13
2	I should drink the coffee	33.33%	34
3	The milk has made the coffee too cold, I should heat it up or add more hot coffee	2.94%	3

4	I need more information	50.98%	52
	Total	100%	102

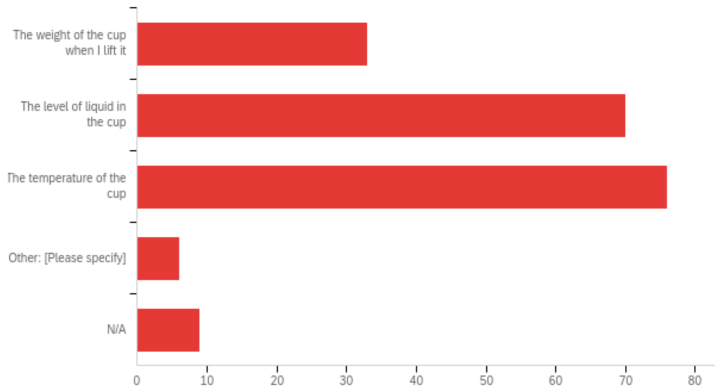
Q17 - Please rank how important the following additional information would be to help you make this decision. 0 represents not at all important, 5 represents extremely important.

#	Field	Minimum	Maximum	Mean	Std Deviation	Variance	Count
1	The weight of the cup when I lift it	0.00	5.00	3.02	1.52	2.30	63
2	The level of liquid in the cup	0.00	5.00	3.59	1.40	1.96	78
3	The temperature of the cup	0.00	5.00	4.28	1.11	1.22	96
4	Other (Please Specify)	1.00	5.00	4.00	1.31	1.71	7

Q17_4_TEXT - Other (Please Specify)

Other (Please Specify) - Text
The temperature of the liquid in the cup would be more important since it may be hotter than the outside of the cup.
Angle or Distance
Again, I need to know how fast everything moves, in order to pour or drink from the cup without spilling
Need to stir
POUR MORE IF TOO HOT OR PREFER MORE MILK
temperature of coffee
the colour of the coffee after it is mixed with milk

Q18 - If you think a combination of information would be more helpful than one type, please select which ones you would prefer a combination of.

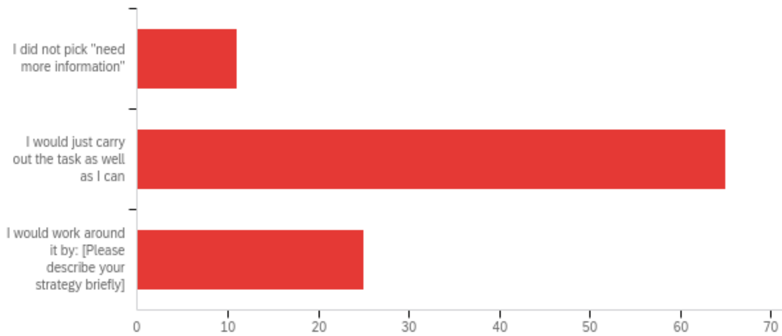


#	Answer	%	Count
1	The weight of the cup when I lift it	17.01%	33
2	The level of liquid in the cup	36.08%	70
3	The temperature of the cup	39.18%	76
4	Other: [Please specify]	3.09%	6
5	N/A	4.64%	9
	Total	100%	194

Q18_4_TEXT - Other: [Please specify]

Other: [Please specify] - Text
The temperature of the liquid
Speed of the moving arm
Again, the speed of movements
AMOUNT PREFERENCE
Where cup is placed
Colour of the coffee after it was mixed with milk

Q19 - Since you don't have access to any additional information, how would you navigate this situation?



#	Answer	%	Count
1	I did not pick "need more information"	10.89%	11
2	I would just carry out the task as well as I can	64.36%	65
3	I would work around it by: [Please describe your strategy briefly]	24.75%	25
	Total	100%	101

Q19_3_TEXT - I would work around it by: [Please describe your strategy briefly]

I would work around it by: [Please describe your strategy briefly] - Text
Bring the cup close to sniff the contents and feel the temperature of the surrounding air with my lips.
Since the robotic arm is the one holding the cup, I'm not worried about burning my hand, so I would carefully sip the coffee as I normally would.
bringing the cup to my lips and touching it to my lips (maybe sipping) to get a sense of how hot it is
Slowly begin to sip coffee.
Bringing the cup closer to see the level of coffee and hopefully determine an approximate temperature of the liquid
After I pick up the cup, put my lips to the cup and decide then if I should blow on it or take a sip.
trying to test the temp by touching the side of the cup with my cheek before attempting to drink it.
I guess since I have done this before, I would be able to trust the robotic are to bring the cup close to my mouth to take a careful sip

I would carry carefully and take a tiny sip to assess temperature. Hopefully the robot arm moves smoothly and evenly.

Move the arm very slowly placing the cup right in front of my lips. Purse my lips close to the liquid, gauging the temperature and carefully dip my upper lip into the liquid for temperature and if safe then for taste

Again risking safety as you can’t feel it or even get close to it

I would take a sip to determine if the coffee were too hot or too cold.

I would bring it close to my mouth and see if I can determine the temperature

maneuvering to lips and taking very small sip to test temperature

bring it close and take a small sip

bringing cup close to lips and see if i can determine temp

bringing the cup slowly and carefully toards me and observing whether steam or heat is coming from the cup. If not, I may proceed to taste it. If I taste it and it is cold, I may choose to heat it.

Bring cup to mouth and sip slowly to see the temperature.

equip the arm with a thermometer

I would bring it close to my mouth and test it by sipping.

I would first take a sip to test the temperature.

Place cup on table and try to observe if steam is coming off the coffee and possibly height of liquid.

Taste it and take more action

Leave it for a while and try. If too cold, heat it up

I would first take a small sip and then decide

APPENDIX B: CONSENT FORMS

This appendix includes two consent forms for experiments performed in this thesis. The consent forms were reviewed and approved by the Purdue IRB. The IRB approval for both experiments were obtained under number IRB-2020-17742.

RESEARCH PARTICIPANT CONSENT FORM (1)
Multimodal Feedback Interface for Assistive Robotic Manipulator
Prof. Bradley Duerstock and Prof. Juan Wachs
Biomedical Engineering
Purdue University

<u>Key Information</u>
Please take time to review this information carefully. This is a research study. Your participation in this study is voluntary which means that you may choose not to participate at any time without penalty or loss of benefits to which you are otherwise entitled. You may ask questions to the researchers about the study whenever you would like. If you decide to take part in the study, you will be asked to sign this form, be sure you understand what you will do and any possible risks or benefits. You may also indicate preference for use of photographs or videos and future use of your data in the appropriate sections below.

The main purpose of this study is to develop an effective multimodal feedback interface for users of assistive robotic arms. Such a feedback interface would allow users to access properties that they cannot access visually and are deprived from accessing due to the lack of direct contact with task.
The main objectives of this study are:

To design an effective multimodal feedback interface that delivers feedback of nonvisual task-related properties to the user.

To validate the designed interface against the case of no feedback.

To study user choice in the utility of the available feedback.

The research project is expected to take ~18 months.

What is the purpose of this study?
The purpose of this set of experiments is to identify an effective combination of mapping of the properties to the available feedback modalities. We will determine this using the data collected from testing out the different possible combinations with participants, and analyzing cognitive load and accuracy.
We would like to enroll 45 people in this study.

<u>What will I do if I choose to be in this study?</u>
During your participation:
Prior to the experiments you will out a preliminary questionnaire that will collect information about your mobility limiting condition (if applicable) and screen for potential CoVid-19 risk factors.
You will attend the experimental sessions following CoVid-19 safety guidelines.
Prior to the start of the experiment, you will train on the device for a brief period. This will allow you to get familiarized with the control of the robot and the feedback types.
You will be handed a vessel at the robotic arm, controlled by the 3D joystick. Feedback properties will be turned on.
You will evaluate each property (for example temperature as too hot, hot, lukewarm, cold, too cold) while completing a pouring task. You will assess three vessels for each property to modality combination. This will be one set of trials.

You will complete a rating of your effort and cognitive load after each set of trials.
You will repeat this procedure for six sets of trials.
Additionally, photographs will be taken to demonstrate the setup of the system. Short videos may also be taken to demonstrate specific procedures or testing. Please indicate your permission for using photographs and videos in the confidentiality section below. Data may also be used in the future. Please indicate your preference for future use in the 'Future Use' section below.

How long will I be in the study?
One visit is expected to take ~1-2 hours. You will complete 6-10 visits depending on the duration per visit. Scheduling of visits will depend on your schedule.

What are the possible risks or discomforts?
This study is not expected to be much riskier than risks encountered in daily life.
There are a few potential sources of risk in this study for which mitigation strategies are implemented:
There will be a heating element placed on your skin for thermal feedback. A temperature sensor will continuously measure the temperature of this element, and it will not be allowed to reach beyond 120F. This is 20F below pain inducing temperature. Further, the thermal feedback provided to you will be far below 120F. There is also an 'off' switch for all the feedback modalities while the system is running, as an additional precaution.
You will be operating a robotic arm with a 3D joystick. The arm is programmed to move very slowly, and you will be in control of its movements. The arm will be securely mounted on a base. There will also be an off switch for the arm as an added precaution.
Breach of confidentiality is always a risk with data, but we will take precautions to minimize this risk as described in the confidentiality section.

Are there any potential benefits?

The main benefit of this study is intended to be to improve the experience of users of assistive robotic arms. You may also enjoy interacting with the system and the robot.

Are there costs to me for participation?

You may incur a travel cost to the location of the study (Purdue university), depending on your circumstances. No other costs are anticipated.

This section provides more information about the study

What happens if I become injured or ill because I took part in this study?

If you feel you have been injured due to participation in this study, please contact:
Mandira Marambe
413-930-0001
mmarambe@purdue.edu

Purdue University will not provide medical treatment or financial compensation if you are injured or become ill as a result of participating in this research project. This does not waive any of your legal rights nor release any claim you might have based on negligence.

Will information about me and my participation be kept confidential?

The project's research records may be reviewed by the study sponsor/funding agency, Food and Drug Administration (if FDA regulated), US DHHS Office for Human Research Protections, and by departments at Purdue University responsible for regulatory and research oversight.
The project's research records may be reviewed by departments at Purdue University responsible for regulatory and research oversight. Photographs or digital images and/or video of you performing the tests may be used for scientific publications and conference presentations with explicit permission from you. No records will ever be kept associating your name or any other identifiable personal information with these or any other data and information collected for this study. All identifiable data and research records will be stored in a locked cabinet. Electronic video recordings will be stored on a secure, password protected server which only the research team will have access to. Each participant will be assigned an arbitrary code that is linked to their identity. The key for these codes will be kept in a location separate from the data. Only the research team will have access to the identified data.

_______ I give permission to use my photographs or video images for presentations and publications.

_______ I do not give permission to use my photographs or video images for presentations and publications.

What are my rights if I take part in this study?
You do not have to participate in this research project. If you agree to participate, you may withdraw your participation at any time without penalty.
You may contact Mandira Marambe (information below) if you wish to withdraw your data from the study.
Who can I contact if I have questions about the study?

If you have questions, comments or concerns about this research project, you can talk to one of the researchers. Please contact
Bradley Duerstock: 765-496-2364 (PI)
Mandira Marambe: 413-930-0001 (First point of contact)
To report anonymously via Purdue's Hotline see www.purdue.edu/hotline

If you have questions about your rights while taking part in the study or have concerns about the treatment of research participants, please call the Human Research Protection Program at (765) 494-5942, email (irb@purdue.edu) or write to:
Human Research Protection Program - Purdue University
Ernest C. Young Hall, Room 1032
155 S. Grant St.

West Lafayette, IN 47907-2114

Future Use

May we share your accuracy and cognitive load data information without your name or identifying information attached with other researchers for future research projects related to other topics? Yes No

Documentation of Informed Consent

I have had the opportunity to read this consent form and have the research study explained. I have had the opportunity to ask questions about the research study, and my questions have been answered. I am prepared to participate in the research study described above. I will be offered a copy of this consent form after I sign it.

____

Participant's Signature Date

____

Participant's Name

____

Researcher's Signature Date

RESEARCH PARTICIPANT CONSENT FORM (2)
Multimodal Feedback Interface for Assistive Robotic Manipulator
Prof. Bradley Duerstock and Prof. Juan Wachs
Biomedical Engineering
Purdue University

Key Information

Please take time to review this information carefully. This is a research study. Your participation in this study is voluntary which means that you may choose not to participate at any time without penalty or loss of benefits to which you are otherwise entitled. You may ask questions to the researchers about the study whenever you would like. If you decide to take part in the study, you will be asked to sign this form, be sure you understand what you will do and any possible risks or benefits. You may also indicate preference for use of photographs or videos and future use of your data in the appropriate sections below.

The main purpose of this study is to develop an effective multimodal feedback interface for users of assistive robotic arms. Such a feedback interface would allow users to access properties that they cannot access visually and are deprived from accessing due to the lack of direct contact with task.

The main objectives of this study are:

To design an effective multimodal feedback interface that delivers feedback of nonvisual task-related properties to the user.

To validate the designed interface against the case of no feedback.

To study user choice in the utility of the available feedback.

The research project is expected to take ~18 months.

What is the purpose of this study?

The purpose of this set of experiments is to identify an effective combination of mapping of the properties to the available feedback modalities. We will determine this using the data collected from testing out the different possible combinations with participants, and analyzing cognitive load and accuracy.

We would like to enroll 45 people in this study.

What will I do if I choose to be in this study?

During your participation:

Prior to the experiments you will out a preliminary questionnaire that will collect information about your mobility limiting condition (if applicable) and screen for potential CoVid-19 risk factors.

You will attend the experimental sessions following CoVid-19 safety guidelines.

Prior to the start of the experiment, you will train on the device for a brief period. This will allow you to get familiarized with the control of the robot and the feedback types.

You will be handed a vessel at the robotic arm, controlled by the 3D joystick.

You will complete a pouring task, using the feedback as an aid to make decisions relevant to the task. You will turn feedback modalities on and off as you see fit. Each trial will be classified

as a success or failure based on the decision you make. You will assess ten vessels for each set of trials.
You will complete a rating of your effort and cognitive load after each set of trials.
You will repeat this procedure for ten more trials without feedback.

Additionally, photographs will be taken to demonstrate the setup of the system. Short videos may also be taken to demonstrate specific procedures or testing. Please indicate your permission for using photographs and videos in the confidentiality section below. Data may also be used in the future. Please indicate your preference for future use in the 'Future Use' section below.

How long will I be in the study?

One visit is expected to take ~1-2 hours. You will complete 2-4 visits depending on the duration per visit. Scheduling of visits will depend on your schedule.

What are the possible risks or discomforts?

This study is not expected to be much riskier than risks encountered in daily life.
There are a few potential sources of risk in this study for which mitigation strategies are implemented:
There will be a heating element placed on your skin for thermal feedback. A temperature sensor will continuously measure the temperature of this element, and it will not be allowed to reach beyond 120F. This is 20F below pain inducing temperature. Further, the thermal feedback provided to you will be far below 120F. There is also an 'off' switch for all the feedback modalities while the system is running, as an additional precaution.
You will be operating a robotic arm with a 3D joystick. The arm is programmed to move very slowly, and you will be in control of its movements. The arm will be securely mounted on a base. There will also be an off switch for the arm as an added precaution.
Breach of confidentiality is always a risk with data, but we will take precautions to minimize this risk as described in the confidentiality section.

Are there any potential benefits?

The main benefit of this study is intended to be to improve the experience of users of assistive robotic arms. You may also enjoy interacting with the system and the robot.

Are there costs to me for participation?

You may incur a travel cost to the location of the study (Purdue university), depending on your circumstances. No other costs are anticipated.

This section provides more information about the study

What happens if I become injured or ill because I took part in this study?

If you feel you have been injured due to participation in this study, please contact:
Mandira Marambe
413-930-0001
mmarambe@purdue.edu
Purdue University will not provide medical treatment or financial compensation if you are injured or become ill as a result of participating in this research project. This does not waive any of your legal rights nor release any claim you might have based on negligence.

Will information about me and my participation be kept confidential?

The project's research records may be reviewed by the study sponsor/funding agency, Food and Drug Administration (if FDA regulated), US DHHS Office for Human Research Protections, and by departments at Purdue University responsible for regulatory and research oversight.

The project's research records may be reviewed by departments at Purdue University responsible for regulatory and research oversight. Photographs or digital images and/or video of you performing the tests may be used for scientific publications and conference presentations with explicit permission from you. No records will ever be kept associating your name or any other identifiable personal information with these or any other data and information collected for this study. All identifiable data and research records will be stored in a locked cabinet. Electronic video recordings will be stored on a secure, password protected server which only the research team will have access to. Each participant will be assigned an arbitrary code that is linked to their identity. The key for these codes will be kept in a location separate from the data. Only the research team will have access to the identified data.

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____

____

Participant's Signature Date

____

Participant's Name

____

____

Researcher's Signature Date

APPENDIX C: EXPERIMENTAL PROCEDURES

This appendix includes step-by-step protocols for the experiments performed in this thesis. These protocols were reviewed and approved by the Purdue IRB. Appendix C1 lists the protocols for the screening experiments while Appendix C2 lists the protocol for the validation experiments. The IRB approval for both experiments were obtained under number IRB-2020-17742.

C1: SCREENING EXPERIMENT

System: For each of the following experiments, the subject will control an assistive robotic arm via a haptic device configured as a 3D joystick, and will receive haptic, vibrational, visual, and thermal sensory feedback through the same haptic device, vibrating tactors placed on the arm, a display rendered on a computer screen, and a peltier device placed on the arm.

Experiment 01: Screening Experiments

For the pouring task,

1. The subject was asked to provide some background information including age and if relevant, the nature of their physical disability. Information was recorded without the subject's name or other personal identification factors. Prior to the experiment, the subject also completed two minutes of only responding to the DRT to collect a baseline.
2. The subject was introduced to the robot and trained on it, including completing practice trials.
3. The subject completed the pairwise comparison rating for metric weighting (see end of this section)
4. The subject trained on feedback prior to each trial. The training procedure involved walking the subject across the feedback range in ascending and descending order twice, and then providing random renderings to assess.
5. Vessels holding fluids of different weights and temperatures are placed in front of the subject. The subject was tasked with categorizing properties, for example, temperature as too hot for consumption, hot, lukewarm, cold, very cold or weight as empty, less than half full, half full, more than half full, full, etc. The subject also simultaneously responded to the Detection Response Task stimulus using a push button.

6. The subject was handed a vessel using the robotic arm, controlled by the haptic device.
7. The subject categorized each property while executing a pouring task (The subject must be controlling the robot while assessing such that cognitive load is captured for the event when attention is split between modalities and task.).
8. The subject assessed three vessels (trials) for each assignment pair. Each set of trials will collect information about one modality assignment for each property, resulting in a total of 36 trials for the pouring task. The subject made three visits, one for each property.
9. The subject completes the subjective preference rating (see end of this section) after each set of trials.
10. The subject will repeat these steps for the second task and assess a second set of properties (with some overlap) for the same feedback modalities.

Covid-19 Protocols:

- Subjects were screened for symptoms and potential contact with patients verbally/via text communication prior to experiments
- Subjects and researchers were required to wear masks for the duration of the experiments.
- The equipment and devices in contact with the subject were sanitized prior to each session.
- Subjects were brought in for experiments one by one. Only the subject and the graduate student researcher will occupy the research space during a session.
- Subjects were provided with sanitizer after the experiment.

Metric weighting

You are going to use this robot that you just trained on to make and drink a cup of coffee. This includes pouring coffee and milk in the cup, then deciding to drink it. Select which of the following factors is more important in each pair.

The initial temperature, weight, or amount of liquid in the vessel	Or	The **change** in temperature, weight, or amount of liquid in the vessel
Your attention on controlling the robot to perform the tasks		The overall mental demand of performing the task
Your attention on controlling the robot to perform the tasks		The initial temperature, weight, or amount of liquid in the vessel
How you get information about temperature, weight, liquid level, etc. (e.g. on a screen, audio, vibration, etc.)		The overall mental demand of performing the task
The **change** in temperature, weight, or amount of liquid in the vessel		The overall mental demand of performing the task
How you get information about temperature, weight, liquid level, etc. (e.g. on a screen, audio, vibration, etc.)		Your attention on controlling the robot to perform the tasks
How you get information about temperature, weight, liquid level, etc. (e.g. on a screen, audio, vibration, etc.)		The **change** in temperature, weight, or amount of liquid in the vessel
The overall mental demand of performing the task		The initial temperature, weight, or amount of liquid in the vessel
The **change** in temperature, weight, or amount of liquid in the vessel		Your attention on controlling the robot to perform the tasks
The temperature, weight, or amount of liquid in the vessel		How you get information about temperature, weight, liquid level, etc. (e.g. on a screen, audio, vibration, etc.)

Temperature Preference Score

For this set of tasks, please select the more demanding of each pair.

Thermal	Or	Visual
Audio		Thermal
Visual		Audio
Audio		Vibration
Visual		Vibration
Vibration		Thermal

C2: VALIDATION EXPERIMENT

Experiment 02: Validation Experiments

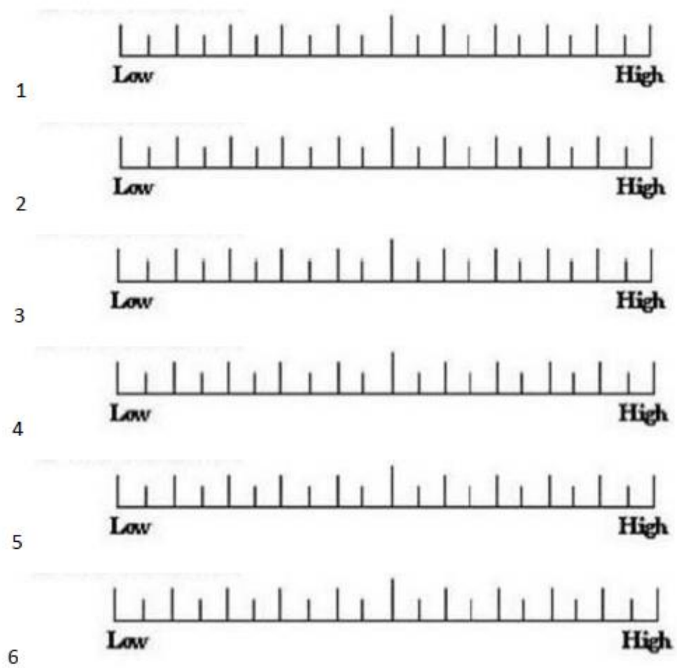
1. The subject was asked to provide some background information including age and if relevant, the nature of their physical disability. Information was recorded without the subject's name or other personal identification factors.
2. The same robot and training procedures as in Appendix C1 were followed prior to the experiment.
3. For this experiment, the subject was tasked with going through a decision-making process relevant to the pouring task. The subject was tasked with making decisions in three use cases, including pouring at a given temperature, detecting an empty vessel, and estimating the tilt angle.
4. Decisions were evaluated as successes and failures to obtain task success rate. The response time was also recorded with a stopwatch.
5. The subject completed two trials per use case first without feedback using alternative strategies, then with the solution, and finally with the arbitrary mapping.
6. The subject completed a subjective mental demand rating (see end of this section) after each trial.
7. The subject will repeat these steps for each trial.

Covid-19 Protocols:

- Subjects were screened for symptoms and potential contact with patients verbally/via text communication prior to experiments

- Subjects and researchers were required to wear masks for the duration of the experiments.
- The equipment and devices in contact with the subject were sanitized prior to each session.
- Subjects were brought in for experiments one by one. Only the subject and the graduate student researcher will occupy the research space during a session.
- Subjects were provided with sanitizer after the experiment.

Subjective Mental Demand Rating



VITA

Mandira Marambe grew up in tropical Colombo, Sri Lanka. She attended Bishop's College, Colombo from 2001 to 2015, where she studied mathematics, further mathematics, physics, and chemistry for her British Advanced Level examinations and developed an interest in engineering. Deciding to pursue her aspirations across the globe, she relocated to the east coast of the United States in August 2015. She attended Smith College, Massachusetts where she received her Bachelor of Science in Engineering Science in 2019. During her undergraduate studies, she was fortunate to have several internships and research experiences and complete an industry-sponsored capstone design project. In Fall 2019, she began her graduate studies at Purdue University where she completed this thesis work and received her Master of Science in Biomedical Engineering in August 2021.