Abstract

From Distraction to Interaction:
Leveraging Robot-Driven Interplay for Effective Technical Education Amid Interruptions

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This dissertation investigates the dynamic interplay between robotics and human adaptability in environments characterized by frequent interruptions, with a special focus on technical education and privacy considerations. Our research begins by examining the pervasive issue of interruptions in various settings, emphasizing their impact on productivity and safety. It then explores strategies that leverage technology, particularly robotics, to enhance human interruption tolerance and performance.

A significant portion of the research is dedicated to understanding how robotics can aid individuals with Autism Spectrum Disorders (ASD). This exploration is extended to broader educational contexts, where robotics are employed to improve learning outcomes and skill acquisition in technical education. We conduct empirical studies to validate the model's effectiveness, focusing on learning outcomes, skill development, and the productive interaction between robots and human learners.

Additionally, the dissertation addresses the crucial aspects of privacy and ethical design in the deployment of robotics, highlighting the importance of aligning technological advancements with ethical standards and privacy concerns. Advanced techniques like differentially private algorithms and maximal information coefficient analysis are discussed, underscoring their role in maintaining data utility while protecting individual privacy.

The key contributions of our research include providing broad understanding of the role of technology, particularly robotics, in enhancing human adaptability in environments characterized by frequent interruptions; offering insights into the importance of privacy and ethical design in the development of user-centric robots; presenting evidence of the effectiveness of a robot-driven interactive learning model in various fields of technical education; and demonstrating the applicability of robot-driven pedagogical methods beyond specific disciplines, showcasing the versatility of our approach in various training settings.

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Leveraging Robot-Driven Interplay for Effective Technical Education Amid Interruptions

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Chapter 1

Introduction

The central research problem of this dissertation revolves around the pervasive issue of interruptions in contemporary environments. The effects of interruptions often include errors and delays, potentially resulting in high monetary costs, injury, and death. For example, interruptions of airline pilots during ground turn-around operations can result in downstream delays with cascading consequences, leading to losses ranging between 32.9 billion and 41 billion for airlines, passengers, and society (Gontar et al., 2017; Ball et al., 2010; Liu et al., 2019). High losses are also prevalent in other sectors of society. A study from the Journal of Nursing Management indicated that 49% of $38,063$ medication administration errors were attributable to interruptions (Johnson et al., 2017). Furthermore, medical errors have been estimated to result in up to 251,000 preventable deaths annually (Pereira-Lima et al., 2019; James, 2013; Weingart et al., 2000) and account for a significant amount of iatrogenic injury (Jha et al., 2013), as well as financial losses exceeding billions of dollars annually (Van Den Bos et al., 2011).

Beyond economic repercussions and safety concerns, interruptions often result in decreased workplace productivity (Chisholm et al., 2000; Dabbish and Kraut, 2004), and may even lead to social isolation, particularly among adults with Autism Spectrum Disorders (Orsmond et al., 2013; Mazurek, 2014). The predominant strategy to mitigate these effects has been to reorganize the work environment to minimize interruption frequency (Westbrook et al., 2017). Developing the ability to effectively manage attention between tasks and training for seamless recovery from interruptions are crucial for all individuals facing such disruptions.

Given that many interruptions are unpredictable and unavoidable, a viable approach lies in reducing the resulting errors and delays. A notable approach is the method proposed by Donaldson et al., focusing on error reduction in the American health system (Donaldson et al., 2000). This method recommends a design process encompassing "problem simulation training and practice in problem recovery" (Donaldson et al., 2000). In environments where tasks are regularly interrupted, training tailored to specific tasks and their associated interruptions is invaluable (Donaldson et al., 2000; Ruskin et al., 2021).

While existing methods for managing interruptions show promise, there is room for additional contributions. This dissertation, drawing upon research in human-robot co-creativity (Fitzgerald et al., 2017), introduces a model of cooperative engagement between humans and robots, specifically designed to enhance the management of interruptions in the context of robot-assisted technical training in educational settings. Our empirical studies delve into the impact of robot-driven interventions on learning outcomes, skill development, and the estimation of expertise in technical subjects, emphasizing the dynamic interaction between the robot and its human learner counterparts. This model seeks to validate and emphasize a collaborative framework where the integration of technological tools, adaptive robot behaviors, and human insights strives to exceed the results attainable by the efforts of the robot's human collaborator alone (Van Dijk et al., 2023). Essentially, it advocates for a specialized approach that leverages the collaborative dynamics between technology and human learners, aiming to enrich the learning experience and outcomes.

Our approach, drawing on seminal works in human-robot interaction and collaboration, demonstrates the practical applicability of these concepts in educational settings, especially in technical training (Caterino et al., 2023; Hayes and Scassellati, 2014). Beyond merely deploying advanced tools, this integration involves nurturing a dynamic relationship between technology and learners.

Furthermore, harmonizing this collaborative interplay with data privacy and ethical considerations introduces additional complexity. It is imperative to ensure that our solutions are not only effective but also adhere to ethical standards and respect individual rights and societal norms. Therefore, this dissertation aims to explore and articulate strategies that capitalize on this collaborative interplay, presenting innovative methods to address the challenges posed by interruptions in the contemporary world.

This research problem is addressed through a series of interconnected studies, each contributing to a comprehensive understanding of how to mitigate the disruptive effects of interruptions. This approach involves an in-depth examination of training methodologies aimed at improving interruption tolerance. It also encompasses the development and implementation of robot solutions, specifically tailored for distinct populations as well as broader demographic groups. Additionally, the research addresses critical aspects of privacy and ethical considerations pertinent to the technological adoption process. The insights derived from these studies are crucial in formulating effective strategies. These strategies not only leverage advancements in robotics but also align them with human cognitive and behavioral patterns, thereby managing interruptions more efficiently.

Foremost among the questions underpinning our research are: Can structured training methods significantly impact the interruption tolerance of individuals in high-interruption environments, such as airline ground turn-around operations or digital workspaces? Furthermore, does such training lead to measurable changes in terms of time, error rates, and subjective focus levels post-interruption?

Chapter 2 of this dissertation investigates whether pedagogic constructs can enhance performance under interruptions. Notably, in the studies described in Chapter 2, robots are not involved. This chapter focuses on assessing the influence of interruption duration and demands (Monk et al., 2008). Our findings reveal that certain pedagogical methods lead to improvements in handling interruptions. Specifically, we discovered that structured training methods, grounded in cognitive and behavioral principles, significantly enhance individuals' interruption tolerance. This improvement manifests as quantifiable increases in productivity and decreases in error rates. Empirical research was conducted to evaluate the effectiveness of these methodologies, offering a critical analysis of their strengths, limitations, and potential for application. Our research demonstrates the feasibility of training individuals to manage interruptions through repetitive exposure. Furthermore, we found that improvement is not hindered by context (Cades et al., 2011), implying that such training methods could be effectively applied in human-robot interaction contexts.

In Chapter 3, we explore the potential of social robotics in providing job-relevant interruptions training for an understudied population: individuals with Autism Spectrum Disorders (ASD) (McKenna et al., 2020; Scassellati, 2007). The challenge of managing interruptions is particularly pronounced for individuals with ASD, given the social skills deficits many of them exhibit, which can exacerbate the effects of workplace distractions, unpredictability, and uncertainty (Kenyon, 2015). Addressing these specific challenges is not merely an academic pursuit; it holds substantial real-world significance, impacting the autonomy and quality of life of these individuals (Lindsay et al., 2018; Scott et al., 2017). Our research demonstrates that users readily accepted the social robot in their homes, perceiving the training it provided as relevant, useful, and important. Furthermore, they showed improvement in managing workplace-relevant interruptions.

In Chapter 4, we continue to explore the pervasive nature of interruptions, extending our focus beyond home environments to include academic settings. Building upon the insights from Chapter 3, which highlighted the potential of social robotics in aiding individuals with ASD in managing interruptions at home, Chapter 4 broadens the narrative. It expands the scope to a more diverse population and provides a detailed examination of the specialized approach previously introduced, evaluating its applicability in an educational context (Brumby et al., 2013). This chapter delves into the dynamic interplay between technology and human learners, with a particular emphasis on the role of the robot in facilitating team-centric collaborative tasks. These tasks are crafted to enable the robot's human collaborator to recover more seamlessly from interruptions, especially during the performance and learning of technical tasks.

We assess the effectiveness of approaches wherein the robot uses context-aware perception and tracks the human's task status and progression throughout interruptions. Crucially, the robot embeds cues within the environment, anticipating that these cues will subtly prompt and reorient the human collaborator back into the workflow (Trafton et al., 2005; Falkland et al., 2020). This nuanced method of interruption management involves the robot's capacity to encode essential task details into environmental cues rather than direct intervention. These strategically placed cues are designed to offer indirect guidance, assisting the human partner in resuming the interrupted workflow more intuitively (Falkland, 2023). Our evaluations demonstrate that robots, by embedding these environmental cues, substantially aid in improving the management of interruptions. This approach, akin to their impact on specialized populations, is shown to be significantly beneficial across a broader demographic, highlighting the robot's role to not only complement but significantly amplify human capabilities in managing interruptions.

Our focus progresses by delving into a critical and rapidly evolving domain: technical education (Venkatraman et al., 2018). In an era where digital technology is advancing at an unprecedented rate, traditional educational methods are becoming increasingly insufficient (Sayfullayeva et al., 2021). Chapter 4 also addresses the urgent need for advanced technical education methodologies that effectively bridge the gap between theoretical knowledge and practical application. This chapter is dedicated to integrating robot-driven interplay into technical education in environments characterized by interruptions. The goal is to enhance the effectiveness of technical education through robot-driven interactive learning. We utilize HVAC system maintenance and troubleshooting tasks as a benchmark for measuring the impact of robotics on learning outcomes, skill acquisition, and performance in technical subjects (Trčka and Hensen, 2010; Afram and Janabi-Sharifi, 2014). Our evaluations demonstrate that the robot's capacity to offer adaptive feedback, personalized guidance, and hands-on troubleshooting support significantly boosts educational effectiveness. Ultimately, this chapter aims to showcase how this unified approach can open new pathways for pedagogic innovation in the field of technical education (Van Dijk et al., 2023; Mayer, 2014).

As we approach the penultimate chapter of this dissertation, we consider the broader implementation of robotics, addressing the increasing concerns related to ethics and privacy becomes crucial. Chapter 5 delves into these critical issues, focusing specifically on the factors that influence the adoption of robots, with a special emphasis on privacy and ethical design (Rueben et al., 2018; Lutz and Tamò-Larrieux, 2021). One of the central endeavors of this chapter is to align the innovative potential of robotics with stringent privacy and ethical standards (Kaminski et al., 2016). In this context, we explore the potential incorporation of differentially private algorithms, a cutting-edge technique in the domain of privacy-preserving technology. Differentially private algorithms are designed to provide a framework for data analysis that respects individual privacy. They introduce a measure of 'noise' to the data or to the queries made on the data, thereby obscuring individual contributions while not significantly undermining the accuracy of the analysis. This method allows for the extraction of valuable insights and the making of informed decisions based on aggregate information, all while prioritizing the privacy of individual data subjects. By considering the application of differentially private algorithms in robotic systems, we aim to navigate a path that balances the utility and effectiveness of data-driven technologies with robust protections for individual privacy (Schulz and Herstad, 2018).

The dissertation culminates with Chapter 6, which synthesizes insights gleaned from the preceding chapters to propose advanced pedagogical constructs for technical education. This chapter demonstrates the impact of robotics on managing interruptions, user-privacy-centric robot design, and individualized learning approaches. Chapter 6 elaborates on the contributions, implications, and utility of this research, while also acknowledging the work that remains to address the limitations of our study. Our key contributions include:

1. Providing a holistic understanding of how technology, particularly robotics, can enhance human adaptability in environments characterized by frequent interruptions.

2. Offering insights into how privacy and ethical considerations can inform the development of user-centric robots. This emphasizes the importance of user privacy and ethical design in fostering trust and promoting broader adoption of robotics.

3. Presenting evidence that a robot-driven interactive learning model, when applied to various fields of technical education, leads to significant improvements in learning outcomes and skill acquisition. This offers insights into how adaptive

and personalized educational technologies can cater to diverse learning styles, thus contributing to broader theories of differentiated instruction and personalized learning.

4. Demonstrating the applicability of robot-driven pedagogical methods beyond HVAC systems to include disciplines such as Automotive Maintenance, Computer System Building, and more. This encompasses both academic and vocational training settings, illustrating the versatility of our approach.

As outlined in this introduction, the central aim of this dissertation is to explore the intersection of technology, particularly robotics, with human adaptability in contexts laden with interruptions, privacy considerations, and technical education challenges. Traversing a spectrum of environments and populations, ranging from individuals with Autism Spectrum Disorders to learners in technical education, this research offers comprehensive insights into how robotics can enhance learning and adaptability. The subsequent chapters will delve into each aspect of this research in greater detail, encompassing empirical studies on interruption management and examining the ethical implications of robotics in education. This journey not only augments the existing body of knowledge but also paves the way for practical applications and future scholarly inquiry.

Chapter 2

Enhancing Performance Under Interruptions: An Empirical Investigation

In the modern workplace, the prevalence of interruptions is a ubiquitous challenge, presenting a substantial barrier to optimal performance and efficiency. This chapter seeks to explore the extent to which structured pedagogical constructs can ameliorate the disruptive effects of interruptions on task performance. Unlike other sections of this dissertation, Chapter 2 specifically excludes the consideration of robotic agents, focusing solely on human cognitive processes and the dynamics of interruption, resumption, and task performance error. The primary objective is to assess the influence of interruption characteristics–specifically, their duration and cognitive demands–on the efficacy of task resumption (Labonté and Vachon, 2021; Trafton et al., 2005; Monk et al., 2008; Trafton et al., 2012).

This chapter aims to dissect the effectiveness of various pedagogical methods designed to enhance interruption tolerance. These methods are grounded in cognitive and behavioral principles and are hypothesized to foster significant improvements in handling interruptions (Altmann and Trafton, 2020; Trafton et al., 2003). This is not only expected to manifest in heightened productivity but also in the reduction of error rates.

2.1 Background

The propensity for interruptions to engender significant disruptions in workflow is well-documented (Labonté and Vachon, 2021; Altmann and Trafton, 2020; Trafton et al., 2003), with implications ranging from diminished productivity (Chisholm et al., 2000; Dabbish and Kraut, 2004) to escalated error rates and even safety violations (Pereira-Lima et al., 2019; James, 2013). The cognitive toll of interruptions, particularly their impact on working memory and attention regulation (Anderson and Douglass, 2001), necessitates a strategic approach to mitigate these effects. The current study is predicated on the concept that through structured training and exposure, individuals can develop a heightened tolerance to interruptions. Such training harnesses cognitive and behavioral principles (Jones and Moss, 2019) to bolster individuals' ability to manage interruptions, thereby enhancing overall task performance.

The generalizability of these training effects is a focal point of this investigation. Traditional belief suggests that skills and strategies developed in one context may not seamlessly transfer to another (Cades et al., 2011); however, our study challenges this notion. By demonstrating that improvements in interruption management are not context-specific, as shown in the significant reduction in resumption lag (Jones and Moss, 2019), we posit that the strategies and skills honed through our pedagogical methods have broad applicability, including but not limited to, scenarios involving human-robot interactions.

Our approach aligns with the comprehensive framework proposed by Donaldson et al. (2000), advocating for the implementation of training interventions that simulate problems and provide opportunities for practicing recovery strategies. This method is further supported by insights from Cades et al. (2007) and Trafton et al. (2012), who explored the impact of task types and interruption patterns on task performance and recovery. The integration of these perspectives informs our training design, ensuring a methodology that addresses the multifaceted challenges posed by interruptions in various contexts.

The necessity for strategic, evidence-based training is accentuated when considering the dynamic and often unpredictable nature of modern work environments. The increasing reliance on digital tools and the proliferation of multitasking underscore the urgency of developing methodologies to manage interruptions effectively. As such, our study not only responds to an immediate practical need but also contributes to the theoretical understanding of cognitive resilience in the face of interruptions.

The innovative aspect of this research lies in its empirical approach to evaluating the effectiveness of structured training interventions. By adopting a data-driven methodology, this study moves beyond theoretical discourse to provide actionable insights. The empirical evidence generated through this research is a testament to the potential of structured training to significantly enhance interruption management capabilities (Jones and Moss, 2019). Moreover, the findings regarding the transferability of skills across different tasks and contexts provide a promising avenue for future research and practical application in diverse fields, ranging from industrial operations to educational settings and beyond.

In essence, strategies for mitigating the impact of interruptions are varied and can be broadly categorized into three principal approaches, each suggesting different mechanisms for enhancing interruption management skills. The first approach posits that individuals can develop efficient procedural rules or strategies through the repeated execution of specific primary-interrupting task pairs (Anderson and Lebiere, 2014). This perspective implies that a comprehensive investigation into how individuals acquire specific procedural rules would necessitate a diverse and extensive array of primary-interrupting task pairings, shedding light on task-specific learning and adaptation.

The second approach advocates that heightened familiarity with the primary task leads to faster task resumption and improved interruption management (Cades et al., 2006, 2011). Existing research supports the notion that practicing interruption tasks enhances interruption tolerance (Cades et al., 2006). However, further exploration is needed to understand whether this improvement extends to scenarios where primary tasks and interrupting tasks are practiced both separately and in conjunction with interruptions, thereby offering a broader perspective on task familiarity and interruption resilience.

The third approach suggests the possibility of a self-led general learning process, a concept that has been demonstrated in the context of two similar tasks (Jones and Moss, 2019). Yet, the extent to which this generalization process applies to two cognitively distinct tasks remains an open question, hinting at the potential for a more universal form of cognitive adaptability in the face of interruptions.

In light of the diverse perspectives offered by existing literature and the gaps identified in conventional methods for mitigating the effects of interruptions, we propose three primary inquiries. These inquiries aim to explore the conditions under which practice-based training yields the most significant reductions in errors and delays caused by interruptions. By examining the various underlying mechanisms of practice that contribute to enhanced resilience to interruptions, this research endeavors to offer a more comprehensive understanding of effective interruption management strategies.

Our study's alignment with the comprehensive framework proposed by Donaldson et al. (2000), combined with the insights from Cades et al. (2007) and Trafton et al. (2012), positions our research at the intersection of cognitive psychology, workplace efficiency, and educational methodology. This multidisciplinary approach is reflective of the complexity of interruption management as a field of study and underscores the necessity of integrating diverse perspectives to develop effective solutions.

As we advance into the fabric of interruption management strategies, it is imperative to recognize the role of individual differences in the effectiveness of training interventions. The cognitive styles, learning preferences, and adaptability of individuals can significantly influence the outcomes of the training. Future research should consider these factors to personalize and optimize training interventions for different individuals and groups.

2.2 Research Aim and Questions

The primary aim of this study is to empirically evaluate the efficacy of structured training methods in improving individuals' resilience and performance in the face of interruptions. We aim to answer the following pivotal questions:

1. How do structured pedagogical methods sculpt the tolerance to, and management of, interruptions in task performance? What are the underlying cognitive mechanisms influenced by these methods?

2. To what extent do these methods manifest in quantifiable outcomes, specifically in terms of enhancements in productivity and reductions in error rates? What metrics best capture these improvements?

3. Are the benefits of such training methods universally applicable, transcending the boundaries of specific tasks and contexts, or are they confined to the conditions under which they were developed?

In addressing these questions, this study endeavors to contribute an understanding of interruption management, providing empirical evidence to support the development and implementation of effective training strategies.

2.3 Study Design

Employing a multi-faceted study design, we use a 2 x 2 x 2 x 2 mixed factorial framework, crafted to unravel the effects of various training conditions on interruption tolerance. This design framework facilitated a granular analysis, allowing us to isolate and evaluate the influence of specific variables.

2.3.1 Performance Metrics

We have chosen to employ four primary performance metrics: interruption lag, resumption lag, accuracy, and response speed. These metrics, entrenched in the standard practices of interruption studies (e.g., Trafton et al. (2005); Altmann and Trafton (2020)), have been further refined and expanded in our study to offer a multi-dimensional perspective on training efficacy.

- **Resumption Lag**: This metric quantifies the time, in seconds, required for a participant to mentally regroup and resume the primary task following an interruption. Serving as a direct indicator of the cognitive load imposed by the interruption, resumption lag is pivotal for evaluating the efficiency of task resumption strategies.

- **Interruption Lag**: This metric measures the duration, in seconds, that a participant takes to address an interruption once it occurs. It is a critical gauge of a participant's responsiveness and effectiveness in redirecting their focus from the primary task to the interrupting task, a skill of paramount importance in environments where multitasking is the norm.

- **Accuracy**: In our pursuit of a comprehensive assessment of interruption management skills, we sought tasks that could accurately measure distinct cognitive capabilities. This metric is defined uniquely for each primary task:

  - For a task that evaluates strategic problem-solving, we selected an activity involving the rearrangement of objects according to specific rules. Here, accuracy is gauged not just by task completion but by the efficiency of the solution, measured by the number of moves executed beyond the optimal solution. This measure not only reflects the participant's ability to plan and strategize but also their adaptability in adjusting strategies based on the evolving task requirements.
  - For a task that assesses memory retention and recall, we incorporated an activity that requires participants to remember and reproduce a sequence of visual information. In this task, accuracy is determined by the correctness of the sequence recalled by the participant. This metric is particularly insightful as it serves as a testament to the participant's ability to retain, process, and reconstruct visual information over short periods, highlighting their short-term memory and attention to detail.

  These tasks were chosen for their ability to elicit and measure key cognitive skills essential for efficient interruption management, ensuring that our study could provide an analysis of the training's impact on these crucial capabilities.

- **Response Speed**: This metric captures the total time, in seconds, taken by a participant to complete a task. It is indispensable for assessing the impact of interruptions on overall task efficiency and for quantifying enhancements in task execution speed as an outcome of the training.

These metrics collectively offer an understanding of how training influences participants' ability to handle interruptions. By analyzing participants' performance across all four metrics, we aim to ascertain the presence and extent of acquired interruption tolerance skills, thereby providing empirical support for the effectiveness of our training interventions.

2.3.2 Task Selection

Following the establishment of our performance metrics, we selected tasks that not only represent common cognitive demands in various work environments but also allow for precise measurement of our performance metrics.

Primary Tasks:

The Tower of Hanoi: A strategic problem-solving task, the Tower of Hanoi, was chosen for its relevance to everyday cognitive tasks that require planning and sequential processing. Its inclusion allows for the exploration of how interruptions can impact tasks that necessitate a high level of cognitive control and foresight. The Tower of Hanoi puzzle begins with the discs arranged in a scattered fashion across three pegs. Despite this initial scattering, the discs maintain a consistent order by size, with smaller discs atop larger ones. The primary objective of the puzzle is to relocate the entire stack to the rightmost peg, adhering to the rule that only smaller discs may

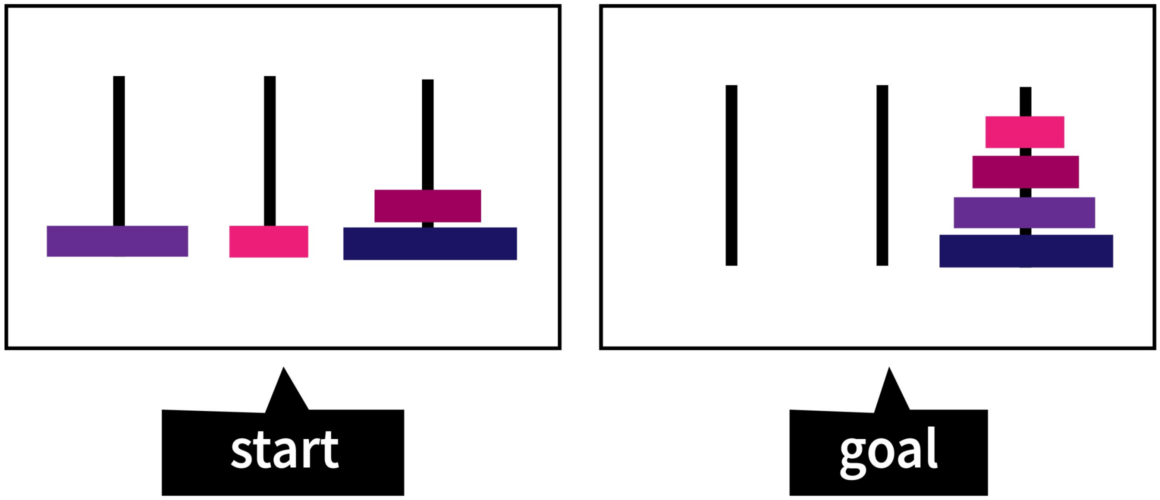


Figure 2.1: In the Tower of Hanoi task, participants are instructed to move discs to create the goal formation. There are many starting positions but only one goal formation.

be placed on top of larger ones. Each move involves transferring a single disc from the top of one stack to either an empty peg or on top of a larger disc on another peg, as illustrated in Figure 2.1. This task is recognized as a low-memory strategy task analogue (Rudner et al., 2009). It allows participants to adopt a methodical approach to problem-solving, where the sequence of moves can be adjusted and recalculated as needed. Interruptions typically impact the performance speed rather than the accuracy, as the task structure permits participants to pause, reassess, and replan their strategy upon resumption, thereby preventing errors and unnecessary moves.

Path Recall Task: Focusing on memory and sequence recall, this task represents activities where continuity and the ordering of actions are crucial. It helps in understanding the impact of interruptions on tasks that demand a strong reliance on working memory and the ability to remember and execute a series of steps in a precise order. The path recall task is designed to assess an individual's memory and sequence recall capabilities. In each instance of the task, the participant is presented with a

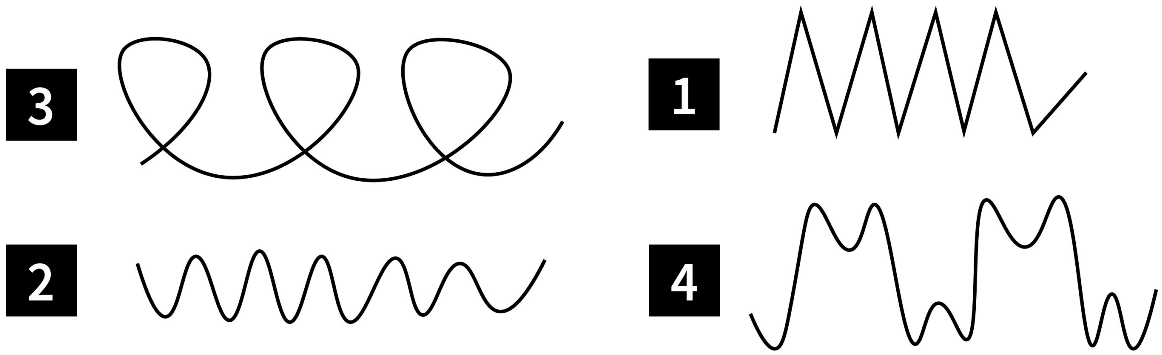


Figure 2.2: In the Path Recall Task, participants are instructed to reconstruct the sequence of paths followed by a line segment in the previous four videos. The images here display the complete paths, but it is important to note that participants only view a portion of each path at any given time in the videos. The numbers in the images represent the order in which the videos appeared, and participants must recall and match this order based on their memory of the line segments' movements.

sequence of four short videos. Each video displays a line segment tracing a distinct path across the screen. The paths vary in their patterns, including a curly path, a zigzag path, a sine wave path, and an odd-harmonics sine wave path. Crucially, the videos only reveal a portion of the path at any given time, compelling the participant to mentally construct and memorize the entire trajectory of the line segment as it progresses.

The sequence of the videos is randomized for each task question, adding an additional layer of complexity and ensuring that rote memorization from previous questions does not aid performance. After viewing the four videos, the participant is then presented with complete images of the paths, fully traced, corresponding to the paths undertaken by the line segments in the videos, as illustrated in Figure 2.2.

At this juncture, the participant's task is to reconstruct the sequence of the videos based on their memory of the line segments' movements. They must drag and drop numbers to correctly assign a position to each completed path, reflecting the order in which they appeared in the video sequence. This task not only tests the participant's memory for the paths themselves but also their ability to recall the specific sequence of the paths, a challenge that closely mimics real-life tasks requiring the accurate recall of sequences and procedures after an interruption.

Interrupting Tasks:

Stroop-like Interference Task: Drawing on the principles of the well-established Stroop task, known for its utility in measuring cognitive interference and control (Scarpina and Tagini, 2017), our adapted Stroop-like task is designed to examine the participant's ability to manage task performance amidst interference. This involves navigating between a highly practiced skill (reading) and a simpler, yet less practiced skill (naming colors). The task aims to provide insights into the participant's cognitive flexibility and control in the face of competing cognitive demands. The task presents two cards: the first displays the name of a color (e.g., "black"), while the second features a color name printed in a color that does not match the word (e.g., the word "red" printed in black ink). This incongruence between the word meaning and the ink color introduces a conflict that the brain must resolve, a process that mirrors the cognitive recalibration required when an interruption occurs. Participants are tasked with determining whether the color of the text on one card matches the name of the color on the other card, responding by clicking *Yes* or *No*, as depicted in Figure 2.3. The inclusion of this task in the study serves a dual purpose. First, it allows for the quantification of the cognitive cost associated with task-switching and attention reallocation, which are critical when managing interruptions. Second, it provides in-

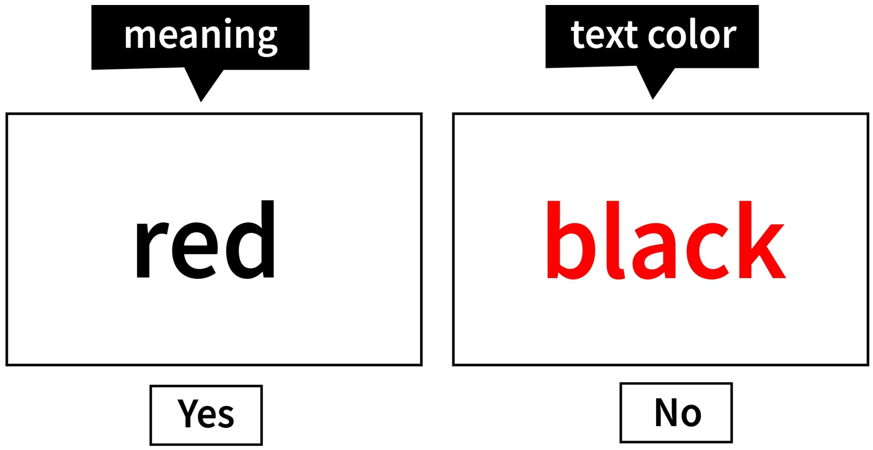


Figure 2.3: The Stroop-like interruption task requires participants to determine if there is a match between the text meaning on the left card and the text color on the right card. Responses are submitted by selecting "Yes" for a match in both meaning and color, and "No" for non-matching cards. In this example, the correct response is "Yes".

sights into the participants' ability to maintain task performance under conditions of conflicting information, a skill that is paramount in environments where interruptions are frequent and often require immediate cognitive processing.

Comparative Math Questions: This task was selected for its capacity to engage participants in analytical and numerical processing, simulating a common type of interruption encountered in many professional settings. In such scenarios, individuals are frequently required to momentarily disengage from their primary task to address analytical demands or perform numerical problem-solving, making this task highly representative of real-world interruptions.

The structure of the comparative math task involves the presentation of two cards, each displaying a simple arithmetic problem involving addition, subtraction, or multiplication of two single-digit numbers. The participant's challenge is to compute the results quickly and accurately, and then determine which of the two cards represents the larger numerical value. Illustrated in Figure 2.4, the task demands the execution

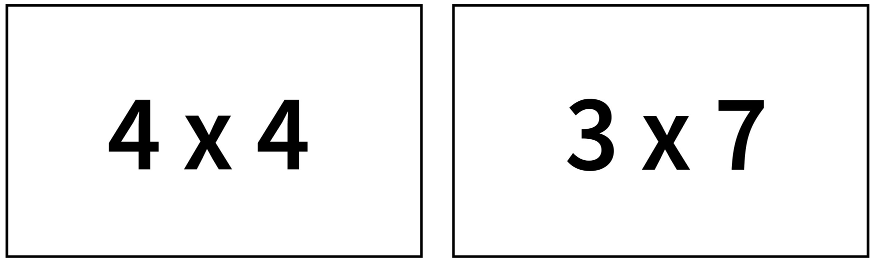


Figure 2.4: In the math interruption task, participants are asked to solve two mathematical expressions and select the card with the greater value.

of basic arithmetic operations and the comparative analysis of the outcomes.

In contrast to the Stroop-like task, the comparative math task places a direct demand on the participant's attentional resources for calculation and numerical processing. This distinction in cognitive demands ensures a diverse range of interruption types are examined. Moreover, the inclusion of this task is supported by findings that engaging in complex problem-solving, such as mathematics, can disrupt the participant's ability to maintain and rehearse information from the primary task (Zish et al., 2020).

2.3.3 Study Variables

We identified and manipulated four specific variables within our study design:

1. **Training (Interleaved vs. Consecutive Interruptions):**

   (a) Purpose: To assess the differential impact of interruptions that are interleaved with primary tasks as an intervention versus interruptions that are presented consecutively after the completion of primary tasks.

   (b) Rationale: This variable allows us to explore how the timing and integration of interruptions with primary tasks influence cognitive load and task resumption strategies, offering insights into the most effective training methodologies for minimizing the disruptive effects of interruptions.

2. **Task Novelty (Consistent vs. Varied Tasks Across Phases):**

   (a) Purpose: This study aims to investigate the impact of task type variation on performance metrics. Specifically, it examines the effects of training participants on one task type during the intervention phase of a three-phase study, and then switching to a different task type in both the pre-intervention and post-intervention phases, as compared to maintaining a consistent task type throughout all phases.

   (b) Rationale: This variable probes the generalizability and transferability of interruption management skills, testing whether skills learned in one context (task type) can be effectively applied in another, thereby contributing to the development of versatile interruption management strategies.

3. **Type of Primary Task (Tower of Hanoi vs. Path Recall Task):**

   (a) Purpose: To evaluate how different types of primary tasks, each with unique cognitive demands (strategic problem-solving vs. memory recall), affect performance metrics.

   (b) Rationale: By comparing the impact of interruptions on tasks with varying cognitive requirements, this variable provides a deeper understanding of how task nature influences the cognitive strategies employed to manage interruptions and maintain task performance.

#	**Pre-Intervention**	**Intervention**	**Post-Intervention**
1	$Tower\ /\ Math$	$Path\ /\ Math$	$Tower/Math$
2	$Tower/Stroop$	$Path/Stroop$	$Tower/Stroop$
3	$Path/Math$	$Tower/Math$	$Path/Math$
4	$Path/Stroop$	$Tower/Stroop$	$Path/Stroop$
5	$Tower/Math$	$Tower/Stroop$	$Tower/Math$
6	$Tower/Stroop$	$Tower/Math$	$Tower/Stroop$
7	$Path/Math$	$Path/Stroop$	$Path/Math$
8	$Path/Stroop$	$Path/Math$	$Path/Stroop$
9	$Tower/Math$	$Path \rightsquigarrow Math$	$Tower/Math$
10	$Tower/Stroop$	$Path \rightsquigarrow Stroop$	$Tower/Stroop$
11	$Path/Math$	$Tower \rightsquigarrow Math$	$Path/Math$
12	$Path/Stroop$	$Tower \rightsquigarrow Stroop$	$Path/Stroop$
13	$Tower/Math$	$Tower \rightsquigarrow Stroop$	$Tower/Math$
14	$Tower/Stroop$	$Tower \rightsquigarrow Math$	$Tower/Stroop$
15	$Path/Math$	$Path \rightsquigarrow Stroop$	$Path/Math$
16	$Path/Stroop$	$Path \rightsquigarrow Math$	$Path/Stroop$

Table 2.1: Each row represents a unique training variation. The first column represents the variation number. The notation A/B denotes that the primary task A is being interrupted by interrupting task B. In contrast, $A \rightsquigarrow B$ denotes that primary task A precedes B and participants are performing a series of task A and then a series of task B.

4. **Type of Interrupting Task (Stroop-like vs. Comparative Math Task):**

   (a) Purpose: To assess whether different types of interrupting tasks, each demanding distinct cognitive processes (conflict resolution vs. analytical problem-solving), affect performance differently.

   (b) Rationale: This variable enables us to explore whether the nature of the interrupting task influences the cognitive cost of task switching and the effectiveness of interruption handling strategies.

2.3.4 Training Variations and Sequential Phases

The study is structured around 16 unique variations of our training intervention, each representing a distinct combination of the four study variables. The variations, labeled 1 to 16, are detailed in Table 2.1, offering a comprehensive breakdown of each training variation.

The intervention for each participant unfolds across three structured phases, each serving a specific purpose:

1. **Pre-Intervention Phase**: This phase involves an initial task assessment aimed at measuring baseline performance on the primary and interrupting tasks, prior to the introduction of any training intervention. This benchmarking is vital, serving as a comparative reference point for assessing performance shifts attributable to the training intervention.

2. **Intervention Phase**: At the heart of the study lies the Intervention phase, where participants are immersed in one of the 16 training variations. This phase is crafted to deliver targeted training interventions, with each variation uniquely designed to bolster the participant's capacity to manage interruptions and foster an enhanced tolerance to such disruptions.

3. **Post-Intervention Phase**: The culmination of the intervention is marked by the Post-Intervention phase. Participants re-engage with the same set of tasks as in the Pre-Intervention phase, allowing for a direct comparison of post-intervention performance against the initial benchmarks. This phase is instrumental in capturing the tangible outcomes of the training, highlighting any notable improvements or changes in task performance as a result of the intervention.

Crucially, each training variation maintains consistency in task presentation during both the pre- and post-intervention phases. This ensures that any observed differences in performance can be accurately attributed to the influence of the intervention phase, thereby allowing for a precise measurement of improvement. Systematically varying the training conditions across the 16 unique variations, the study is positioned to unravel and pinpoint the factors that significantly contribute to an enhanced tolerance to interruptions and a more efficient recovery from such disruptions.

2.3.5 Performance Metrics, Recruitment, Screening, and Data Collection

In this study, we integrate a multifaceted approach to evaluate the efficacy of training variations, employing four primary metrics to gain a comprehensive understanding of participants' cognitive responses. To facilitate this analysis, we developed a systematic framework for participant engagement and automated data collection. The study, built with Unity3D, was delivered online, accessible to participants through the Prolific platform (Palan and Schitter, 2018). Upon entry, participants were oriented with a study briefing and a demographic survey.

Before embarking on the study phases (pre-intervention, intervention, and post-intervention), participants underwent a detailed tutorial, ensuring a clear understanding of the tasks. Upon completion, participants were assigned a unique identifier to claim their compensation through Prolific. The data, once collected, underwent processing by our team and was securely stored, setting the stage for an in-depth analysis in line with our cognitive performance metrics.

Recruitment through Prolific attracted 257 initial responses. Ensuring data quality, our screening process filtered participants based on criteria such as adulthood, English fluency, no prior participation in our studies, and a Prolific approval rate above 95%. To safeguard against factors that might skew the analysis, we excluded participants with conditions like color blindness and those who failed to demonstrate comprehension in a preliminary tutorial requiring three consecutive correct responses.

Furthermore, we refined our dataset by excluding results from participants scoring below 60% accuracy in any phase or showing more than two minutes of inactivity, thus focusing on data reflecting genuine engagement and comprehension. This led to the exclusion of seventeen participants due to low accuracy scores ($N = 2$) or timed-out responses ($N = 15$). The final dataset for our study comprised 240 participants, with a balanced sampling that ensured an equal distribution between male and female participants. This even representation formed the basis of our analysis.

2.4 Results

Our analytical approach primarily employed Analysis of Variance (ANOVA), encompassing both repeated measures and mixed-model methodologies. To adhere to the normality assumptions, Q-Q plots and Shapiro-Wilk tests were utilized (Shaphiro and Wilk, 1965). For homoscedasticity, accuracy measurements underwent a square transformation. The independence of observations was maintained within and across the variational groups, and dependent variables were quantified at the interval level to facilitate meaningful comparisons.

In the computation of Cohen's d, our methodology was nuanced, reflecting the complexity of our data. For Mixed-Model ANOVA, the classic computation of Cohen's d was employed. Conversely, for repeated measures ANOVA, we adapted our approach to align with the paired nature of our data, utilizing Cohen's d_z specifically for paired samples (Goulet-Pelletier and Cousineau, 2018). This dual approach ensured that our effect size measurements were attuned to our data's structure.

2.4.1 Overall Effects and Their Interactions

Our initial analysis employed a mixed linear model to examine the comprehensive effects and interactions of our primary dependent variables – Variations and Phases. This model facilitated the extraction of main effects and the detailed exploration of two-way interactions between these factors, effectively capturing the dynamics within the dataset. The model was particularly suited for analyzing the correlation of observations within individual subjects across various phases, ensuring a thorough understanding of the data. Additionally, it incorporated random effects, accommodating individual variability and adding a layer of depth to the analysis. A significant focus was placed on resumption lag.

Resumption Lag: The model's intercept established the baseline level for resumption lag at 4.612 seconds, indicating a pronounced inherent challenge in task resumption. This baseline was statistically significant compared to zero ($p \leq 0.001$), signifying that the observed resumption lag of 4.612 seconds is a substantial factor and not merely a random variation. This emphasizes the intrinsic difficulty associated with resuming tasks. Further analysis of the influence of variations on resumption lag revealed notable discrepancies.

In this analysis, we formulated a model encompassing all main effects and two-way interactions between variations and phases, with a particular focus on the impact on resumption lag. The model's intercept was set at 4.612 seconds, representing the baseline level of resumption lag when all predictors are at their reference levels, denoting a statistically significant baseline level of resumption lag before accounting for the influence of variations and phases.

When examining the effects of variations on resumption lag, we identified significant differences for numerous variations compared to the baseline group (variation 1). Specifically, the model revealed significant effects of variation 3 ($\beta = 5.952$, $p \leq 0.001$), variation 4 ($\beta = 8.166$, $p \leq 0.001$), variation 7 ($\beta = 6.021$, $p \leq 0.001$), variation 8 ($\beta = 7.357$, $p \leq 0.001$), variation 11 ($\beta = 5.752$, $p \leq 0.001$), variation 12 ($\beta = 7.585$, $p \leq 0.001$), variation 15 ($\beta = 5.704$, $p \leq 0.001$), and variation 16 ($\beta = 5.970$, $p \leq 0.001$). Estimated coefficients are denoted as β.

The post-intervention phase exhibited a general trend of decreased resumption lag ($\beta = -0.762$, $p = 0.089$); however, this trend from the pre-intervention to the post-intervention phases did not reach statistical significance. No significant changes were observed in the other phases.

Moreover, the interaction effects on resumption lag were significant, suggesting that the variations in resumption lag from the pre-intervention phase to the post-intervention phase differed significantly when compared to the baseline group. Notable interaction terms included variation 4 ($\beta = -1.243$, $p = 0.050$) and variation 16 ($\beta = -1.569$, $p = 0.013$), indicating substantial changes in resumption lag due to these specific training variations.

Interruption Lag: The Mixed Linear Model (MixedLM) identified the baseline for interruption lag at 5.416 seconds, marking a significant initial delay in handling interruptions as compared to zero ($p \leq 0.001$). This analysis revealed substantial variability in interruption lag across different conditions. Notably, the comparison between the Post phase and the Pre phase indicated a significant reduction in interruption lag, suggesting that the Post phase was characterized by notably shorter lags. This observed decrease in the Post phase implies an enhancement in the participants' capability to manage interruptions, presumably influenced by the training interventions.

Upon examining the influence of variations on interruption lag, the model discerned significant differences for several variations when compared to the baseline group (variation 1). Noteworthy findings include the significant effect of variation 2 ($\beta = -1.413$, $p \leq 0.001$), variation 4 ($\beta = -1.055$, $p = 0.016$), variation 6 ($\beta = -1.919$, $p \leq 0.001$), variation 8 ($\beta = -1.462$, $p \leq 0.001$), variation 10 ($\beta = -1.574$, $p \leq 0.001$), variation 12 ($\beta = -1.100$, $p = 0.012$), variation 13 ($\beta = -1.288$, $p = 0.003$), variation 14 ($\beta = -1.045$, $p = 0.017$), and variation 15 ($\beta = -0.879$, $p = 0.044$).

The analysis also highlighted a significant phase effect on interruption lag, particularly notable in the post-intervention phase ($\beta = -1.502$, $p \leq 0.001$), while no significant effects were observed for other phases.

Moreover, interaction effects on interruption lag were found to be significant, indicating that the changes in interruption lag from the pre-intervention phase to the post-intervention phase varied significantly among the variations in comparison to the baseline group. Significant interaction terms included variation 2 ($\beta = 0.885$, $p = 0.028$), variation 4 ($\beta = 0.906$, $p = 0.025$), and variation 5 ($\beta = 1.569$, $p \leq 0.001$), highlighting shifts in interruption lag due to these specific training variations.

Accuracy in the Path Recall Task: Employing the mixed linear model, we integrated all main effects and two-way interactions between variations and phases. The model's intercept was set at 0.822%, establishing the foundational level of accuracy in the path recall task when all predictors are at their reference levels ($p \leq 0.001$). This value represents the baseline performance in terms of accuracy before considering the potential impacts of variations and phases.

Upon examining the influence of variations on accuracy within the path recall task, we found that no variation yielded a significant effect ($p > 0.05$). However, the analysis highlighted a significant phase effect on accuracy. Specifically, a comparison between the post-intervention and pre-intervention phases revealed a meaningful increase in accuracy in the post-intervention phase ($\beta = 0.081$, $p \leq 0.001$).

Further scrutiny was given to the interaction effects between variations and phases concerning accuracy in the path recall task. Among these, the interaction term for variation 12 stood out as significant ($\beta = -0.069$, $p = 0.0405$), suggesting a distinct influence of this specific variation on accuracy, particularly when considering the interaction with different phases of the study.

Optimality of Performing the Tower of Hanoi: As highlighted earlier, optimality is quantified by the discrepancy between the participant's number of steps taken and the minimum number of steps theoretically required to solve the puzzle.

A smaller differential indicates superior performance, denoting efficiency in puzzle-solving. In our analysis, the mixed linear model was employed, integrating all main effects and two-way interactions between variations and phases. The intercept was set at 1099.566%, signifying the baseline level of optimality when all predictors are at their reference levels ($p \leq 0.001$).

Delving into the effects of variations on optimality within the Tower of Hanoi task, notable findings emerged. Specifically, variation 6 was associated with a significant improvement in optimality ($\beta = -139.082$, $p = 0.027$), indicating a reduction in the number of steps close to the optimal number of steps tp take. Similarly, variation 9 also exhibited a significant enhancement in optimality ($\beta = -134.925$, $p = 0.032$). However, the other variations related to the Tower of Hanoi task did not manifest statistically significant alterations in optimality.

Moreover, the analysis showed a substantial phase effect on optimality in the Tower of Hanoi task. Notably, the post-intervention phase marked a significant improvement in optimality ($\beta = -178.141$, $p = 0.005$), underscoring enhanced performance in this phase. The other phases did not exhibit significant changes in this regard.

We also investigated interaction effects on optimality in the Tower of Hanoi task. Although most interaction terms did not attain statistical significance ($p > 0.05$), the overall analysis underscores a complex interplay among variations, phases, and their interactions.

Speed of Task Completion: A reduction in time is indicative of enhanced performance, reflecting increased speed. The mixed linear model was employed to encompass all main effects and two-way interactions between variations and phases.

The intercept was established at 48.345 seconds, representing the baseline speed in task completion when all predictors are at their reference levels ($p \leq 0.001$).

In our analysis of the variations' impact on speed in task completion, specific patterns emerged. Notably, significant improvements in speed were observed in variation 3 ($\beta = -28.827$, $p \leq 0.001$) and variation 4 ($\beta = -26.969$, $p \leq 0.001$). These findings indicate a marked decrease in the time taken to complete tasks, suggesting enhanced efficiency. However, the remaining variations did not demonstrate statistically significant changes in speed.

Additionally, the phase effect on task completion speed was pronounced. The post-intervention phase was characterized by a notable improvement in speed ($\beta = -15.243$, $p \leq 0.001$), pointing to a significant enhancement in performance. No similar significant effects were detected in the other phases.

Interaction effects on speed in task completion were examined. Significant interaction terms were identified, including variation 3 ($\beta = 14.335$, $p \leq 0.001$) and variation 4 ($\beta = 13.854$, $p \leq 0.001$). While these terms exhibit positive coefficients, their interpretation necessitates careful consideration within the overall model context and the specific dynamics of the interaction terms. It is crucial to note that positive coefficients in this setting may not straightforwardly signify a deterioration or improvement in speed but might instead encapsulate interactions between variations and phases. This is particularly pertinent given the varying time durations associated with the different primary tasks involved. Other variations did not exhibit significant interaction effects on speed.

2.4.2 Effect of Training

Our investigation focused on determining the efficacy of practice-based interruptions training. This was quantitatively measured through observed improvements in key performance metrics: resumption lag, interruption lag, task completion speed, and response accuracy, comparing outcomes between the pre- and post-intervention phases across all training variations.

To assess the impact of the intervention on these performance metrics, we employed repeated measures ANOVA. This analysis allows each performance metric to be treated as a dependent variable, enabling us to monitor the evolution of these variables for each participant through different study phases. By employing repeated measures ANOVA, we leveraged the mean as the aggregation function to scrutinize the within-subject effects.

The core objective of this approach was to discern any statistically significant changes in performance metrics that could be directly attributed to the training interventions. This method is instrumental in unraveling how these variables systematically affect the performance metrics of participants. Our analysis culminated in the observation of statistically significant improvements across each performance metric. These enhancements were evident when comparing participant performances from the pre-intervention phase to those in the post-intervention phase across all variations of training, as depicted in Figure 2.5. For resumption lag, the 240 participants demonstrated an average of 6.95 seconds for each resumption ($SD = 5.37s$) in the pre-intervention phase, which decreased to an average of 5.89 seconds ($SD = 4.66s$)

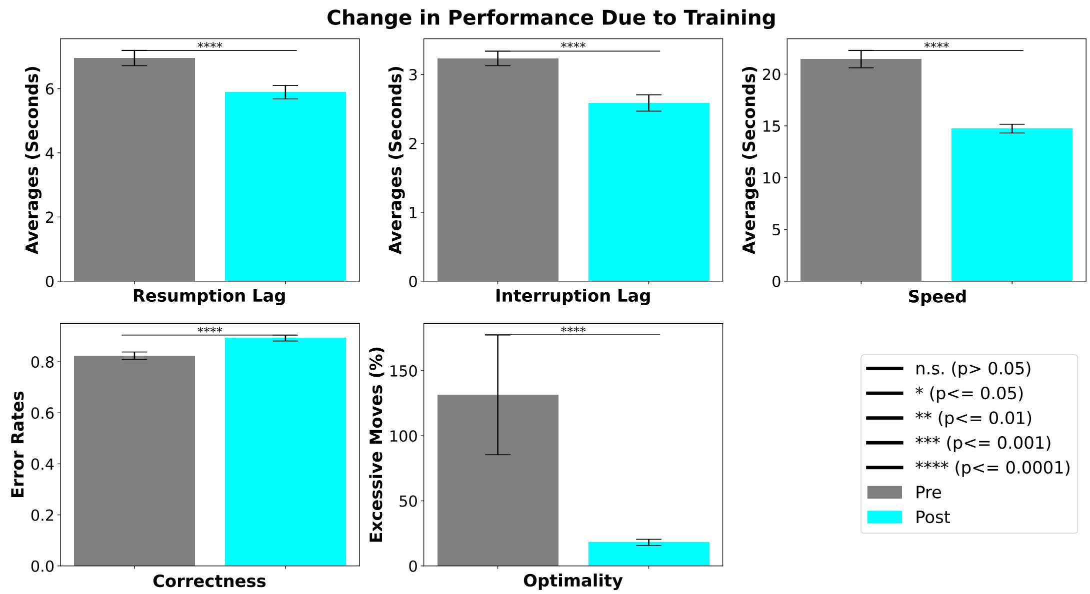


Figure 2.5: Change in performance due to training. The averages and 95% confidence intervals are shown for the resumption lag, interruption lag, and speed (task completion time), as well as the inaccuracies or error rate of the path recall task and number of excessive moves during the Tower of Hanoi task. Changes in each performance metric between the pre- and post-intervention phases show significant improvements resulting from training.

in the post-intervention phase. The training intervention led to a reduction in participants' resumption lag by approximately 15.3% or 1.07 seconds between phases, regardless of the tasks they trained on. These improvements were statistically significant ($F(1, 239) = 63.29$, $p \leq 0.001$), with an effect size (Cohen's d_z) of 0.51, indicating a moderate effect.

For interruption lag, participants demonstrated an average of 3.23 seconds for each interruption ($SD = 2.35s$) in the pre-intervention phase, which decreased to an average of 2.59 seconds ($SD = 2.64s$) in the post-intervention phase. The intervention reduced participants' interruption lag by 20.0% or 0.65 seconds between phases, regardless of the tasks they trained on. These improvements were significant ($F(1, 239) = 55.81$, $p \leq 0.001$), with a Cohen's d_z of 0.48, indicating a small to moderate effect size.

Regarding the path recall task, 120 participants experienced it as their primary training task (variations 3, 4, 7, 8, 11, 12, 15, and 16). In the pre-intervention phase, participants had a benchmark average error of 0.82% ($SD = 0.32\%$) on each path recall task, which increased to an average error of 0.89% ($SD = 0.26\%$) in the post-intervention phase. The intervention increased participants' error rates by approximately 8.4% between phases. These changes were significant ($F(1, 119) = 27.31$, $p \leq 0.001$), with a Cohen's d_z of 0.48, indicating a moderate effect.

For the Tower of Hanoi task, experienced by the remaining 120 participants, there was an average of 131% ($SD = 1027\%$) excessive moves to complete each task during the pre-intervention phase. This improved to an average of 18% ($SD = 53.70\%$) excessive moves in the post-intervention phase, reducing participants' excessive moves by 86%. These improvements were significant ($F(1, 119) = 29.28$, $p \leq 0.001$), with a Cohen's d_z of 0.49, indicating a moderate effect.

For response speed, participants showed a benchmark average of 21.45 seconds ($SD = 26.73s$) for each primary task completion time in the pre-intervention phase. This improved to an average of 14.73 seconds ($SD = 13.40s$) in the post-intervention phase, enhancing participants' response speed by 31% or 6.72 seconds. These improvements were also significant ($F(1, 239) = 122.71$, $p \leq 0.001$), with a Cohen's d_z of 0.72, indicating a moderate, non-trivial effect.

These results reveal significant improvements in each performance metric across all training variations. To assess the potential influence of the specific amount of practice on the primary tasks over time, we conducted a comparative analysis. Training variations involving consistent exposure to the same primary task across all three phases (variations 5-8 and 13-16) were compared with those involving less exposure to the same primary task, limited to two of the three phases (variations 1-4 and 9-12).

This comparative analysis yielded noteworthy insights. No significant differences were observed in the extent of improvements between training variations with more exposure to the same task and those with less exposure. Specifically, the difference in average improvement for resumption lag between the more and less exposed variations was negligible at 0.03 seconds ($SD = 0.01s$; $z = 0.11$, $p = 0.91$). For interruption lag, the difference was -0.22 seconds ($SD = 0.11s$; $z = -1.30$, $p = 0.19$); for accuracy in the path recall task, the difference was -0.01% ($SD = 0.01\%$; $z = 0.41$, $p = 0.68$); for accuracy in the Tower of Hanoi task, the difference was -17.66% ($SD = 8.83\%$; $z = 0.38$, $p = 0.71$); and for response speed, the difference was -0.98 seconds ($SD = 0.49s$; $z = 0.81$, $p = 0.42$).

This analysis suggests that the extent of exposure or practice with the primary tasks alone does not solely account for the observed improvements resulting from the training intervention. The statistically significant enhancements observed between the pre- and post-intervention phases across all study variations and performance metrics underscore the efficacy of our training intervention in improving individuals' tolerance to interruptions in these tasks.

2.4.3 Effect of Training with Novel Primary Tasks

We investigated whether training with novel primary tasks could augment the observed tolerance to interruptions. Specifically, we aimed to discern if engaging with new, unfamiliar tasks could also be an effective mechanism for building interruption tolerance. To this end, we applied our established analytical approach—comparing performance metrics between the pre-intervention and post-intervention phases—to the training variations involving novel primary tasks (variations 1-4 and 9-12). A total of 120 participants were exposed to these training variations featuring novel primary tasks. Our analysis confirmed that training with novel primary tasks led to statistically significant improvements across all performance metrics. See Figure 2.6.

For resumption lag, the 120 participants exhibited an average of 7.10 seconds for each resumption ($SD = 5.74s$) in the pre-intervention phase, which decreased to 6.05 seconds ($SD = 5.09s$) in the post-intervention phase. The training reduced participants' resumption lag by about 15.8% or 1.05 seconds between phases, regardless of the primary task. Improvements were statistically significant ($F(1, 119) = 24.48$, $p \leq 0.001$), with a Cohen's d_z of 0.45, indicating a small effect size.

For interruption lag, participants demonstrated an average of 3.31 seconds for each interruption ($SD = 2.34s$) in the pre-intervention phase, decreasing to 2.58 seconds ($SD = 1.85s$) in the post-intervention phase. The intervention reduced participants' interruption lag by 22.88% or 0.67 seconds between phases, regardless of the tasks they were trained on. These improvements were significant ($F(1, 119) = 55.36$, $p \leq 0.001$), with a Cohen's d_z of 0.67, indicating a moderate effect size.

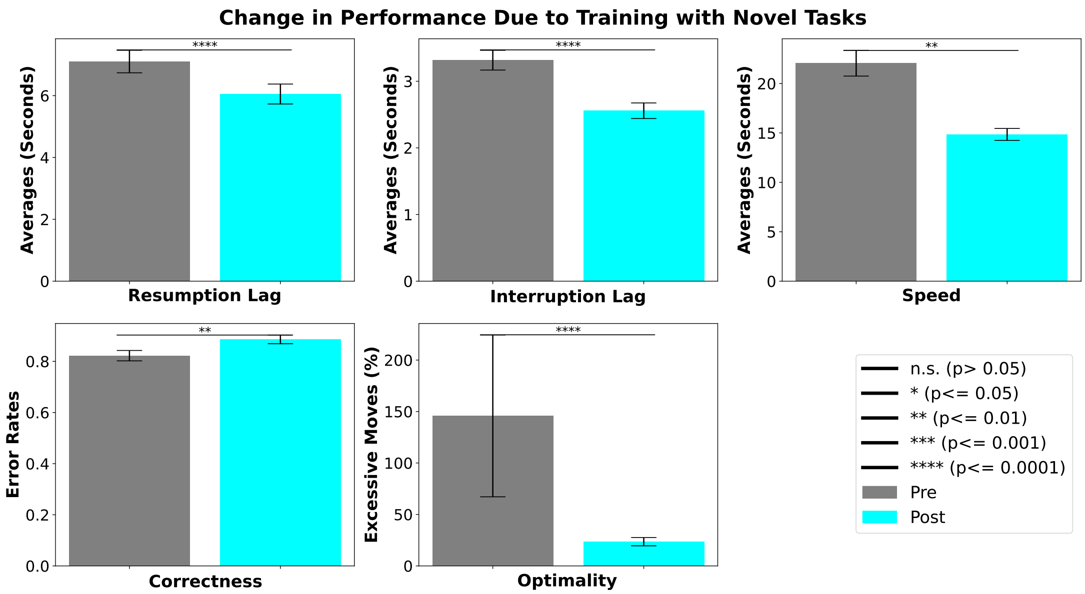


Figure 2.6: Change in performance due to training with novel tasks. The averages and 95% confidence intervals are shown for the resumption lag, interruption lag, and speed (task completion time), as well as the inaccuracies or error rate of the path recall task and number of excessive moves during the Tower of Hanoi task. Changes in each performance metric between the pre- and post-intervention phases show significant improvements resulting from training interventions with novel primary tasks.

In terms of accuracy in the path recall task, participants had an average error of 0.82% ($SD = 0.32\%$) in the pre-intervention phase, compared to 0.89% ($SD = 0.27\%$) in the post-intervention phase. The training intervention increased participants' error rates by about 7.74% between phases. These changes were significant ($F(1, 59) = 11.13$, $p \leq 0.001$), with a Cohen's d_z of 0.43, indicating a moderate effect that is not trivial.

For the Tower of Hanoi task, participants exhibited an average of 145% ($SD = 1240\%$) excessive moves to complete the task in the pre-intervention phase, improving to 23.56% ($SD = 63.58\%$) in the post-intervention phase. The training intervention reduced participants' excessive moves by 122%. These improvements were also significant ($F(1, 59) = 11.09$, $p \leq 0.001$), with a Cohen's d_z of 0.43, reflecting a moderate effect.

For response speed, participants showed a benchmark average of 20.06 seconds ($SD = 29.15s$) for task completion in the pre-intervention phase, which improved to 14.84 seconds ($SD = 13.53s$) in the post-intervention phase. The training intervention enhanced participants' response speed by 32.69% or 7.21 seconds. These improvements were also significant ($F(1, 119) = 51.77$, $p \leq 0.001$), with a Cohen's d_z of 0.66, indicating a moderate, non-trivial effect.

2.4.4 Effect of Training with Novel Interrupting Tasks

We explored whether training with novel interrupting tasks could serve as an effective method for enhancing tolerance to interruptions. Employing the same analytical methods as before, we analyzed the performance metrics for training variations that introduced novel interrupting tasks (variations 5-8 and 13-16). Our findings affirm that training with novel interrupting tasks led to statistically significant improvements across all performance metrics, as depicted in Figure 2.7.

For resumption lag, the 120 participants exhibited an average of 6.81 seconds for each resumption ($SD = 4.96s$) in the pre-intervention phase. This average decreased to 5.73 seconds ($SD = 4.19s$) in the post-intervention phase. The training reduced participants' resumption lag by about 15.85% or 1.08 seconds between phases, independent of the tasks they were trained on. These improvements were statistically significant ($F(1, 119) = 43.34$, $p \leq 0.001$), with a Cohen's d_z of 0.60, indicating a moderate effect size. For interruption lag, participants demonstrated an average of

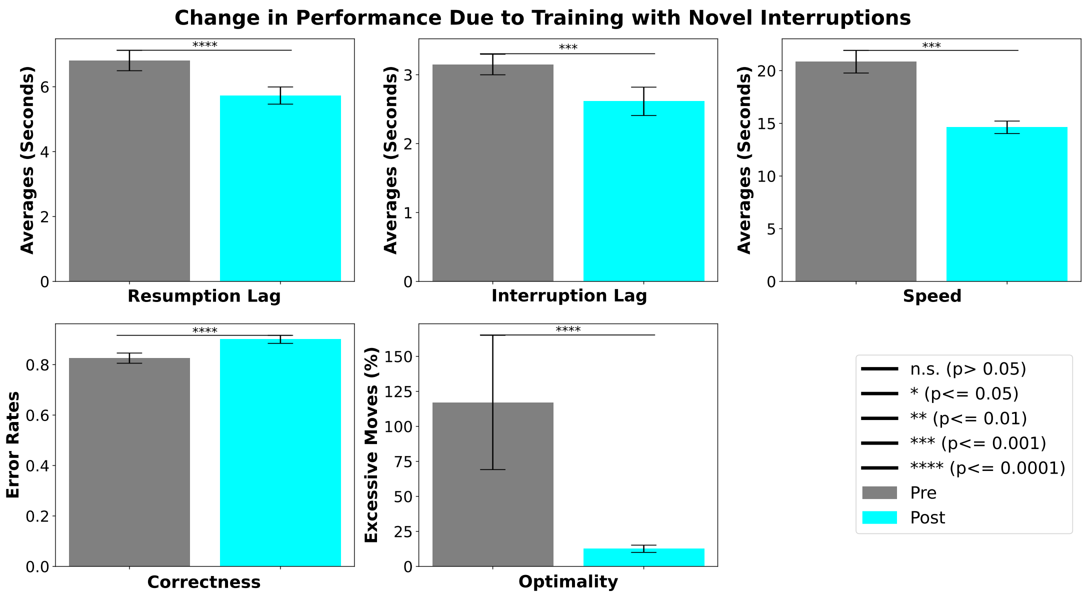


Figure 2.7: Change in performance due to training with novel interruptions. The averages and 95% confidence intervals are shown for the resumption lag, interruption lag, and speed (task completion time), as well as the inaccuracies or error rate of the path recall task and number of excessive moves during the Tower of Hanoi task. Changes in each performance metric between the pre- and post-intervention phases showed significant improvements resulting from training interventions with novel interrupting tasks.

3.15 seconds for each interruption ($SD = 2.35s$) in the pre-intervention phase. This reduced to 2.61 seconds ($SD = 3.25s$) in the post-intervention phase, marking a reduction in interruption lag by 16.97% or 0.53 seconds due to training. These improvements were significant ($F(1, 119) = 14.81$, $p \leq 0.001$), with a Cohen's d_z of 0.35, suggesting a small effect size.

In terms of accuracy, participants had a benchmark average error of 0.83% ($SD =$ 0.32%) on each path recall task in the pre-intervention phase, compared to 0.90% ($SD = 0.25\%$) in the post-intervention phase. The training intervention increased participants' error rates by approximately 0.07% between phases. These changes were significant ($F(1, 59) = 16.32$, $p \leq 0.001$), with a Cohen's d_z of 0.52, indicating a moderate effect that is noteworthy.

For the Tower of Hanoi task, participants initially had an average of 117% ($SD =$ 757.99%) excessive moves to complete each task during the pre-intervention phase. This improved to 12.57% ($SD = 40.83\%$) excessive moves in the post-intervention phase, signifying a reduction of 89.26% in excessive moves due to the training. These improvements were also significant ($F(1, 59) = 25.97$, $p \leq 0.001$), with a Cohen's d_z of 0.66, reflecting a moderate effect.

For response speed, participants had a benchmark average of 20.85 seconds ($SD =$ $24.05s$) for task completion in the pre-intervention phase. This improved to 14.62 seconds ($SD = 13.25s$) in the post-intervention phase, enhancing participants' response speed by 29.88% or 6.23 seconds. Improvements were also significant ($F(1, 119) =$ 82.59, $p \leq 0.001$), with a Cohen's d_z of 0.83, indicating a large effect size.

In conclusion, the results suggest that incorporating a novel interrupting task during training can effectively enhance performance across each evaluated metric.

2.4.5 Effect of Training Method

Our analysis probed the transferability of the interruption tolerance skills acquired through our training interventions. We aimed to discern if training with interspersed interruptions yielded performance compared to training with interruption-like tasks and primary tasks presented independently. We used a mixed-model ANOVA to evaluate the impact of these two methods on performance, comparing training variations that integrate primary tasks with interruptions (variations 1-8) against those presenting primary and interrupting tasks separately, in sequence (variations 9-16).

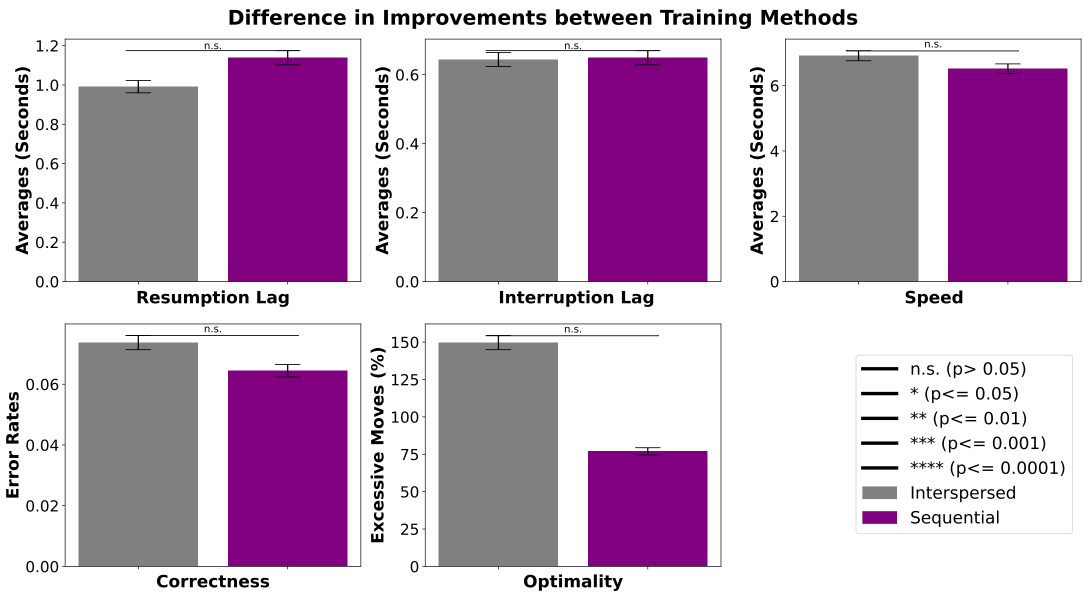


Figure 2.8: Difference in improvements between training methods. The averages and 95% confidence intervals are shown for the resumption lag, interruption lag, and speed (task completion time), as well as the inaccuracies or error rate of the path recall task and the number of excessive moves during the Tower of Hanoi task. We observe no no statistically significant differences in the magnitude of improvement between the two training methods.

Although improvements in interruption tolerance were noted across all training variations, analysis showed no statistically significant differences in the magnitude of improvement between the two training methods, as depicted in Figure 2.8.

For changes in resumption lag, participants undergoing training with interspersed interruptions demonstrated an average improvement of 0.99 seconds ($SD = 0.70s$), while those with consecutively presented tasks showed an average improvement of 1.14 seconds ($SD = 0.81s$). The difference between these training methods was not statistically significant ($z = 0.55$, $p = 0.58$), with a calculated Cohen's d of 0.07, indicating a small effect size.

Regarding changes in interruption lag, participants experienced an average improvement of 0.64 seconds ($SD = 0.46s$) for training with interspersed interruptions, compared to an average improvement of 0.65 seconds ($SD = 0.46s$) for training with separate tasks. The difference in improvement was not significant ($z = -0.03$, $p = 0.98$), yielding a Cohen's d of 0.01, reflecting a small effect size.

In terms of accuracy changes, training variations with interspersed interruptions led to an average error rate reduction of 0.07% ($SD = 0.05\%$) for each path recall task, while variations with consecutively presented tasks resulted in an average reduction of 0.06% ($SD = 0.05\%$). This difference was not significant ($z = -0.35$, $p = 0.73$), with a calculated Cohen's d of -0.03, suggesting a negligible effect size.

For the Tower of Hanoi task, training with interspersed interruptions led to an average reduction of excessive moves by 150% ($SD = 105.85\%$), whereas training with separate tasks resulted in a reduction of 76.94% ($SD = 54.40\%$). The difference between these training methods was not significant ($z = 1.56$, $p = 0.12$), and the calculated Cohen's d was 0.06, indicating a small effect size.

In response speed, training with interspersed interruptions yielded an average improvement of 6.92 seconds ($SD = 4.89s$) in task completion time, whereas training with separate tasks showed an average improvement of 6.52 seconds ($SD = 4.61s$). The difference between these training methods was not significant ($z = 0.33$, $p = 0.74$), with a calculated Cohen's d of 0.06, suggesting a small effect size.

In conclusion, the absence of statistically significant differences between the two training methods across performance metrics implies that both approaches are comparably effective in enhancing one's tolerance to interruptions.

Figure 2.9: Difference in improvements between training methods due to novel tasks. The averages and 95% confidence intervals are shown for the resumption lag, interruption lag, and speed (task completion time), as well as the inaccuracies or error rate of the path recall task and the number of excessive moves during the Tower of Hanoi task. We observe significant differences in participants' improved accuracy and speed (task completion time) when comparing the training variations that present varying primary tasks with interruptions to the training variations that present primary tasks and interrupting tasks separately.

Effect of Training Method with Novel Primary Tasks

While our previous findings did not distinguish one interruptions practice approach as more effective than another, we further explored the influence of presenting a novel task during training on the efficacy of each training approach. Specifically, we compared the training variations that presented primary tasks interspersed with interruption tasks (variations 1-4) against those that presented primary tasks and interruption tasks consecutively (variations 9-12), with a focus on variations involving novel tasks. Our analysis revealed statistically significant differences in participants' improvement between these two training approaches in terms of accuracy and speed (time to completion) performance metrics, as depicted in Figure 2.9.

For changes in resumption lag, participants undergoing training with interspersed interruptions showed an average improvement of 1.03 seconds ($SD = 0.73s$), while those with consecutively presented tasks demonstrated an average improvement of 1.07 seconds ($SD = 0.76s$). The difference between these training methods was not statistically significant ($z = -0.09$, $p = 0.93$), with a calculated Cohen's d of 0.01, indicating a small effect size.

Regarding changes in interruption lag, participants experienced an average improvement of 0.89 seconds ($SD = 0.63s$) for training with interspersed interruptions, compared to an average improvement of 0.62 seconds ($SD = 0.44s$) for training with separate tasks. The difference in improvement was not significant ($z = 1.33$, $p = 0.18$), yielding a Cohen's d of 0.01, reflecting a negligible effect size.

In terms of accuracy changes, training variations with interspersed interruptions led to an average error rate reduction of 0.1% ($SD = 0.07\%$) for each path recall task, while variations with consecutively presented tasks resulted in an average reduction of -0.03% ($SD = 0.02\%$). This difference was significant ($z = -1.98$, $p \leq 0.05$), with a calculated Cohen's d of 0.21, suggesting a small effect size.

For the Tower of Hanoi task, training with interspersed interruptions led to an average reduction of excessive moves by 201% ($SD = 142\%$), whereas training with separate tasks resulted in a reduction of 42.84% ($SD = 30.29\%$). The difference between these training methods was also significant ($z = 2.00$, $p \leq 0.05$), and the calculated Cohen's d was 0.11, indicating a small effect size.

In response speed, training with interspersed interruptions yielded an average improvement of 8.12 seconds ($SD = 5.75s$) in task completion time, while training with separate tasks showed an average improvement of 6.29 seconds ($SD = 4.45s$). The difference between these training methods was not significant ($z = 0.92$, $p = 0.36$), with a calculated Cohen's d of 0.05, suggesting a negligible effect size.

In conclusion, the presence of a novel primary task during training led to significantly different improvements between the two training methods, particularly in terms of accuracy and speed. Considering the observed improvements in resumption and interruption lags, both training with interspersed interruptions, and the separate sequential tasks and interruptions approach, could serve as effective methods for improving tolerance to interruptions when faced with novel primary tasks.

Effect of Training Method with Novel Interrupting Tasks

Our investigation further delved into whether the presence of a novel interrupting task during training influenced the efficacy of each training method. Specifically, we compared the training variations that integrated primary tasks with novel interruptions (variations 5-8) against those that presented primary tasks and novel interrupting tasks separately (variations 13-16), as depicted in Figure 2.10.

While we previously identified improvements in tolerance to interruptions, particularly in terms of accuracy in training variations involving novel tasks, our current analysis found no statistically significant differences in the magnitude of improvement between these two training approaches with novel interruptions.

For changes in resumption lag, participants undergoing training with interspersed interruptions showed an average improvement of 0.95 seconds ($SD = 0.67s$), while those with consecutively presented tasks demonstrated an average improvement of

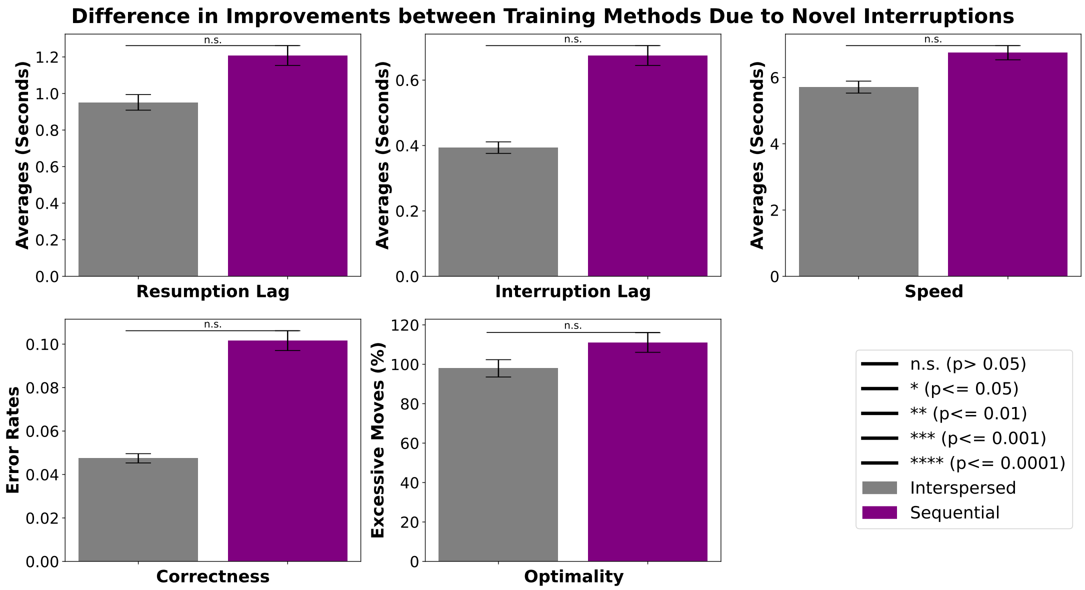


Figure 2.10: Difference in improvements between training methods due to novel tasks. The averages and 95% confidence intervals are shown for the resumption lag, interruption lag, and speed (task completion time), as well as the inaccuracies or error rate of the path recall task and the number of excessive moves during the Tower of Hanoi task. We observe no no statistically significant differences in the magnitude of improvement when comparing the training variations that present varying primary tasks with novel interruptions to the training variations that present primary tasks and interrupting tasks separately in sequence.

1.21 seconds ($SD = 0.85s$). The difference between these training methods was not statistically significant ($z = 0.79$, $p = 0.43$), with a calculated Cohen's d of 0.17, indicating a small but potentially meaningful effect size.

Regarding changes in interruption lag, participants experienced an average improvement of 0.39 seconds ($SD = 0.28s$) for training with interspersed interruptions, compared to an average improvement of 0.68 seconds ($SD = 0.48s$) for training with separate tasks. The difference in improvement was not significant ($z = 1.02$, $p = 0.31$), yielding a Cohen's d of 0.06, reflecting a very small or negligible effect size.

In terms of accuracy changes, training variations with interspersed interruptions led to an average error rate reduction of 0.05% ($SD = 0.03\%$) for each path recall task, while variations with consecutively presented tasks resulted in an average reduction of 0.10% ($SD = 0.07\%$). This difference was not significant ($z = 1.51$, $p = 0.13$), with a calculated Cohen's d of -0.29, suggesting a small to medium effect size.

For the Tower of Hanoi task, training with interspersed interruptions led to an average reduction of excessive moves by 97.94% ($SD = 69.25\%$), whereas training with separate tasks resulted in a reduction of 111.04% ($SD = 78.52\%$). The difference between these training methods was not significant ($z = -0.27$, $p = 0.79$), and the calculated Cohen's d was 0.01, indicating a negligible effect size.

In response speed, training with interspersed interruptions yielded an average improvement of 5.71 seconds ($SD = 4.04s$) in task completion time, while training with separate tasks showed an average improvement of 6.75 seconds ($SD = 4.77s$). The difference between these training methods was not significant ($z = -0.76$, $p = 0.45$), with a calculated Cohen's d of 0.08, suggesting a negligible effect size.

In conclusion, the absence of statistically significant differences between the two training methods across performance metrics implies that both approaches are comparably effective in enhancing one's tolerance to interruptions when novel interrupting tasks are introduced.

2.4.6 Effect of Task Types

We delved into the influence of task type on the efficacy of our training intervention. While direct comparisons of performance averages by task type are not feasible, the improvements in time-based performance metrics due to training with specific tasks

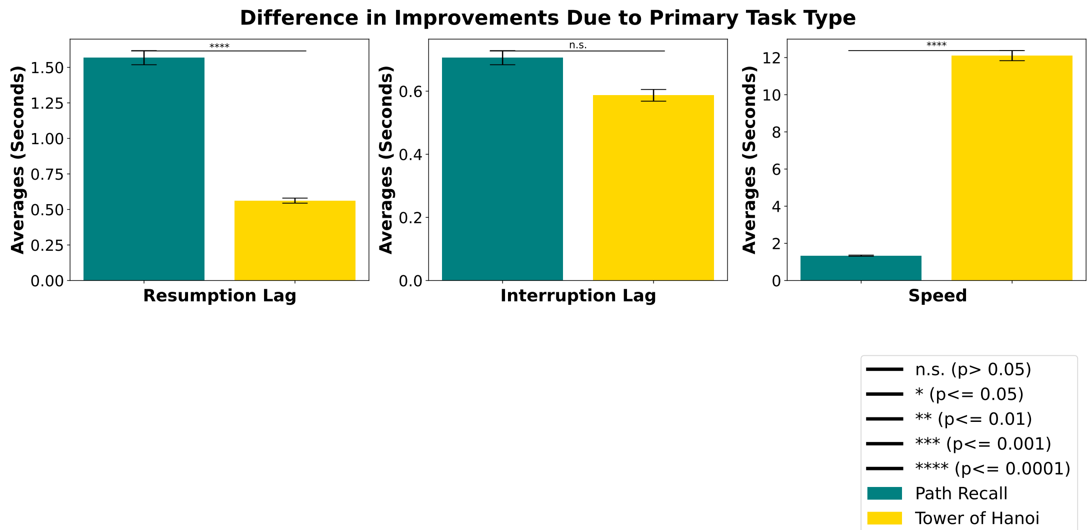


Figure 2.11: Difference in improvements due to primary task type. Changes in each performance metric show significant differences in participants' improved resumption lag, response accuracy, and speed due to the primary task type (i.e., the path recall or Tower of Hanoi) presented during the training intervention.

are comparable. We commenced by contrasting the enhancements resulting from training variations that introduced the path recall task (i.e., variations 3, 4, 7, 8, 11, 12, 15, and 16) with those from training variations that presented the Tower of Hanoi task (i.e., variations 1, 2, 5, 6, 9, 10, 13, and 14). Our findings indicate that the task type significantly influences the degree of improvement, as shown in Figure 2.11.

For changes in resumption lag, participants undergoing training with the path recall task showed an average improvement of 1.57 seconds ($SD = 1.11s$), while those trained with the Tower of Hanoi task exhibited an average improvement of 0.56 seconds ($SD = 0.40s$). This difference was statistically significant ($z = 3.881$, $p \leq 0.001$), with a calculated Cohen's d of 1.47, indicating a large effect size.

Regarding changes in interruption lag, participants trained with the path recall task experienced an average improvement of 0.71 seconds ($SD = 0.50s$), compared to 0.59 seconds ($SD = 0.41s$) for those trained with the Tower of Hanoi task. The difference in improvement was not significant ($z = 0.69$, $p = 0.49$), yielding a Cohen's d of 0.001, indicating a very small or negligible effect size.

For the change in accuracy, even though participants' measures of the correctness of responses to the path recall task were not comparable to participants' approximation of optimal performance of the Tower of Hanoi tasks, we report the statistical comparisons of both performance metrics to provide a full and detailed account of the findings. Participants trained with the path recall task showed an average improvement of 0.07% ($SD = 0.05\%$) in accuracy, while those trained with the Tower of Hanoi task exhibited an average reduction of 113.32% ($SD = 80.13\%$) in excessive moves. This difference was significant ($z = -4.87$, $p \leq 0.001$), with a calculated Cohen's d of -0.45, indicating a moderate effect size.

For changes in response speed, participants trained with the path recall task showed an average improvement of 1.34 seconds ($SD = 0.94s$) in task completion time, while those trained with the Tower of Hanoi task demonstrated an average improvement of 12.10 seconds ($SD = 8.55s$). The difference between these training methods was significant ($z = -10.856$, $p \leq 0.001$), with a calculated Cohen's d of -1.13, indicating a very large effect size.

We further investigated whether the observed variations in the degree of improvement were merely a result of increased exposure to a primary task over time. Comparisons were conducted between training variations that presented the path recall task in two of the three phases (variations 3, 4, 11, and 12) and those with more exposure to the path recall task in all three phases (variations 7, 8, 15, and 16). A similar analysis was performed for the Tower of Hanoi task, contrasting variations with the task in two of the three phases (variations 1, 2, 9, and 10) against those with more exposure in all three phases (variations 5, 6, 13, and 14).

No significant differences were observed in the degree of improvement between training variations with more or less exposure to the path recall task. Specifically, for changes in resumption lag, the difference in average improvements was -0.10 seconds ($SD = 0.05s$; $z = -0.22$, $p = 0.83$); for changes in interruption lag, the difference was -0.16 seconds ($SD = 0.08s$; $z = -0.68$, $p = 0.50$); for changes in accuracy, the difference was -0.01% ($SD = 0.01\%$; $z = 0.41$, $p = 0.68$); and for changes in response speed, the difference was -0.30 seconds ($SD = 0.15s$; $z = 0.86$, $p = 0.39$).

Other than for interruption lag, no significant differences were observed in the degree of improvement between training variations with more or less exposure to the Tower of Hanoi task. Specifically, for changes in resumption lag, the difference in average improvements was 0.05 seconds ($SD = 0.22s$; $z = 0.209$, $p = 0.834$); for changes in interruption lag, the difference was 0.29 seconds ($SD = 2.89s$; $z = 2.446$, $p = 0.014$); for changes in accuracy, the difference was 113.14 ($SD = 647.49$; $z = 0.379$, $p = 0.705$); and for changes in response speed, the difference was 0.41 seconds ($SD = 16.39s$; $z = 1.165$, $p = 0.244$).

In conclusion, the task type significantly impacts the extent of improvement due to training, with notable variations in the degree of enhancement across different metrics. However, the degree of exposure to a specific primary task over time does not appear to significantly influence the magnitude of improvement, suggesting that the observed benefits of the training are not solely a result of increased task familiarity.

2.5 Discussion and Implications

The findings from this study offer compelling support for the effectiveness of pedagogical interventions in enhancing interruption tolerance and managing the disruptive effects of interruptions. The significant improvements observed across key performance metrics post-intervention not only validate the efficacy of the training methods employed but also highlight their potential for broader application.

Generalizability of Training Effects One of the most striking outcomes of this study is the generalizability of the training effects. The improvements in interruption management were not confined to the specific tasks or interruptions encountered during the training, indicating a remarkable level of skill transferability. This suggests that the cognitive strategies and skills honed through the structured, practice-based training have far-reaching implications, extending their potential applicability to diverse operational settings, including those involving complex human-robot interactions. The versatility of the training methods used in this study underscores their potential to be adapted and integrated into various professional environments, enhancing the overall workflow efficiency and reducing the cognitive load associated with interruptions.

Contributions to Interruption Management Discourse

This research makes a significant contribution to the discourse on interruption management, a field that is becoming increasingly relevant in our multifaceted and interruption-rich world. By providing empirical evidence for the feasibility and effectiveness of specific training interventions, this study paves the way for a understanding of how individuals can be equipped to better manage interruptions. The insights gleaned from this study are particularly valuable for sectors where precision and quick cognitive recovery are paramount, such as healthcare, aviation, and information technology.

Avenues for Future Research

The findings from this study also open several avenues for future research. There is an opportunity to delve deeper into how different types of tasks and interruptions influence the effectiveness of training interventions. Further research could explore the long-term effects of such training, assessing the durability of the interruption management skills acquired. Additionally, future studies could examine the integration of technological aids, such as AI-driven task management systems, to support interruption management, potentially leading to a synergistic enhancement of human cognitive resilience in conjunction with structured training methods.

Optimizing Performance in the Face of Interruptions

Ultimately, this research emphasizes the importance of developing strategies to optimize human performance in the face of interruptions. The findings underscore the need for a proactive approach in designing work environments and training programs that not only mitigate the disruptive effects of interruptions but also empower individuals to manage these interruptions effectively. By integrating the insights from this study into practical applications, we can make strides towards creating more resilient, efficient, and safer work environments.

2.6 Practical Implications and Recommendations

The insights derived from this research hold significant practical implications, particularly for high-stakes environments where the cost of interruptions can be substantial. In sectors like healthcare, aviation, and information technology, where precision and rapid cognitive recovery are not just beneficial but essential, the application of structured interruption management training could be a game-changer, substantially enhancing outcomes and safety.

For practitioners and organizational leaders, this study underscores the value of embedding cognitive resilience training within regular professional development programs. Our research indicates potential benefits of cognitive resilience training in high-stakes environments. While it appears to enhance individual performance, it may also modestly contribute to the broader operational efficiency and safety within organizations. This suggests that integrating such training into professional development programs could be beneficial, although further research and customization to specific sector needs are recommended for optimal effectiveness and relevance. The training methods explored and validated in this study can serve as a foundational blueprint for the development of customized training modules. These modules can be tailored to meet the unique demands and contextual specifics of various sectors, ensuring relevance and maximum impact.

Moreover, this research advocates for a proactive, rather than reactive, approach to interruption management. It encourages organizations to strategically consider the cognitive aspects of work design, integrating interruption management strategies into standard operational protocols. By doing so, organizations can significantly bolster their employees' capacity to handle interruptions, transforming potential disruptions into manageable incidents with minimal impact on workflow continuity.

2.7 Limitations and Directions for Future Research

While the findings of this study are offer significant insights into the efficacy of structured training interventions in interruption management, it is crucial to acknowledge the inherent limitations that may influence the interpretation and generalizability of the results.

Firstly, one notable limitation of our experimental design is the absence of a pure control condition. The lack of a control group in this study poses challenges in isolating the specific impact of our practice-based interventions from potential external factors. Without a baseline for comparison, it becomes challenging to discern whether the observed improvements in participants' abilities to handle interruptions are solely attributable to the training variations or if they could be influenced by extraneous variables. This limitation underscores the importance of incorporating a control condition in future studies to enhance the validity of the findings. A well-structured control condition would provide a clearer understanding of the unique contributions of practice-based interventions and enable a more precise attribution of the observed changes to the specific training methods employed.

Secondly, while the controlled nature of the study environment was beneficial for isolating specific variables and effects, it may not fully capture the complexity and unpredictability inherent in real-world settings. The artificiality of a controlled environment can limit the applicability of the findings to naturalistic scenarios, where numerous uncontrolled variables may interact with the training interventions. To address this limitation, future research should aim to bridge this gap by implementing and testing these training methods in situ. Conducting studies in naturalistic settings, such as actual workplaces, could provide an understanding of the interventions' effectiveness, the dynamics of interruption management, and how these factors interact in real-life scenarios.

Thirdly, while this study primarily focused on cognitive and behavioral strategies, the potential role of technological solutions in supporting interruption management remains an exciting frontier for exploration. Future research could delve into the interplay between human cognitive resilience training and technological aids, such as AI-driven task management systems or context-aware interruption management software. Understanding how these technologies can complement human strategies may pave the way for a synergistic approach to managing interruptions, combining the strengths of human adaptability and technological precision.

Lastly, the generalizability of the training's effectiveness across diverse demographic groups and professional backgrounds is a critical consideration. The responses to and benefits from the training interventions may vary based on factors such as age, cultural background, or field of expertise. Future research should focus on a more inclusive and varied participant pool, enabling a comprehensive analysis of how different individuals or groups respond to the training. This direction could lead to the development of more personalized, inclusive, and effective intervention strategies, catering to the unique needs and characteristics of various populations.

While this study lays a solid foundation for understanding and improving interruption management through structured training, there is a wealth of opportunities for future research to expand, refine, and apply these insights. By addressing the limitations and exploring the suggested avenues, subsequent studies can continue to enrich our understanding and enhance our capability to navigate and manage interruptions in an increasingly complex and demanding world.

2.8 Summary

Chapter 2 has explored the domain of interruption management, presenting a body of empirical evidence that elucidates the effectiveness of structured, practice-based training interventions. These interventions have been shown to significantly enhance individuals' ability to manage interruptions, underlining the pivotal role of cognitive resilience in today's dynamic workplace environments.

We recognize that our exploration into interruption management and cognitive resilience training has set the stage for further innovative applications. The methodologies and findings discussed here pave the way for more targeted and specialized interventions, addressing the needs of diverse populations and operational contexts.

In Chapter 3, we extend the narrative of interruption management to a particularly pertinent and impactful domain: the potential of social robotics in providing job-relevant interruptions training for an understudied population–individuals with Autism Spectrum Disorders (ASD). Given the unique challenges faced by individuals with ASD, particularly in navigating workplace distractions, unpredictability, and social interactions, this next chapter delves into how the principles and findings from the structured, practice-based training explored in Chapter 2 can be applied and tailored through the medium of social robotics. We examine the acceptance, effectiveness, and transformative potential of social robotics in not just managing but mastering workplace-relevant interruptions, aiming to enhance autonomy and improve the quality of life for individuals with ASD.

Chapter 3

Cultivating Workplace Adaptability and Competence: The Role of Social Robotics in Skills Training for Adults with ASD

Much of the material presented in this chapter is derived from a previously published paper.[1]

In the contemporary workplace, proficiently managing interruptions is not merely a commendable skill but an essential pillar for career success and adaptability. This truth holds even greater weight for individuals with Autism Spectrum Disorders (ASD). Confronted with a spectrum of social and communicative challenges, these individuals often perceive the dynamic and unpredictable nature of workplace environments as particularly overwhelming (American Psychiatric Association, 2022). Further, Johnson et al. (2020) reveal that adults with ASD excel when engaged with technology-based interventions specifically designed for their distinct learning profiles. These interventions are crucial for honing vital work-related skills, demonstrating the significant advantages of customizing support to match the individual cognitive ca-

[1] See Ramnauth et al. (2022) for more details.

pabilities and preferences of those with ASD. This chapter explores the synergy between social robotics and career development, spotlighting the role of an innovative autonomous robot system, the Interruptions Skills Training and Assessment Robot (ISTAR). ISTAR offers essential job-relevant interruptions training tailored for this frequently overlooked demographic.

While the integration of social robots in therapeutic and training frameworks is not a novel concept, harnessing this technology to address the specific employability hurdles encountered by adults with ASD has only been investigated by a few (Bruyère et al., 2020). Our exploration is driven by the critical imperative to bridge the divide between the intrinsic abilities of individuals with ASD and the intricate demands of contemporary workplaces. Amidst the rising prevalence of ASD, the stark contrast in employment rates for this group signals a pressing call for interventions. Such initiatives are imperative to endow these individuals with the requisite competencies to not only navigate but also flourish in professional environments.

3.1 Background

Employability transcends the mere acquisition of a job; it embodies the capacity to maintain employment, excel in a role, and adapt to the evolving demands and multifaceted challenges that the workplace presents. For individuals with ASD, the hurdle often lies not in a lack of technical skills or intelligence but in navigating the social and adaptive nuances crucial in today's collaborative and dynamic work environments. Interruptions, a ubiquitous element in professional settings, can manifest as anything from a colleague's query to an abrupt shift in task priorities. While these disruptions are generally manageable for most, they can be profoundly disorienting for individuals with ASD, potentially leading to significant stress, decreased productivity, and even job loss (Wei et al., 2018; Harmuth et al., 2018).

3.1.1 Job Skills Training for Adults with ASD

The challenge of handling interruptions is particularly pronounced for individuals with ASD, where the social skills deficits common among many exacerbate the impact of workplace distractions, unpredictability, and uncertainty (Kenyon, 2015). Addressing this complex issue requires a multifaceted approach that includes customized, long-term supports and accommodations within nurturing communities and informed workplaces, contributing to successful employment outcomes for individuals with ASD (Harmuth et al., 2018).

Effective strategies for gainful employment among individuals with ASD encompass onsite training that incorporates environmental assessments to identify and reduce distractions, as well as personalized, job-specific training that focuses on managing interruptive tasks (Hendricks, 2010). Unlike other technologies, a robot's physical presence in training scenarios commands attention and promotes engagement, offering a tangible, interactive experience that makes it difficult for users to ignore or silence its prompts for interaction (McKenna et al., 2020; Scassellati, 2007).

Socially Assistive Robots (SARs), a specialized subset of social robotics, merge traditional robotics with computational methods to provide personalized, socially situated, and physically co-present interactions, making SARs particularly suited for individuals with ASD (Matarić and Scassellati, 2016). The design and application of SARs, ensure that these robots are not just passive tools but active participants in the training process, capable of adjusting their behavior and feedback to meet the individual's unique learning pace and style. This approach underscores the significance of social interaction and engagement in the training process, aligning with the overarching goals of ISTAR to provide effective, user-friendly, and socially attuned training for individuals with ASD.

3.1.2 Improving Tolerance to Interruptions Through Practice-Based Training

Empirical evidence supports the notion that practice-based training with interruptions can significantly benefit individuals (Zish et al., 2020; Hodgetts and Jones, 2006; Cades et al., 2011). Key metrics such as *resumption lag* – the time needed to mentally regroup and return to the primary task post-interruption (Altmann and Trafton, 2004) – and *interruption lag* – the time taken to address the interrupting task – are instrumental in assessing the impact of such training. Studies indicate that repeated exposure to interruptions, coupled with task-specific training, can effectively reduce these lags, thereby enhancing overall task performance (Cades et al., 2011). The interaction between individuals with ASD and embodied artificial agents is increasingly evidenced to promote prosocial behaviors, sustain attention, induce spontaneous and socially appropriate responses, diminish stereotyped behaviors, optimize cognitive learning, and enhance social engagement (Diehl et al., 2012; Srinivasan et al., 2015; Robins et al., 2012; Scassellati et al., 2012; Pennisi et al., 2016).

3.2 Research Aim and Theoretical Framework

We leverage a theoretical framework that primarily revolves around the concept of social robotics as a potent medium for delivering specialized training tailored to individuals with unique learning needs, particularly those with Autism Spectrum Disorders (ASD). It is grounded in the belief that every individual's learning and developmental needs are unique, especially for those with ASD, and advocates for personalized, user-centric approaches in designing and deploying assistive technologies like social robots. Further, we posit that properly designed social robots can go beyond the traditional boundaries of therapy and skill development. This implies that such robots can offer more engaging, intuitive, and effective ways to enhance social and professional competencies among individuals with ASD.

This research hypothesizes that a robot can complement existing skill development approaches to the significant betterment of individuals with ASD. The primary objectives, therefore, center on the development, refinement, and evaluation of such a system:

1. **Design and Iterative Refinement of ISTAR:** To architect and continually refine ISTAR's features, ensuring that its operations are marked by responsiveness, autonomy, and a deep alignment with user preferences. This objective is pivotal in creating a system that is not only technically proficient but also

empathetically attuned to the users' unique contexts and needs.

2. **Evaluating Acceptance and Impact:** To critically assess how adults with ASD receive ISTAR and to evaluate its efficacy in improving their ability to manage job-related interruptions. This involves a comprehensive analysis of user engagement, satisfaction, and the system's practical impact on enhancing workplace competencies.

3. **Exploring Broader Implications:** To delve into the wider implications of deploying social robotics in enhancing employability and life quality for individuals with ASD. This objective seeks to uncover the potential ripple effects of such technological interventions in fostering inclusivity and empowerment in professional and social settings.

This chapter describes the process of conceptualizing, developing, and evaluating a technological solution.

3.3 Methodological Approach

To improve tolerance to real-world interruptions, the system should provide workplace-relevant interruptions training through role-playing. With efficient and relevant training, we expect users will improve their tolerance for workplace interruptions where, over time, the interruptions will become less disruptive, allowing them to return to their primary task quickly. ISTAR is designed not just as a tool but as a companion that situated in the personal spaces of individuals with ASD to provide tailored, realistic, and engaging training. The development of ISTAR is grounded in a deep understanding of the unique needs and preferences of adults with ASD, ensuring that the technology is not just effective but also acceptable and comfortable for the end-users. Hence, the development and assessment of ISTAR followed a user-centered methodology, involving a multi-stage process that prioritized the feedback and preferences of the end-users – adults with ASD. The methodology was structured to ensure that the system was not only technically sound but also socially and contextually relevant.

3.3.1 Needs Assessment and Conceptualization:

In the initial phase, a series of consultations were conducted with occupational therapists, psychologists specializing in ASD, and, crucially, adults with ASD themselves. The aim of these sessions was to understand the specific challenges experience by adults with ASD. The insights gained from these consultations were instrumental in shaping the design objectives for ISTAR, ensuring that the system aligns closely with the real-world needs of its users.

The design of ISTAR is centered around four primary goals, each grounded in the feedback and observations from these initial consultations:

1. **Embodied:** ISTAR is conceived as an embodied system, taking the form of a social robot. This embodiment is critical as it has been shown to produce measurable learning outcomes (Leyzberg et al., 2012), enhance training compliance (Bainbridge et al., 2008), and facilitate the expression of realistic, socially appropriate cues that foster suitable responses from users (Fiore et al., 2013).

2. **In-the-Home:** The system is designed to operate within the user's home. This home-based approach not only circumvents potential workplace stigma but also eliminates the need for users to disclose their diagnosis at work. Unlike systems designed for clinical or laboratory environments where conditions are controlled (McKenna et al., 2020; Belpaeme et al., 2018), ISTAR is tailored to the dynamic and unstructured nature of home environments, necessitating sophisticated sensing capabilities and behavioral decision-making.

3. **Autonomous:** ISTAR is developed to function autonomously, negating the need for continuous technical oversight or control post-deployment. This autonomy ensures that the system can independently manage its operations, making it user-friendly and accessible for individuals without technical expertise.

4. **Realistic:** The system is programmed to simulate interactions that closely mirror real workplace interruptions, responding in real-time with human-like behaviors such as naturalistic gaze, movement, and speech. This realism is paramount to ensure that the training is relevant, engaging, and effectively prepares users for actual workplace scenarios.

Leveraging the valuable feedback from the needs assessment phase, a conceptual model of ISTAR was formulated. This model prioritizes intuitive interaction, adaptability to the unique profiles of individual users, and the capacity to emulate realistic workplace interruptions, thereby laying a strong foundation for the subsequent phases of design and development.

3.3.2 Design and Development

The transition from a conceptual model to a tangible, functioning system was orchestrated by a multidisciplinary team consisting of engineers, user experience (UX) designers, and ASD specialists. This collaborative synergy was pivotal in materializing the vision of ISTAR. Central to this phase was the principle of iterative design, ensuring that the development process was dynamic and responsive. Prototypes underwent continuous refinement, guided by a dual focus on user feedback and technical evaluations. This iterative approach was instrumental in achieving a balance between technical robustness and user-centric design.

3.3.3 Interaction

A significant emphasis during the design process was placed on the aesthetic and sensory attributes of the robot. Recognizing the diverse sensory sensitivities among users with ASD (Robertson and Simmons, 2013), the team ensured ISTAR's physical presence was comforting and non-intrusive. This consideration was critical in fostering a user-friendly interface and ensuring that the robot was perceived as a supportive, rather than overwhelming, presence in the home environment.

ISTAR's primary function is to serve as an in-home interruptions training robot. Its design encourages frequent, yet succinct, interactions, engineered to capture and retain the user's attention. These interactions are crafted to simulate the dynamics of real-world interruptions, thereby providing a practical and immersive training experience. Post-interaction, users are subtly prompted to exercise their resilience to

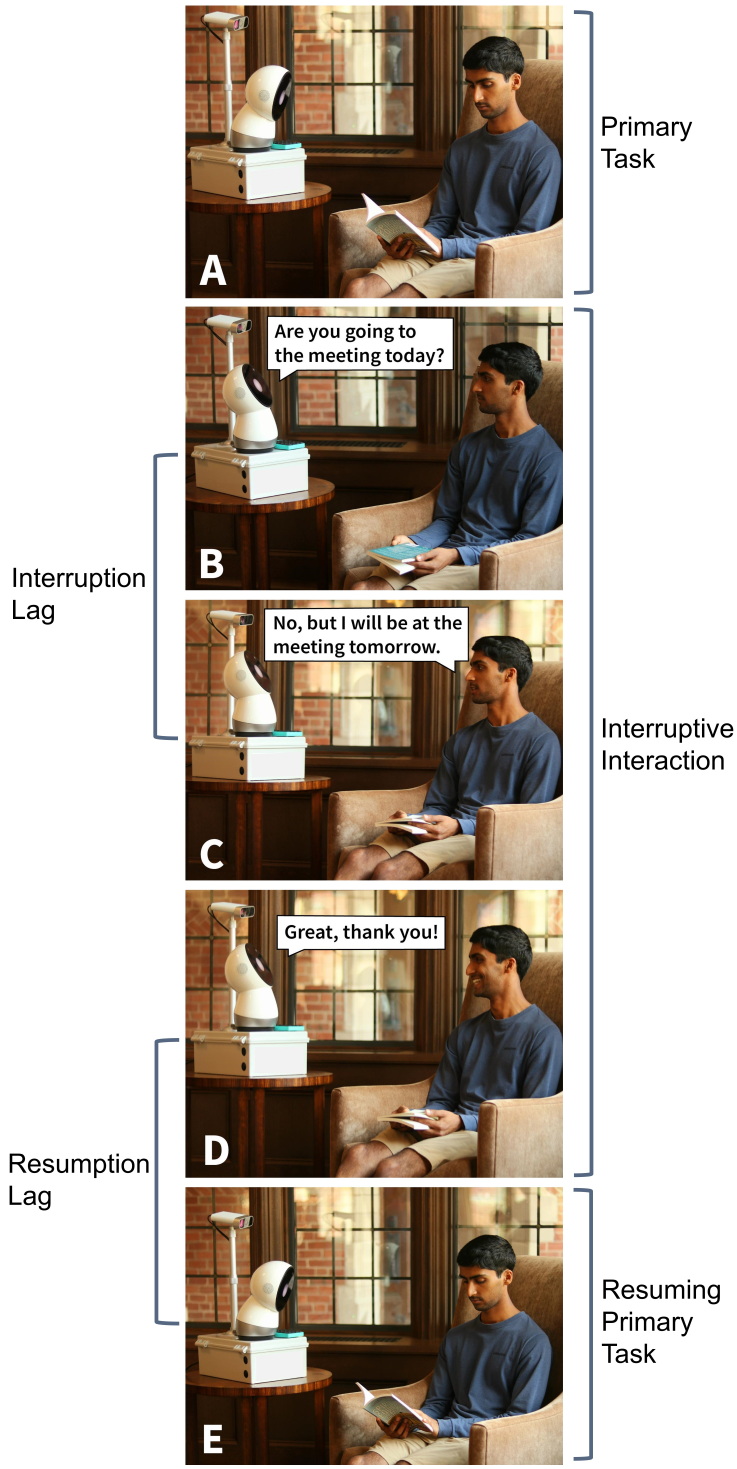


Figure 3.1: ISTAR interruptions: (A) the participant is occupied with a primary task while the robot is performing idling behavior; (B) the robot interrupts the user by asking a work-related question; (C) the user responds to the robot's interruption; (D) the robot thanks the user for their response; finally, (E) the user resumes their original task. We define two metrics to measure resiliency to an interruption: interruption lag and resumption lag.

interruptions by seamlessly transitioning back to their original tasks, a process that is crucial in building interruption management skills.

To elucidate the interaction dynamics of ISTAR, consider the following illustrative scenario (refer to Figure 3.1): The user is engrossed in a primary task, such as reading, with ISTAR positioned unobtrusively on the desk. ISTAR is programmed to detect the presence of the user within its camera's field of view before initiating an interaction. Frame A captures the user deeply focused on the reading task. In Frame B, ISTAR introduces an interruption by posing a question, effectively capturing the user's attention. Frame C depicts the moment the user diverts his focus from the reading task to engage with ISTAR, marking the interruption lag — the interval between ISTAR's initiation of the interruption and the user's shift in attention. Following the interaction, as shown in Frame D, ISTAR acknowledges the user's response and reverts to a state of inactivity. Frame E captures the conclusion of the interaction, with ISTAR returning to its idle state and the user resuming the initial task. The resumption lag, a critical metric in this training, is measured from the end of the interruption to the point where the user fully re-engages with the original task.

ISTAR not only embodies the principles of socially assistive technology but also provides a structured yet flexible framework for enhancing the interruption management skills of individuals with ASD in the comfort and privacy of their homes.

Figure 3.2: Prototype - A Jibo robot is attached to a wooden base. On the base are microphones, a camera, and a toggle switch to power the system on or off. Inside the base is a computer, a battery, a network router, and a cooling fan.

3.3.4 Hardware

Our initial testable system integrated six primary hardware components, as depicted in Figure 3.2. Central to this ensemble is the Jibo robot, standing at 11 inches tall and featuring 3 full-revolute axes for fluid 360-degree movement (MIT Media Lab, 2024). Jibo's sophisticated hardware capabilities enable the programming of

personified behaviors, such as naturalistic gaze and movement, crucial for creating lifelike, engaging interactions. Accompanying Jibo is a compact PC, the operational hub of the system. This unit not only facilitates communication with other hardware components but also monitors the system's overall performance and acts as the local repository for data storage during our in-home system evaluations. Feedback from preliminary survey evaluations conducted with adults with ASD and employers underscored the need for interruptions that elicit a physical response. Consequently, a numeric keypad was integrated to enable interactions requiring users to perform a mental task and input their responses.

Both Jibo and the keypad are securely mounted atop a plastic case, which houses the PC and all ancillary hardware components essential for ISTAR's operation. These components, though not directly interacted with by the user, underpin the functionality of the entire system.

For the requisite in-home sensing, an Azure Kinect DK (Development Kit) camera is positioned on a mast, located just behind and slightly above Jibo's head (Microsoft Corporation, 2019). This placement optimizes the camera's field of vision, providing greater environmental awareness. The Kinect's built-in microphone array is used to capturing audio during training sessions.

Recognizing the importance of a self-reliant system, each ISTAR unit is equipped with a mobile router, complete with a prepaid internet service plan. This setup guarantees a continuous WiFi connection, enabling automatic cloud-based data synchronization and facilitating remote system control for troubleshooting and monitoring purposes during in-home evaluations. Additionally, an uninterruptible battery power supply is included, serving as ISTAR's primary charging station and enhancing system resilience. As a result of these design choices, ISTAR is a plug-and-play system, requiring nothing more than a connection to a power outlet in the user's home. The

Figure 3.3: Deployable Ensemble - A Jibo robot is attached to a sturdy thermoplastic polymer base box. Also on the base is an Azure Kinect mounted on a mast, and a numeric keypad. Inside the base is a computer, an uninterruptible power supply with surge protection, a network router, and a cooling fan.

system's design prioritizes self-reliance and self-containment. Adhering to principles of ergonomic and accessible design, the apparent complexity for the user is minimized by encasing non-interfaceable components within the container which supports both the robot and the external camera. This approach not only streamlines the user's interaction with the system but also significantly reduces the perceived complexity from the participant's perspective. The final iteration of the system, ready for deployment in the user's home, is illustrated in Figure 3.3.

3.3.5 Software

In crafting the ISTAR system, a modular software architecture was employed, ensuring that individual components of the system could be independently updated and refined. This modularity was achieved by structuring the software components as nodes within the Robot Operating System (ROS) (Open Source Robotics Foundation, 2007), a flexible framework that facilitates the development of complex robotic behaviors.

A crucial component in this architecture is the scheduling node. This node is responsible for deciding when the system should capture an image using the Azure Kinect. Captured images serve as input to a pre-trained YOLO (You Only Look Once) neural network (Redmon and Farhadi, 2018), which is utilized to estimate the number of people within the system's field of view. The decision-making process is straightforward yet contextually aware: if the system detects fewer than two people, it proceeds to deliver an interruption. Conversely, if two or more people are detected, ISTAR assumes that it may not be a socially appropriate moment for an interruption and thus abstains from initiating one. Nevertheless, the system is designed to maintain a consistent frequency of interruptions over a designated time window. This is achieved by incrementally adjusting the intervals between interruptions, ensuring that the user experiences the planned number of interactions. These intervals are determined based on a Gaussian distribution, intentionally introducing variability to preclude the user from anticipating subsequent interruptions.

When ISTAR is in a passive state, Jibo adopts a subtle, non-intrusive posture, with its gaze directed towards the floor. Upon being activated to deliver an interruption, Jibo shifts its gaze upwards and plays a pre-recorded audio file of the interruption through its speakers, engaging the user's attention. For interruptions that necessitate a verbal response, the system patiently awaits the user's reply. The spoken response is captured and relayed to the Google Speech-to-Text API for transcription, allowing the user's input to be documented. If the user does not respond within a ten-second window, Jibo gently reprompts the original question, ensuring that the interaction remains engaging and that the user's training is continuous. Once the user's response is received, Jibo acknowledges their participation with a word of thanks and then returns to its idle state, silently looking at the floor.

3.4 Evaluation

The evaluation of ISTAR was designed to be comprehensive, targeting not just the system's functionality and usability, but also delving into the subjective experiences and perceptions of the users.

3.4.1 Evaluation 1: Surveys of the Prototype

To gauge initial user acceptance and gather actionable feedback for system refinement, surveys were conducted with adults with ASD and their employers. This preliminary step was crucial in fine-tuning the system prior to the more extensive in-home evaluations.

Participants were shown three videos, each depicting ISTAR in action, interrupting users engaged in different everyday activities. The scenarios included ISTAR interrupting a user:

1. Playing video games to inquire about a potential shift change at work.

2. Watching a sports game on TV to remind about a work report deadline.

3. Washing dishes to ask for assistance in locating an item in a grocery store.

Respondents assessed various aspects of these demonstrations, evaluating the nature of the interruptions, the robot's behavior, and the overall quality of the interaction. Furthermore, they were queried about their willingness to use such a system and how they envisioned incorporating it into their daily routines

3.4.2 Understanding User and Employer Perspectives

The survey garnered responses from 35 adults diagnosed with ASD and 13 employers of individuals with ASD, providing a diverse perspective on the workplace challenges and the potential impact of ISTAR.

Surveys of Adults with ASD

The demographic composition of the adult participants with ASD was as follows: 89% were students, 31% were employed, 26% were unemployed, and 17% were actively seeking employment. The remaining student-respondents were not currently engaged in the job market. Among the employed adults with ASD (N=11), the most commonly reported workplace distractions included:

1. Interruptions by colleagues on non-work-related matters (73%),

2. Interruptions by supervisors on non-work-related matters (55%),

3. Environmental noise, such as traffic outside the workplace (73%).

In assessing the resemblance of ISTAR's interruptions to those encountered in actual workplace settings, the responses from the participants indicated a spectrum of perceptions: 23% found them to be similar, 50% viewed them as somewhat similar, 28% found them to be different. This variance underscores the subjective nature of how workplace interruptions are experienced and the potential for ISTAR's training to be adjusted to more closely mirror real-world scenarios.

Surveys of Employers

A notable 80% of employers observed a distinct approach in how adults with ASD handle workplace interruptions compared to their neurotypical colleagues. Employers particularly pointed out the challenges in concentrating or returning to the primary task, with many individuals with ASD reportedly developing specific strategies to manage or refocus on their tasks. The employers identified the most common sources of workplace distractions as:

1. Environmental noise (77%),

2. Interruptions by colleagues on non-work-related matters (69%).

These findings illuminate the particular challenges that adults with ASD face in workplace environments and the nature of distractions that are most prevalent. The survey results are invaluable, providing critical insights into the effectiveness and relevance of ISTAR's interventions. They also highlight the importance of tailoring the system to meet the specific needs and experiences of its users, thereby enhancing its potential impact and efficacy in real-world settings. The feedback gathered serves as a vital guide for the ongoing development and refinement of ISTAR, ensuring that the system remains closely aligned with the actual requirements and conditions of the workplace for individuals with ASD.

3.4.3 Evaluation 2: In-Home Deployments:

To comprehensively evaluate ISTAR, a week-long in-home deployment phase was initiated, allowing participants to interact with the system within the familiarity of their living spaces.

The true measure of the system's impact lies in its integration into the homes of adults with ASD. While recognizing that lasting behavioral modifications resulting from the training might necessitate an extended period (Lally et al., 2010), this phase primarily aimed to assess initial acceptance and continuous interaction with ISTAR's training prompts across a one-week span. The insights gleaned from this evaluation would lay the groundwork for potential longer-term deployments, aiming to observe sustained behavioral improvements in the users.

Participants of In-Home Deployments

The in-home deployment phase of the study engaged twelve adults diagnosed with ASD. However, due to unrelated personal circumstances exacerbated by the contemporaneous pandemic, two participants withdrew, resulting in a final participant count of ten. The demographic composition of the participants who completed the evaluation included 8 males and 2 females, with ages ranging from 20 to 42 years ($M = 26.3$, $SD = 6.9$). This distribution typifies the population based on the diagnostic category (American Psychiatric Association, 2022).

Prior to the commencement of the evaluation, participants were asked to complete a series of surveys designed to capture their educational background, employment status, and their level of functioning in the context of ASD, as indicated by the AQ-10 score (Vollmeyer and Rheinberg, 2000). They were also asked to articulate their expectations regarding the training with ISTAR by utilizing the Flow in Work Scale (FWS) Vollmeyer and Rheinberg (2000). Of the ten participants, nine were able to complete the survey independently online, while one participant required the assistance of a caregiver to navigate the survey website and submit their responses.

Employment status among the participants varied: two were employed, five were unemployed but actively seeking employment, and three were not engaged in the job market. Educational backgrounds were varied, with all participants having completed at least secondary school and 80% having pursued higher education in college or vocational training programs. The participant cohort was characterized as high-functioning adults with ASD, with an average AQ-10 score of 4.6 ($SD = 1.6$).

When assessing their susceptibility to everyday distractions, participants rated themselves on a 5-point Likert scale, where *1* signified *not easily at all* and *5* denoted *extremely easily*. The average response indicated that participants were "somewhat easily" distracted, with a mean score of 3.1 ($SD = 1.17$).

Expectations and attitudes towards interacting with ISTAR, as measured by the FWS, revealed a moderate optimism regarding the success probability, an interest in the interaction, and an anticipation for the challenge it presented. Specifically, the participants scored an average of 24.0 ($SD = 5.89$) on *fluency of performance*, 15.0 ($SD = 4.38$) on *absorption of activity*, and 13.0 ($SD = 4.05$) on *perceived fit of demand and skills*. These scores reflect a balanced perspective, recognizing the potential of the ISTAR training while acknowledging the inherent challenges it posed.

Data Collection

The data collection process was designed to capture a comprehensive dataset encompassing video and audio recordings of all training interactions. This dataset detailed each interruption facilitated by ISTAR, the participants' responses, and their activities before and after engaging with the interruption.

An annotation process was implemented for every interruption instance. Three researchers utilized ELAN (Max Planck Institute for Psycholinguistics, 2002), to annotate key moments within each interaction: the time participants diverted their gaze from their primary task following an interruption, their subsequent engagement with the robot, their disengagement, and finally, their return to the initial task. To ensure the reliability of the process, initial transcriptions underwent a double-check for procedural consistency. Post-annotation, the inter-coder reliability was assessed for a randomly selected subset, comprising 25% of all interruptions, annotated by three coders. This step was crucial in addressing the potential ambiguity inherent in interpreting participant behavior within the unstructured home environment. The intraclass correlation coefficient scores were remarkably high, registering at 0.95 for the interruption lag (the duration to shift attention to the robot post-interruption) and 0.90 for the resumption lag (the duration to revert attention to the primary task post-interruption).

Additionally, objective characteristics of the participants' interactions were documented through a survey conducted by a research team member. These transcriptions evaluated aspects such as the length of verbal responses to ISTAR, whether participants returned to their original task or shifted to a new task post-interruption, and the social or physical intensity of tasks both pre- and post-interruption. Given the objective nature of these questions, a binary response format was adopted, rendering the computation of agreement or the necessity for multiple annotators redundant.

Results of In-Home Deployments

Throughout the evaluation period, ISTAR administered a total of 841 interruptions. Of these, 12% were excluded from the analysis as the participants were not present in the room to experience them. On average, each participant was exposed to 73.2 interruptions in total, translating to approximately 12.9 ($SD = 3.4$) interruptions per training session.

In a workplace context, the appropriate handling of interruptions varies by type. For *environmental interruptions*, successful management is defined as the ability to continue one's task with minimal disruption. For *social interruptions*, it is expected that an employee will momentarily pause their task, establish eye contact with the interrupter, and thoroughly address the query before resuming their original task.

In the case of *task interruptions*, while a verbal response may not be imperative, a complete and pertinent response is crucial. A key indicator of the training's effectiveness is the reduction in both interruption and resumption lags, suggesting enhanced proficiency in task-switching and interruption management.

Handling Different Types of Interruptions

According to these predefined criteria:

1. Participants appropriately managed 40% of all environmental interruptions encountered ($N = 237$),
2. Demonstrated a 98% appropriate response rate to social interruptions ($N = 250$),
3. Exhibited a 99% appropriate response rate to task interruptions ($N = 245$).

It was noted that participants engaged in socially appropriate behaviors, such as maintaining eye contact or pausing their tasks to address the interruption, in response to 99% of social and task interruptions. Interestingly, such social behaviors were also observed in 60% of environmental interruptions. A multiple linear regression aimed at predicting interruption lag identified significant influences of the type of interruption ($\beta = 2.37$, $p \leq 0.001$), AQ-10 score ($\beta = 0.45$, $p \leq 0.001$), and cumulative number of interruptions experienced during training ($\beta = -0.01$, $p = 0.01$). The coefficients are denoted as β. The notable reduction in interruption lag as the training progressed underscores the system's efficacy in fostering quicker engagement with interruptions over time.

Similarly, a regression analysis to predict resumption lag pinpointed significant factors including the type of interruption ($\beta = -11.1$, $p \leq 0.001$) and AQ-10 score ($\beta = -1.02$, $p \leq 0.001$). When comparing the disruption caused by each type of interruption, measured in seconds (s), it was found that:

1. Interruption lags were notably shorter for environmental interruptions ($M = 2.24s$, $SD = 4.02s$) compared to social ($M = 3.18s$, $SD = 3.45s$) and task interruptions ($M = 4.66s$, $SD = 4.44s$).
2. The interruption lags for social interruptions were also significantly shorter than those for task interruptions.

In terms of resumption lag:

1. Participants took significantly longer to resume their tasks after environmental interruptions ($M = 15.86s$, $SD = 13.10s$) compared to social ($M = 4.57s$, $SD = 6.82s$) and task interruptions ($M = 7.47s$, $SD = 6.89s$).
2. The resumption lags for task interruptions were also notably longer than those for social interruptions.

These results not only offer an understanding of how participants interacted with ISTAR but also highlight the system's potential in improving the management of various types of interruptions, a critical skill in the workplace for individuals with ASD. The findings, particularly the variations in interruption and resumption lags across different interruption types, provide valuable insights into the nature of interruptions and their impact on individuals with ASD.

3.4.4 User Acceptance and Perceived Relevance

Upon concluding their participation, individuals offered their perspectives on ISTAR by engaging in an online survey and interview, allowing for a comprehensive assessment of their experiences.

Participants employed the Robotic Social Attributes Scale (RoSAS) (Carpinella et al., 2017) to articulate their perception of ISTAR. The system was predominantly viewed in a positive light, being described as warm, competent, and comfortable to interact with (Ramnauth et al., 2022). Notably, terms such as *social*, *responsive*, *interactive*, *capable*, and *organic* frequently surfaced in participants' descriptions, painting a picture of ISTAR as an engaging and intelligent companion.

In evaluating ISTAR's efficacy as a training tool, participants leveraged a 5-point Likert scale, ranging from 1 (*none at all*) to 5 (*a great deal*), to reflect on how the training influenced their tolerance for interruptions outside the training context. The results indicated a positive impact, with an average score of 3.3 (SD = 1.3), suggesting that ISTAR's training sessions extended their benefits beyond the immediate interactions.

Personal anecdotes shared during interviews further illuminated the practical value of training with ISTAR. Participants looking for employment appreciated the system's role in preparing them for real-world interruptions, helping them prioritize tasks and retain focus amidst potential distractions. One participant acknowledged ISTAR's contribution to their current job, noting improved efficiency in resuming work post-interruptions. Interestingly, the training also prompted introspection among participants, with one individual reflecting on the nature and impact of the interruptions they typically initiate in conversations.

The relevance of ISTAR's training to managing real-world interruptions was also quantified using a 5-point Likert scale, where 1 indicated *not relevant* and 5 denoted *extremely relevant*. The participants' feedback yielded a promising average score of 3.9 ($SD = 0.93$), reinforcing the system's applicability and effectiveness in equipping users with practical skills for handling interruptions in diverse settings.

These insights not only affirm the positive reception of ISTAR but also highlight its potential as a transformative tool for enhancing social adaptability and interruption management among adults with ASD. The feedback, encompassing both quantitative assessments and qualitative experiences, underscores the system's potential to make a meaningful difference in the lives of its users.

3.5 Reflective Analysis and Implications of ISTAR's Deployment

We evaluated ISTAR's design was assessed against our outlined design goals, with additional insights drawn from the participants' perceptions and experiences.

Embodied Interaction: ISTAR's embodiment as a social robot proved to be a significant factor in engaging users more effectively than other forms of technology. Participants' feedback, coupled with the observations from the RoSAS evaluations, highlighted ISTAR's naturalistic gaze patterns and body movements, which facilitated meaningful social interaction and practice. The positive remarks from caregivers about the system's physical presence and its ability to 'spark' engagement in users underscore the profound impact of ISTAR's embodiment.

In-Home Accessibility: The system's design as an in-home intervention allowed users to interact with ISTAR intuitively and comfortably. The survey results confirmed that users felt at ease with ISTAR in their personal spaces, with many perceiving the robot as friendly and approachable. This level of comfort was further evidenced by users' willingness to showcase ISTAR to friends, demonstrating the system's successful integration into their daily lives.

Autonomous Operation: ISTAR's ability to operate autonomously over extended periods, delivering numerous training sessions, is a testament to the effectiveness of its computational mechanisms. The system's design, particularly its intuitive setup and usage, was crucial during the pandemic, enabling deployment without direct contact, thus ensuring safety and convenience for users and researchers alike.

Realistic Interactions: The varied nature of ISTAR's interruptions, encompassing environmental, social, and task-related scenarios, aligned well with the real-world experiences of participants. Feedback from adults with ASD and employers suggested that the system's interruptions were representative of actual workplace scenarios. The positive reports from employed participants about improved interruption handling in their jobs validate the practical utility and relevance of ISTAR's training.

Participants' reflections on their experiences with ISTAR, as captured in the post-study surveys and interviews, further affirm the system's effectiveness. Reports of improved tolerance to interruptions, enhanced task prioritization, and increased self-awareness regarding one's interruptive behavior highlight the multifaceted impact of ISTAR. The high scores on the relevance of ISTAR's training, coupled with the significant behavioral improvements observed in interruption and resumption lags, underscore the system's potential as an effective intervention for enhancing interruption management skills among adults with ASD.

While the study's duration was relatively short, the notable progress observed in participants' interruption handling abilities suggests that ISTAR holds promise for longer-term behavioral changes. As an early exploration in the field of in-home social robotics for adults with ASD, this study sets a solid foundation for future research. A more extended study involving a larger sample will be instrumental in evaluating the long-term efficacy of ISTAR and its generalizability to broader workplace environments or human-human interactions.

In sum, interactions with ISTAR have proven to be productive and potentially transformative, marking a significant stride in the use of socially assistive robotics to improve the quality of life and employability of individuals with ASD. The system's success in meeting its design goals, combined with the positive reception and impactful experiences reported by participants, signals a promising path forward for the development and application of similar interventions.

3.6 Challenges and Lessons Learned

The journey of developing and implementing ISTAR also presented its share of challenges. Reflecting on these challenges is not only an exercise in transparency but also a valuable source of lessons for future initiatives in social robotics and ASD-focused interventions.

Customization and Flexibility: One of the foremost challenges was accommodating the diverse needs, preferences, and sensitivities inherent to the ASD spectrum. Recognizing that ASD manifests uniquely in each individual, the project highlighted the necessity for customization and flexibility in the design of ISTAR. Ensuring that the robot could dynamically adjust its behavior in response to user feedback and varying levels of engagement was instrumental in sustaining user interest and enhancing the efficacy of the learning experience.

Embedding Technology in Human Spaces: The integration of ISTAR into the intimate and personal realms of users' lives necessitated a careful balance between technological innovation and a human-centric approach. It was paramount that the robot was perceived not as an intrusive mechanical entity but as a supportive and empathetic presence. This endeavor brought to light the intricacies of human-robot interaction, particularly the significance of non-verbal cues, thoughtful physical design, and the appropriate tone and timing of robotic interventions.

Ethical Considerations: Deploying ISTAR brought forth crucial ethical considerations, notably in terms of ensuring user privacy, safeguarding data security, and respecting the autonomy of the participants. The project served as a reminder of the importance of integrating ethical deliberations into every facet of the design and deployment process, with the well-being and rights of the participants being the paramount concern.

3.7 Future Directions

The ISTAR project opens a multitude of possibilities for future research and development in the intersection of social robotics and ASD.

Longitudinal Studies: There is a compelling need for longitudinal studies to evaluate the enduring impacts of social robot-based training on individuals with ASD. Such studies would be instrumental in understanding the sustainability of the skills imparted and their applicability in real-life situations.

Scalability and Accessibility: A critical direction for future work involves addressing the scalability and accessibility of social robots like ISTAR. Efforts should focus on reducing costs, simplifying the technology for a broader user base, and ensuring that these life-enhancing interventions are within reach for a wider segment of the population.

Broader Application Scenarios: While ISTAR's current application centers around managing workplace interruptions, the potential of social robotics in aiding individuals with ASD extends far beyond. Future endeavors could branch into various domains, such as enhancing social skills, facilitating independent living, or enriching leisure and recreational experiences.

3.8 Summary

Chapter 3 has provided a thorough investigation into the potential of social robotics to significantly enhance the employability and daily living conditions of individuals with ASD. The journey embarked upon with ISTAR, spanning from its initial conception through to its evaluation, has illuminated the capacity inherent in merging advanced technological solutions with an understanding of user-specific needs. The system's favorable reception, coupled with the tangible improvements witnessed in the participants' abilities to navigate workplace interruptions, underscores the success and efficacy of this innovative approach.

Looking ahead, the convergence of social robotics and autism intervention emerges as an promising frontier. The valuable insights garnered from this project extend beyond the academic realm, offering actionable strategies for the development of inclusive and supportive technologies.

Our next step to explore the applicability and efficacy of social robotics in managing interruptions across a broader and more varied population, extending beyond the confines of the home environment. Chapter 4 will delve into the detailed exploration of this expanded study.

Chapter 4

Advancing Robotics in Technical Education: Enhancing Performance and Learning Outcomes Under Interruptions with Interactive Methods

Chapter 4 of this dissertation delves into an exploration of the impact of robot assistance in a simulated workspace, specifically focusing on task efficiency, responses to interruptions, task resumption, and error reduction in task performance. Building upon the foundation laid in the previous chapters, this chapter extends the investigation of robotic intervention from home environments, as discussed in Chapter 3, to more complex and dynamic tasks. The central hypothesis is that robot assistance can significantly enhance the efficiency and accuracy of task performance, especially in environments characterized by frequent interruptions.

The chapter begins by establishing the relevance of studying robotic assistance in academic settings. It outlines the challenges faced by learners and educators in maintaining task efficiency and managing interruptions, which are commonplace in educational environments. The chapter includes a description of the experimental setup, which integrates advanced technologies such as an interactive mock HVAC workspace (Heating, Ventilation, and Air Conditioning system), a Tutorial and Guide application, and, most importantly, a robot assistant designed to facilitate and guide technical tasks.

Central to this chapter is the examination of several key hypotheses. First, we hypothesize that robot assistance leads to improved task efficiency by providing timely guidance and support, enabling learners to complete tasks more quickly and effectively. Second, the study tests the hypothesis that robotic intervention positively influences interruption responses, aiding learners in maintaining focus and reducing the cognitive load associated with task switching. Third, we assess the impact of robot assistance on the resumption of original tasks following interruptions, hypothesizing that robotic cues and guidance lead to a more seamless transition back to the initial task. Lastly, the chapter investigates whether the presence of a robot assistant contributes to a reduction in errors during task performance, thereby enhancing the overall quality of the learning experience.

By examining the role of robot assistance in an educational setting, this chapter aims to evaluate the potential of robotics in enhancing learning experiences, task efficiency, and the management of interruptions in technical education.

4.1 Background

In modern educational landscapes, where students are increasingly interacting with a multitude of technologies, robotics engages students in the practical aspects of building and programming, and significantly contributes to the cultivation of essential competencies (Belpaeme et al., 2018). These include computational thinking, engineering skills, logical-mathematical reasoning, problem-solving capabilities, and scientific inquiry. The tangible and interactive nature of robotic platforms amplifies student engagement and motivation, thereby deepening the immersion and efficacy of the learning process (Zenk et al., 2017).

Moreover, the role of robotics promotes interdisciplinary knowledge and augments critical skills such as creativity, collaboration, communication, and autonomy. The value of co-creative task transfer in robotics suggests a promising avenue for innovative educational practices that leverage robotics to improve learning outcomes in technical education (Fitzgerald et al., 2017). This multifaceted impact renders robotics a resource not only for mainstream education but also for addressing the needs of students requiring specialized educational support. Consequently, educational robotics is progressively being woven into the fabric of pedagogical tools and methodologies, positioning itself as an integral part in the orchestration of interdisciplinary learning experiences (Irfan et al., 2021; Arocena et al., 2022).

The pedagogical strategies employed alongside robotics are diverse and tailored to address various facets of the educational journey. These strategies span a spectrum of methods including problem-based, constructivist, competition-based, discovery-focused, and project-based learning. This rich array of methodologies ensures a comprehensive approach to education, ranging from direct instructional methods to more inductive, student-centered techniques that empower learners to leverage their knowledge in practical, real-world scenarios (Quintero-Pena et al., 2023; Kubilinskienė et al., 2017).

In the context of technical education, an understanding of the cognitive processes underpinning learning is paramount for devising impactful educational interventions. Theories related to cognitive load, attention, memory, and interruption management are important in this discourse, especially considering the influence of diverse learning environments and technological integration. The concept of cognitive load is especially critical in technical domains, where learners frequently grapple with complex information and tasks. Effective management of cognitive load is essential for optimizing learning outcomes and is influenced by the integration of technology, such as robotics. This technology can either introduce an additional layer of complexity or serve as a medium for simplifying and clarifying information processing (Alam, 2022).

Interruptions, a prevalent feature of educational settings, significantly sway learning efficiency and task performance. Students may expedite the completion of primary tasks if they perceive an excessive amount of time spent on interruptive tasks (Brumby et al., 2013; Speier et al., 1999, 2003). This acceleration effect, while aiming to compensate for lost time, is also reflective of an increase in the number of errors (Brumby et al., 2013; Speier et al., 1999, 2003).

The management of interruptions, pivotal in maintaining cognitive continuity, is explored through strategies involving cues and environmental modifications. In an electrical shop or workspace, the thoughtful arrangement of environmental cues significantly enhances task efficiency and safety. Color-coded labels and organized tool storage facilitate swift identification and retrieval of necessary equipment, minimizing downtime between tasks. Visual safety warnings ensure that attention is immediately drawn to potential hazards, fostering a secure working environment. Moreover, strategically placed task checklists offer clear guidance on procedural steps, aiding in the seamless transition between diverse tasks. Audible alarms serve as crucial alerts for test completions or safety concerns, ensuring that focus is appropriately directed. The potential integration of these strategies within collaborative and educational environments that include robots presents a promising avenue for mitigating disruptive influences (Trafton et al., 2005).

Collectively, the integration of robots within learning processes underscores their potential in not only managing interruptions but also in refining the overall quality of the educational experience. This encompasses fostering task efficiency, reducing errors, and nurturing skill mastery, ultimately leading to successful learning outcomes. The rich affordances offered by robotics environments catalyze the application of science literacy-based thinking and contribute substantially to a understanding of systems (Sullivan and Bers, 2013; Salomons, 2022).

Within the sphere of technical education, the role of robot assistance is increasingly clear, serving as a catalyst for an enriched educational paradigm. Robot-assisted learning could aid in developing technical skills and enable the enhancement of the learner's ability to solve complex problems and understand systems. By interacting with robots, students gain firsthand experience in system dynamics and operations, fostering a deep, intuitive understanding of systems-thinking (Sullivan and Bers, 2013). This hands-on engagement with robots not only solidifies theoretical knowledge but also sharpens practical skills, essential for navigating the multifaceted challenges of modern technical landscapes.

The impact of robotic assistance on technical skill acquisition is non-trivial. Through structured interactions and guided learning experiences, robots act as facilitators, transforming abstract concepts into tangible experiences. This transition from theory to practice is instrumental in cultivating problem-solving abilities, enabling learners to devise innovative solutions to real-world technical problems. Moreover, the interactive nature of robots significantly heightens learner engagement, transforming the educational journey into an immersive, captivating experience. This heightened engagement is not merely about maintaining attention; it is about fostering a deep, enduring interest in technical subjects, which is crucial for sustained learning and skill development (Salomons et al., 2022).

However, the integration of robot assistants into technical training environments is not without its challenges. Technical education is inherently complex, requiring an understanding of both the theoretical underpinnings and practical applications of various concepts. Ensuring that robotic systems are sufficiently sophisticated to address these complexities, while remaining accessible and user-friendly, is a delicate balance to strike. Additionally, there is the challenge of seamlessly integrating these systems into existing educational infrastructures, ensuring that they complement rather than disrupt established learning processes. Despite these challenges, the potential benefits of robot-assisted learning – enhanced understanding of systems, accelerated skill acquisition, error reduction, improved tasks performance efficiency, and elevated learner engagement – position robotics to support interactive, experiential learning.

4.2 Research Aim and Theoretical Framework

The primary aim of this research is to explore the multifaceted impact of robot assistance in enhancing the efficacy of technical education. Specifically, the research focuses on assessing the role of robotic systems in augmenting task efficiency, facilitating interruption management, and reducing errors in technical training environments.

The theoretical framework underpinning this research is rooted in a multidisciplinary approach, integrating principles from educational psychology, cognitive science, and robotics. A part of this framework is Cognitive Load Theory (CLT), which provides essential insights into how educational robots can be optimized to enhance learning by effectively managing the cognitive load of learners. This theory posits that instructional design should be aligned with the human cognitive architecture, and that excess cognitive load can impede the learning process (Ginns and Leppink, 2019).

Additionally, the framework incorporates the Theory of Constructivist Learning, emphasizing the significance of hands-on, interactive experiences in fostering a deeper understanding of complex technical systems and concepts (Bada and Olusegun, 2015). This theory supports the idea that learners construct knowledge best through active engagement and personal experience, principles that are well-aligned with the interactive nature of robot-assisted learning.

Furthermore, the framework acknowledges the pivotal role of Attentional Resource Theory in understanding how learners allocate cognitive resources, especially in environments characterized by frequent interruptions (Matthews et al., 2017). This aspect is particularly crucial in technical education, where tasks often require sustained concentration and a high degree of precision (Bruya and Tang, 2018). By integrating robotic systems capable of intelligent interruption management and context-aware cueing, the research aims to explore how these technologies can optimize attention allocation and minimize cognitive load, thereby enhancing learning outcomes (Bruya and Tang, 2018).

In essence, this research is guided by a theoretical framework that seeks to merge theoretical insights with practical applications. It aims to provide an understanding of how robotic systems can be harnessed to create more effective, engaging, and cognitively optimized learning environments in the field of technical education.

4.3 Methodological Approach

This research study integrates advanced robotic tools into the realm of technical education, with a particular focus on HVAC system maintenance and troubleshooting tasks. The methodological framework is designed to assess the impact of robotic assistance on task performance and to refine a predictive model for evaluating HVAC system maintenance and troubleshooting skills. The following sections detail the components of our approach.

Group	Robot Assists (Task 1)	Robot Assists (Task 2)	Complexity (Task 1)	Complexity (Task 2)	Task 1	Task 2
1	Yes	No	Simple	Simple	Identify faulty Condenser Fan	Identify faulty Compressor
2	Yes	No	Complex	Complex	Identify faulty Wire from Contactor Relay	Identify faulty DPDT Relay
3	No	No	Simple	Simple	Identify faulty Condenser Fan	Identify faulty Compressor
4	No	No	Complex	Complex	Identify faulty Wire from Contactor Relay	Identify faulty DPDT Relay

Figure 4.1: Overview of Study Design: 4 Groups with two tasks of equivalent complexities.

4.3.1 Study Design and Experimental Setup

We employ a controlled experimental design, ensuring reliability and validity through a four-group structure based on two criteria: robotic assistance and task complexity. The groups are categorized as follows: one with robotic assistance (experimental group) and one without (control group), each further divided based on the complexity of tasks. Each group tackles two troubleshooting tasks of similar complexity, allowing for analysis of how task complexity and robotic assistance interact and affect performance. Within the groups receiving robotic assistance, the robot aids only in the first of the two troubleshooting tasks, as shown in table 4.1. This approach allows for the evaluation of the impact of technology on learning, focusing on the robot's role in enhancing a human's ability to observe, hypothesize, discover, and conclude.

By comparing the performance on the first and second tasks within these groups, against those without robotic assistance, we can examine the robot's influence on performance metrics.

Task complexity within our mock HVAC system is defined by the number of components involved and their interactions, particularly in pinpointing causes of malfunctions. Complex tasks encompass multiple layers of information, sequential steps, and a deep understanding of how components interrelate. For instance, a simpler task like replacing a blown light bulb clearly links the symptom (a non-functioning lamp) to the problem (a faulty bulb). Conversely, more complex tasks often present ambiguous or indirect malfunction indicators, obscuring the root cause. These tasks require thorough analysis and the elimination of multiple potential causes. An example is diagnosing the source of unusual noises in an HVAC system, which could stem from a variety of issues, ranging from fan problems to loose components. Another instance is determining the reasons behind reduced cooling efficiency, which might be due to factors like duct leaks, refrigerant issues, or compressor malfunctions.

In our study design, each group engages in two distinct troubleshooting tasks. While these tasks are not identical, they are carefully crafted to be comparable in complexity. This approach allows us to maintain consistency in the challenge level across tasks while examining the impact of robotic assistance on task performance and learning outcomes. By comparing performance on two different but similarly complex tasks, we can more accurately assess the extent to which robotic assistance facilitates skill acquisition and problem-solving ability within the domain of HVAC system maintenance and troubleshooting.

4.3.2 Procedure

The experiment began with an orientation and demonstration of the ensemble setup and tasks. Participants then launched an application to input their technical expertise and reviewed session tasks, malfunction handling instructions, and the 45-minute limit. They familiarized themselves with the workspace and could command a robot for actions. A surprise quiz followed, with feedback provided on performance and improvement areas. Participants watched task demonstrations, including mock board operations, and accessed a troubleshooting guide. The guide offered an interactive tutorial on troubleshooting, hierarchically structured for various knowledge levels.

Participants proceeded to interactive demonstrations on using tools and safety equipment, starting with a digital multimeter, followed by an infrared thermometer, and an outlet tester. A 'Process Sequence' flowchart guided them through the maintenance tasks, starting with temperature checks and proceeding to fan, cooling, and heating mode checks. The robot introduced itself, assisted based on participant proficiency, and set malfunctions for troubleshooting in cooling and heating modes. Participants were tasked with describing and identifying malfunctions, and formulating repair plans. Troubleshooting involved guidance from the robot, including component specification checks and manipulation of wires and plugs. The session emphasized analytical skills for fault identification and concluded after restoring mock board functionality and completing heating mode checks.

Core Components: Tools, Safety, and Interactive Elements:

The experiment engaged participants with an ensemble setup including a an Assistive Robot, Tutorial and Guide, a mock HVAC workspace, and Tools and Safety Gear. The main task involved conducting maintenance checks on the mock board, identifying and resolving operational deviations.

1. **Robot's Assistive Actions:** The robot executed a sequence of actions to facilitate the session overall, particularly focusing on the technical skill development of participants in troubleshooting. Initially, the robot introduced itself, showcasing its capabilities and limitations to participants. This occurred at the start of the session, where participants were encouraged to engage with the robot by issuing commands for task performance, (see Figure 4.2).

   As the session progressed, based on its ongoing assessment of each participant's expertise, the robot either swiftly granted access to the mock board and reminded them of their tasks, or delayed access to provide additional safety and task guidance. Participants then commenced the maintenance tasks.

   The robot intervened if participants either mistakenly began an incorrect task at a given juncture or delayed maintenance (excluding delays for tutorial review). For example, the initial task involved a temperature check, necessitating a thermometer, which the robot provided for the first subtask. Robot assistance, from this point, was exclusive to those in the Robot Assistance groups, except for two instances of malfunction alerts regarding the mock board.

   Upon detecting a malfunction, typically in the compressor or condenser fan

	Conditions of Actions				
Robot Actions	Estimated Expertise	Technician's Actions	Task Complexity	Robot Assist/No Assist	Event Order
Introduce self (Gyrates)	Any	Commands Robot	Both Groups	Both Groups	1
Place Multimeter (Boardside)	Any	Commands Robot	Both Groups	Both Groups	1
Remove Tester (Workspace)	Any	Commands Robot	Both Groups	Both Groups	1
Remove Thermomerter (Workspace)	Any	Commands Robot	Both Groups	Both Groups	1
Open to mock board	Intermediate/ Expert	Starts Task	Both Groups	Both Groups	2
Hold board closed	Novice	Starts Task	Both Groups	Both Groups	2
Gesture at Gloves	Any	Starts Task	Both Groups	Both Groups	3
Place Thermometer (Cue)	Any	Delays Checking Temp	Both Groups	Assist	4
Point at Condenser Fan	Any	Checking Cooling Mode	Both Groups	Both Groups	5
Point at Compressor (Bulb)	Any	Checking Cooling Mode	Complex	Both Groups	5
Gesture at Touchscreen	Any	Disregards Interruption	Both Groups	Both Groups	6
Place Multimeter (Cue)	Novice	Doing Interruption	Simple	Assist	7
Place Tester (Cue)	Novice	Doing Interruption	Complex	Assist	7
Place Multimeter (Cue)	Intermediate/ Expert	Doing Interruption	Both Groups	Assist	7
Unplug Condenser Fan	Any	Finished Interruption Task	Simple	Assist	8
Unplug Compressor (Bulb)	Any	Finished Interruption Task	Complex	Assist	8
Remove Tester (Workspace)	Any	Delays Troubleshooting	Simple	Assist	9
Remove Thermometer (Workspace)	Any	Delays Troubleshooting	Both Groups	Assist	9
Demonstrate Socket check	Any	Finished Interruption Task	Complex	Assist	10
Demonstrate Contactor relay check	Any	Checked Socket Power	Complex	Assist	11
Demonstrate Wiring (check points)	Any	Checked Contactor Power	Complex	Assist	12
Point at Blower Fan	Any	Checking Heating Mode	Complex	Both Groups	13
Point at Heater (Red Bulb)	Any	Checking Heating Mode	Complex	Both Groups	13

Figure 4.2: Overview of Robot Actions and Corresponding Conditions.

during the cooling mode where initial faults were set, the robot notified the participant of the suspected issue. Assistance continued only after the participant accurately acknowledged the malfunction.

The robot then guided the troubleshooting process, tailoring its support based on the task's complexity, the participant's assessed expertise, and their actions and feedback. It sequentially offered guidance and tools for accurately diagnosing the malfunction cause. This step-by-step assistance concluded once the troubleshooting was fully resolved, at which point the robot discontinued troubleshooting support but continued to signal potential malfunctions for the second task, as outlined in Figure 4.2.

2. **Tutorial and Guide:** This application, presented on a touchscreen monitor, served as the primary guide for participants through the study session. It recorded activity data, provided step-by-step instructions, and offered, in conjunction with the robot, adaptive guidance and feedback. This component was essential for directing the participants and collecting data on their interactions.

3. **Advanced Electrical Mock HVAC Workspace:** This mock board served as the focal point of the study, meticulously emulating a typical household HVAC system as an interactive, hands-on platform for participants. It incorporated sophisticated fault-setting circuitry concealed beneath its layout, specifically engineered to introduce realistic electrical faults within the power side of the dual, signal and power circuitry for troubleshooting tasks. This design choice aimed to streamline the complexity of troubleshooting tasks while ensuring they

remained challenging and educational. Faults were deliberately programmed into pivotal components, including the condenser fan, compressor, the Double Pole Double Throw (DPDT) relay, and a connecting wire from the Contactor Relay to the Dual Plug Outlet, directing participants' attention to common points of failure within HVAC systems.

Moreover, the mock board was outfitted with force resistance sensors under these components and others, precisely monitoring participant interaction with the system through the use of troubleshooting tools. This feature enabled a comprehensive collection of data regarding participant actions, tool engagement, and the timing of such interactions, greatly enriching the study's depth of analysis.

4. **Toolset and Safety**: Essential tools for the experiments include a digital multimeter for measuring electrical properties, an infrared thermometer for non-contact temperature assessments, and an outlet tester to ensure outlet safety and functionality. The mock board is equipped with safety features, including Ground-Fault Circuit Interrupters (GFCI) in bright yellow, to facilitate safe interactions during electrical maintenance tasks.

These core components collectively facilitated a structured environment where participants could engage in hands-on maintenance tasks, aided by robotic assistance tailored to their individual needs and skill levels. The detailed orchestration of these components not only aimed to enhance technical troubleshooting skills but also to explore the effectiveness of robotic intervention in learning and task execution.

In this setting, the robot was crucial in deepening learners' HVAC system knowledge through direct engagement. By performing 23 actions, including unplugging key components like the condenser fan and compressor and offering voice-guided electrical resistance measurements, it transformed what could be abstract simulations into tangible experiences. For example, the robot's actions demonstrated the dual circuitry for signals and power, and detailed the distinctive setup of external air conditioning units with plug connections, unlike the heating components without plugs.

The robot's interactions not only facilitated an understanding of theoretical concepts such as electrical resistance—the measure of a material's opposition to electric current flow—but also refined practical skills. Learners were engaged in applying these concepts, using tools to measure resistance and identifying deviations from expected specifications, thereby ensuring the correct current flow for the system's optimal operation. Through its suite of actions, the robot bridged the gap between textbook learning and practical application, equipping learners with the skills and confidence to undertake real-world troubleshooting and problem-solving independently.

A Detailed Guide to the Procedural Workflow

With a robust setup in place, we present a detailed guide to the procedural workflow that delves into the step-by-step process that participants followed during the study. This guide outlines the sequence of activities, from initial orientation through to the completion of maintenance tasks, providing insight into how the core components supported participants throughout the experimental trials.

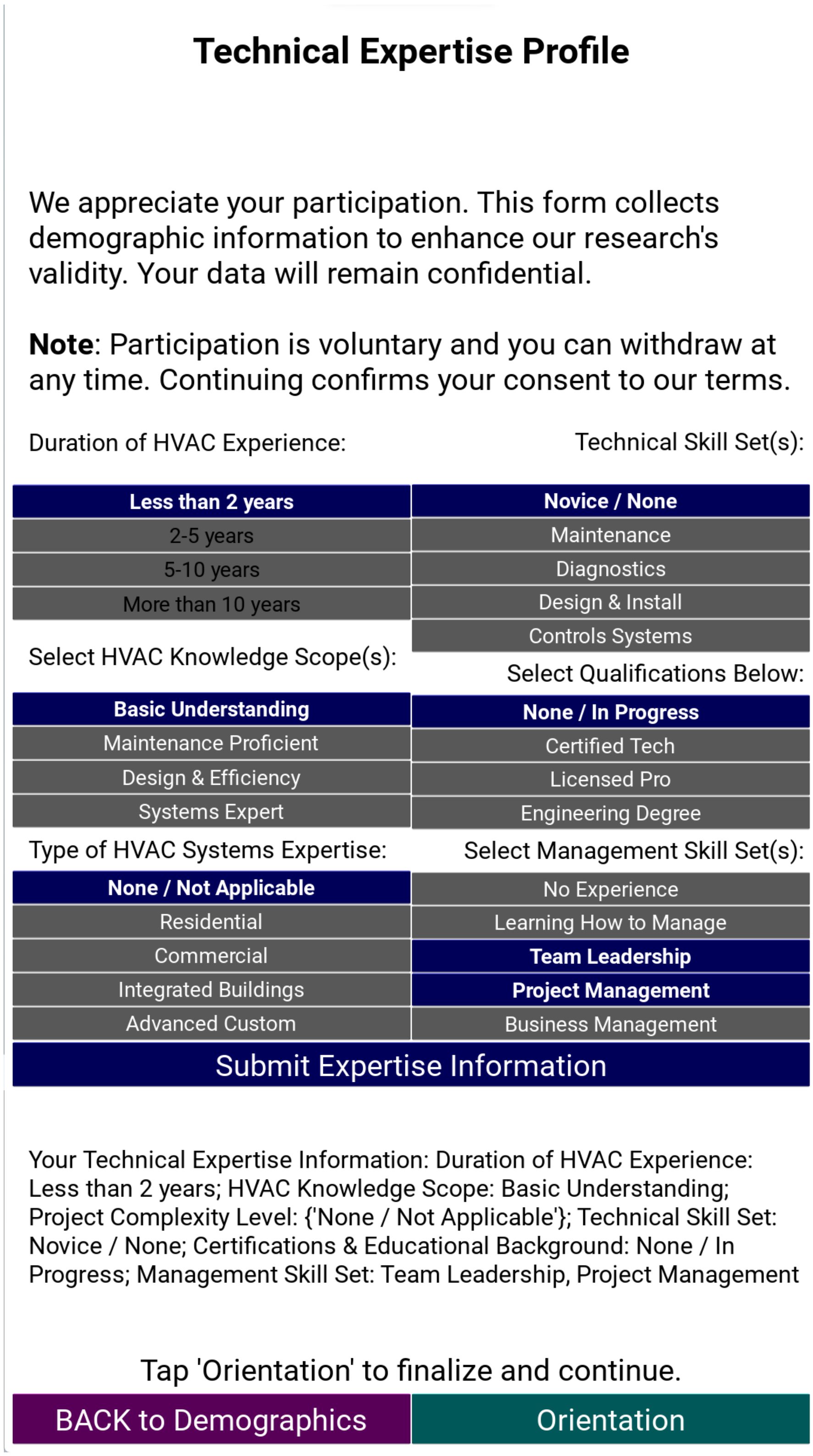


Figure 4.3: Self-Professed Skills Selections.

Welcome and Initial Assessment: Participants were first introduced to the experiment through a comprehensive orientation provided by the facilitator. This initial phase included a detailed walk-through of the ensemble setup and the various tasks they would undertake, complemented by hands-on demonstrations to ensure clarity and readiness. This crucial step not only familiarized participants with the experimental environment but also allowed the facilitator to screen them for any pre-existing high-level HVAC expertise skills. The aim was to gauge the participants' baseline knowledge and ensure a uniform starting point for all, facilitating a more accurate assessment of the robotic assistance's impact.

Following the orientation, participants transitioned to an interactive phase where they began their engagement with the ensemble setup. They launched the designated application, marking the start of their session. This digital interface served a dual purpose: it provided participants with a platform to input their self-assessed technical expertise information, as captured in Figure 4.3, and it introduced them to the session's workflow. The 'Welcome' screen, detailed in Figure 4.4, presented an overview of the tasks awaiting them. This screen not only outlined what was expected during the session but also set the stage for the participants' active engagement in the learning and troubleshooting processes that followed.

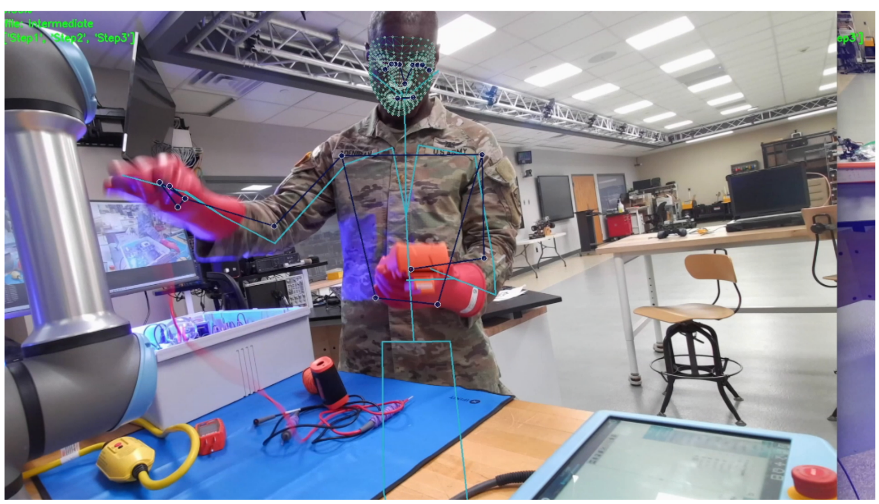
Welcome to the Interactive HVAC Functionality & Troubleshooting Study

You will be engaging with an electrical HVAC mock board—a simulation of a typical household heating, ventilation, and air conditioning system. Throughout this session, you'll undertake maintenance and potential troubleshooting tasks, with the support of a context-aware assistive robot.

Your main objective is to ensure the proper functioning of our mock board HVAC system through a series of checks:

1. **Ensure Ambient Temperature Congruence**
2. **Test Fan Mode Operation**
3. **Test Cooling Mode Operation**
4. **Test Heating Mode Operation**

Rest assured, detailed instructions on how to perform these tasks will be provided, and you can access this guidance at any point during the session from any screen.



Tap 'Workspace Tour' to discover the Workspace setup.

NEXT to Workspace Tour

Figure 4.4: Welcome and Overview of Session.

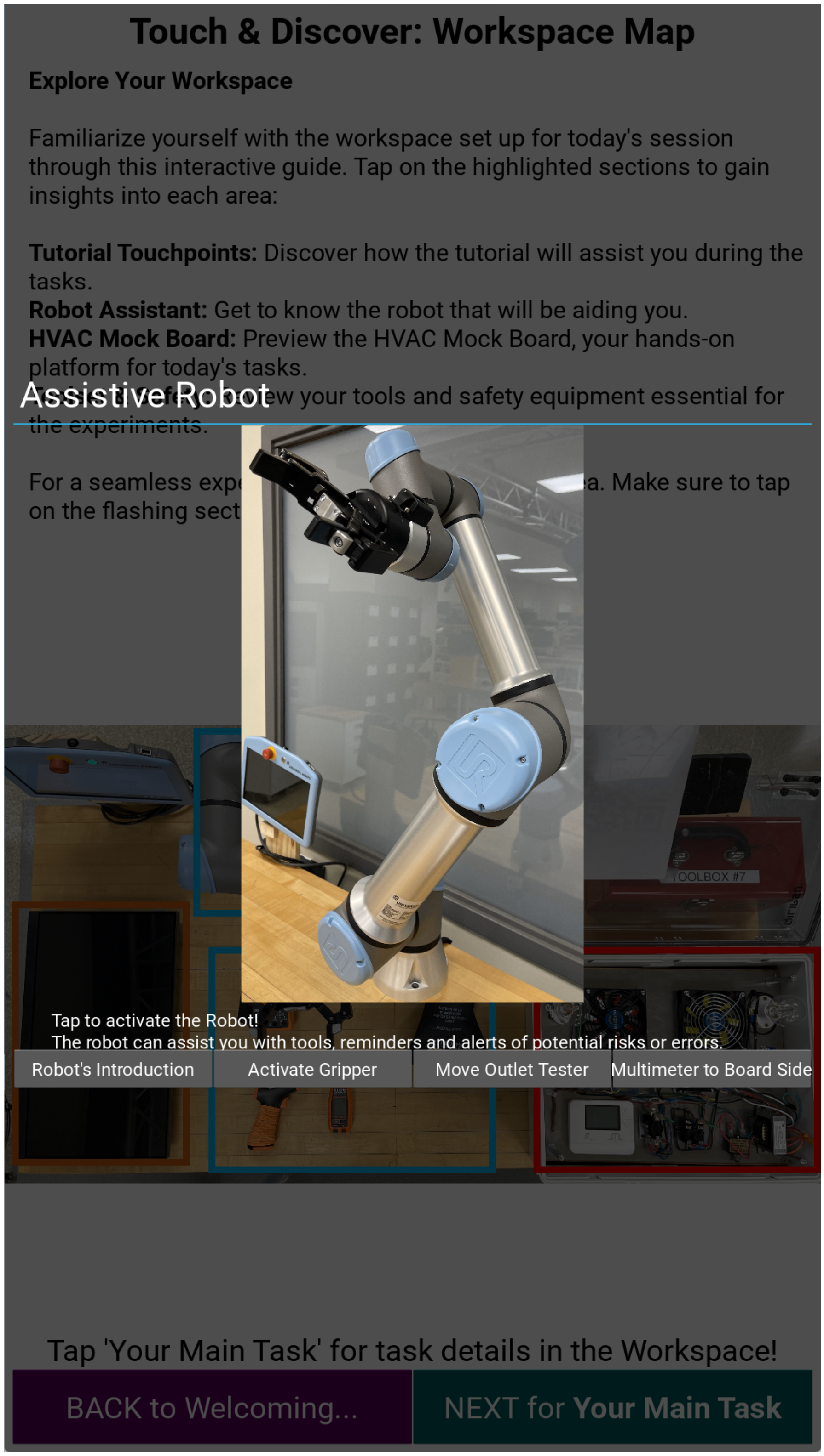


Figure 4.5: Robot Assistant Introduction.

Introduction to the Workspace Map: Following the initial orientation participants explored and familiarized themselves with its various components interactively. By tapping on highlighted sections within the guide, participants could delve deeper into each area's specifics, gaining valuable insights and understanding of their roles and functionalities. The key areas highlighted for exploration included:

1. Tutorial Touchpoints: This section allowed participants to discover how the tutorial would assist them during their tasks, providing a foundation for understanding and engaging with the experimental procedures and objectives.

2. Robot Assistant: Figure 4.5 visually illustrated the robot, enhancing participants' familiarity with this technology. Here, participants had the opportunity to interact directly with the robot, issuing commands for actions such as a self-introduction by the robot, activation of the robot's gripper, moving the outlet tester around the workspace, and relocating the multimeter to the board side.

3. Mock HVAC Workspace: Figure 4.6 offered a visual introduction to the mock board, setting the stage for the practical component of the experiment where participants would apply their skills in a simulated environment.

4. Toolset and Safety: Participants reviewed the essential tools and safety equipment required for the experiments. This section emphasized the importance of safety in the experimental environment, highlighting features such as the bright yellow Ground-Fault Circuit Interrupters (GFCI) designed to facilitate secure interactions during the tasks.

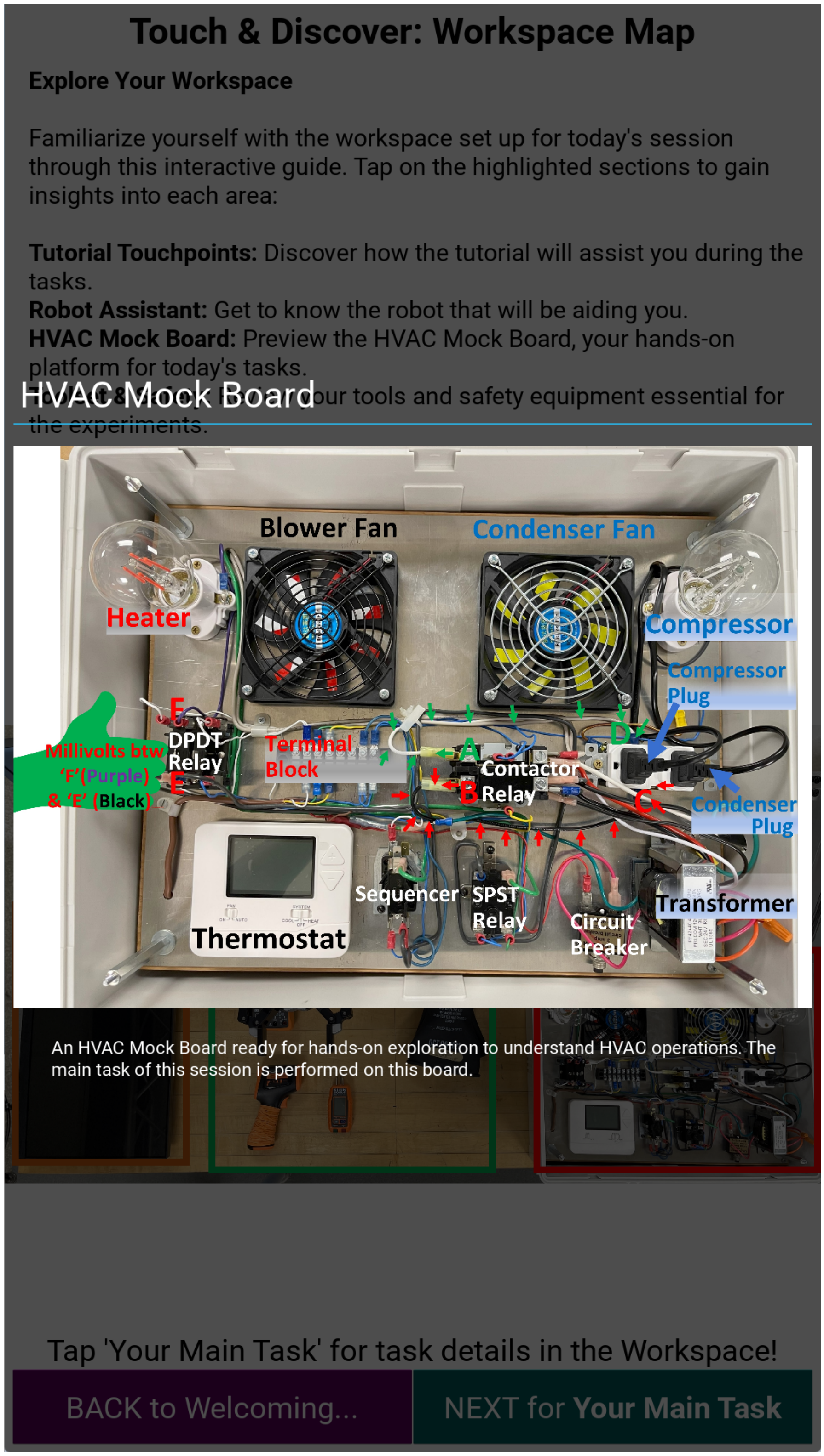


Figure 4.6: Mock Board Information.

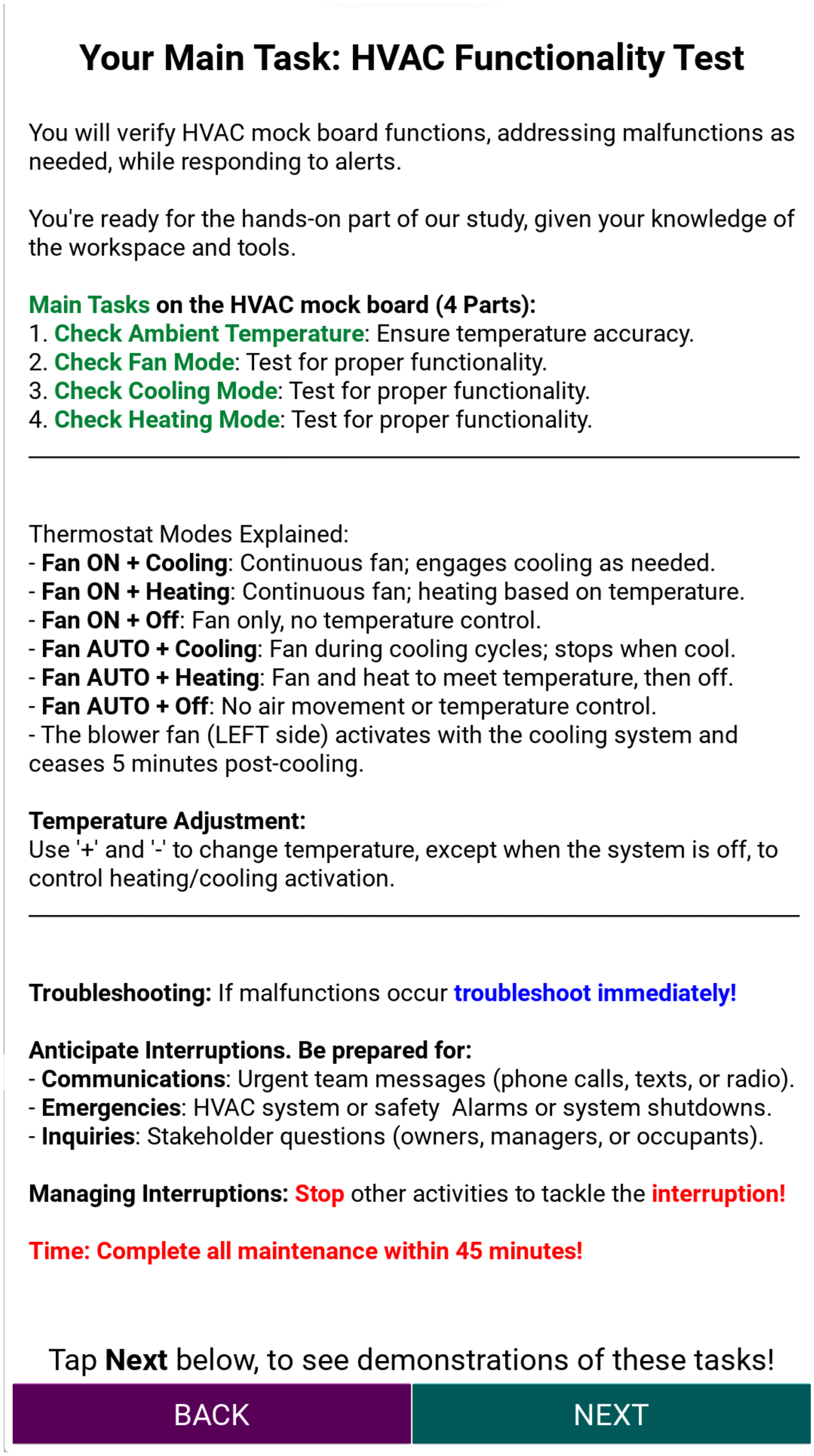


Figure 4.7: Overview of Session.

Main Tasks on the mock HVAC Workspace: The session on the mock HVAC workspace was designed to test participants' ability to perform essential maintenance tasks within a structured framework. The session was structured around four main tasks aimed at assessing the participants' proficiency with the system:

1. Participants started by ensuring the temperature readings matched the actual ambient conditions.

2. Next, they verified the fan's operation, crucial for air circulation.

3. Participants then checked the cooling function for maintaining comfortable temperatures.

4. Finally, the heating was examined to ensure it could adequately warm the space.

In addition to these tasks, participants were educated on the various thermostat modes to navigate the mock HVAC system effectively. **Troubleshooting and Managing Interruptions** were highlighted as critical components of the session. Participants were expected to engage in troubleshooting as soon as malfunctions were detected, and they were also advised to adeptly manage any interruptions that arose, ensuring they were addressed efficiently.

A **45-minute time constraint** was imposed on the maintenance activities to add a level of urgency and realism to the task, challenging participants to work both accurately and efficiently, as depicted in Figures 4.7.

A **Surprise Quiz** followed the session overview, testing their knowledge and attention to detail during the orientation, as shown in Figure 4.8.

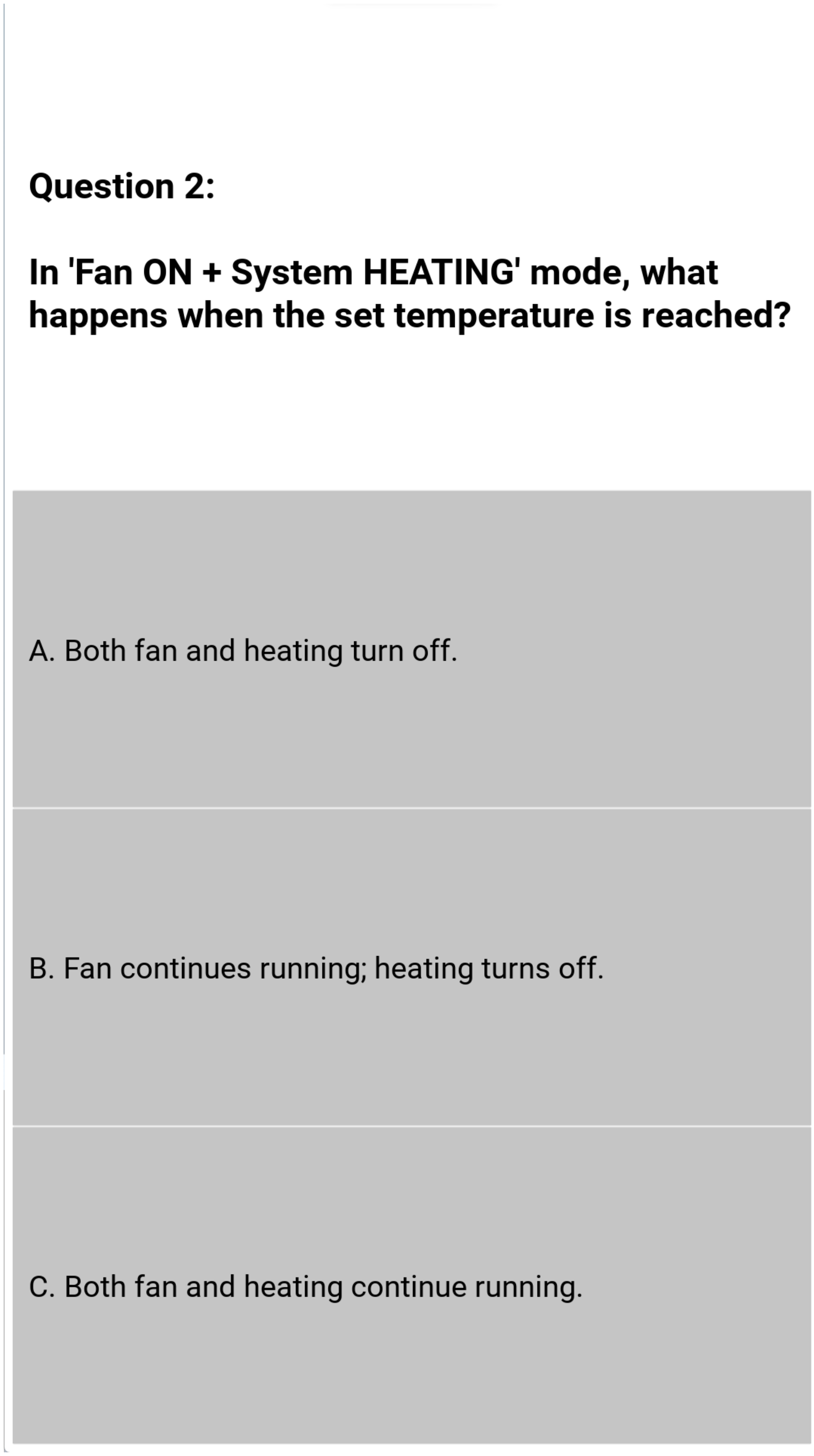


Figure 4.8: Surprise Quiz!

Verifying the Accuracy of Temperature Readings

handheld thermometer and the HVAC mock board's thermostat.

Note: This is a demonstration. Actual task performance will follow after complete instructions.

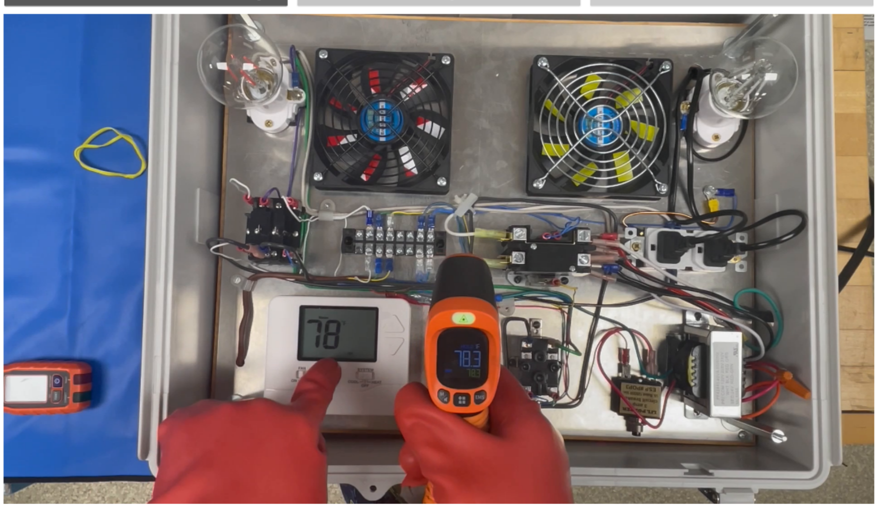
Objective:
- Understand the process of measuring and comparing ambient temperatures.

Expectation:
- The thermostat and thermometer readings should be within 5°C of each other.
- The thermometer readings should be taken at/around the thermostat in the Mock Board.

Demonstration Steps (View the Video Guide Below):
1. **Safety First:** Observe the use of protective equipment.
2. **Thermostat Reading:** Watch how to access and read the mock board's thermostat.
3. **Temperature Measurement:** Learn to measure ambient temperature with the thermometer.
4. **Data Recording:** After you perform the temperature reading you will be required to input the thermometer reading when prompted.

Note: Remember, this is a demonstration. Actual task performance will

Rewind 10 Secs & Play | Play | Pause



If you are ready to continue, tap "Next" below!

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Figure 4.9: Get Temperature Reading.

The guide provided participants with a structured introduction to key maintenance activities on the mock HVAC system, beginning with the **Ambient Temperature Verification Demonstration**. This demonstration was designed to instruct participants on how to ensure the accuracy of temperature measurements by comparing readings from a handheld thermometer with those displayed on the mock HVAC board's thermostat, as depicted in Figures 4.9. The objective was to familiarize participants with the process of measuring and validating ambient temperatures, with an expectation set for the thermostat and thermometer readings to be within a 5°F margin of each other.

Following this, the **Fan Mode Operation Demonstration** offered step-by-step guidance on verifying the fan mode's functionality. Participants learned how to adjust the thermostat settings to activate the fan without triggering the heating or cooling systems, ensuring that only the blower fan on the left side operated, as opposed to the condenser fan on the right side. This demonstration, illustrated in Figure 4.10, aimed to teach participants the correct fan mode configuration and the importance of verifying the appropriate fan operation.

Both demonstrations were planned to provide participants with the necessary skills and knowledge to perform these checks accurately. Participants were informed that the actual task execution would require them to apply these instructions to ensure the system's proper functioning. Moreover, they were prepared to identify and troubleshoot any discrepancies, such as unexpected fan or lamp operations, enhancing their problem-solving skills in a controlled environment.

Verifying the Operation the Fan-Only Mode

Fan Mode Operation Demo
This guide demonstrates how to verify the Fan Mode function on the HVAC mock board. You'll learn to set the thermostat for continuous fan operation without activating heating or cooling systems.

Fan Mode Configuration:
- Set to: Fan ON + System OFF.
- The fan should run, but heating/cooling lamps stay off.
- Only the blower fan (LEFT) operates, not the condenser fan (RIGHT).

Watch the accompanying video for a detailed demonstration.

Demonstration Steps (View the Video Guide Below):
1. Switch the thermostat's "FAN" control to "ON".
2. Ensure only the blower fan is active.
3. Return the "FAN" switch to "AUTO".

Note: If the fan or lamps do not operate as expected, troubleshoot it!

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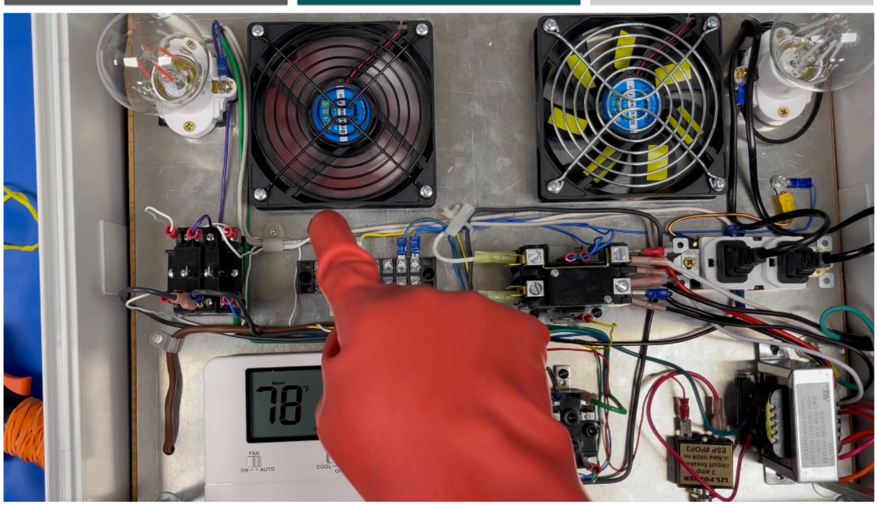

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Figure 4.10: Checking Fan's Functionality.

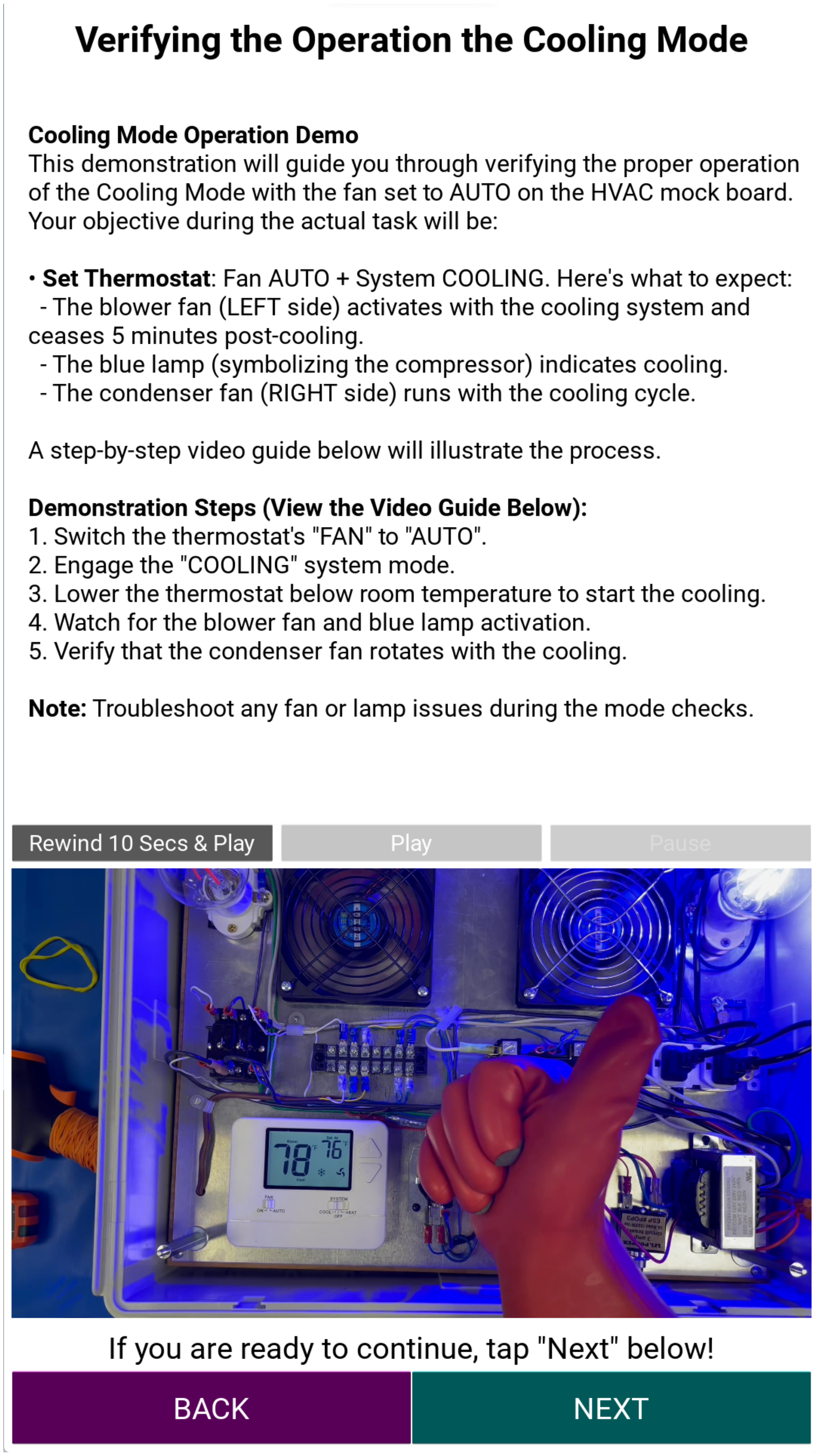

Figure 4.11: Check Cooling's Functionality.

The **Cooling Mode Operation Demonstration** provided a detailed walk-through for participants to verify the functionality of the Cooling Mode on the mock HVAC system, as illustrated in Figure 4.11. Participants were instructed to set the thermostat to enable the cooling system while keeping the fan on AUTO. Expected outcomes of this setting included the activation of the blower fan on the left side in tandem with the cooling system, the blue lamp illuminates for compressor activity, and the operation of the condenser fan on the right during the cooling cycle. Participants engaged the cooling system by adjusting the thermostat below room temperature and observed the specified components' responses to ensure correct operation.

Following the cooling demonstration, the **Heating Mode Operation Demonstration** showed the necessary steps to assess the Heating Mode's function, with visual guidance provided in Figure 4.12. The thermostat was configured to activate the heating system, also with the fan set to AUTO. This configuration was expected to activate the blower fan on the left side and the red lamp, symbolizing heating activity, while ensuring the condenser fan on the right side remained inactive during heating operations. Participants increased the thermostat setting above room temperature to initiate heating and monitored the system's response, including the blower fan and red lamp activation, to verify correct heating mode functionality.

Through hands-on experience with the thermostat settings and observation of the system's components, participants learned to identify and confirm the proper operation of the system in different modes, preparing them for the actual task execution with a focus on accuracy and troubleshooting potential malfunctions.

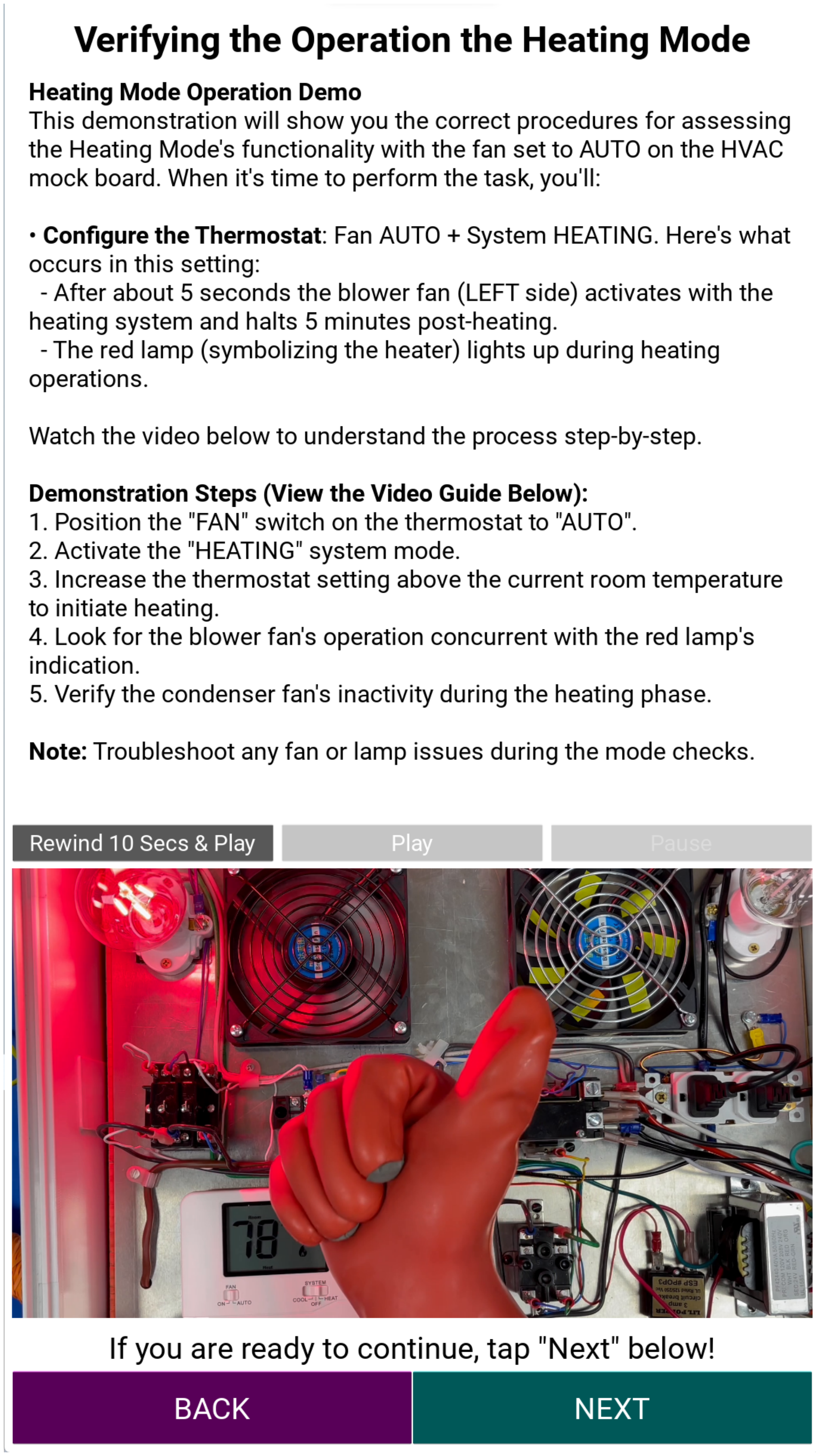

Figure 4.12: Checking Heating's Functionality.

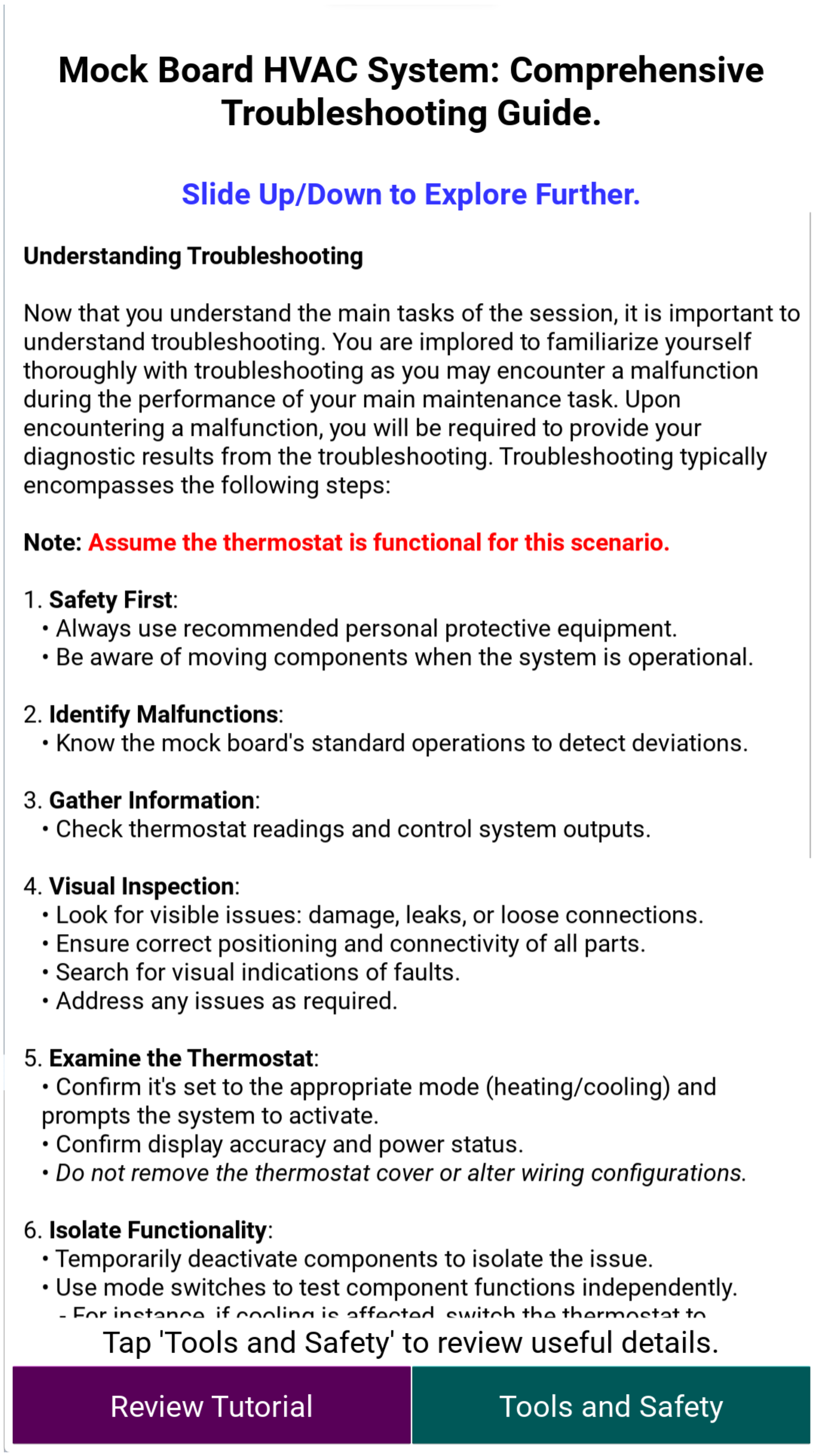

Figure 4.13: Introduction to Troubleshooting Guide.

During the study session, participants were introduced to an **Interactive Troubleshooting Guide**, a crucial tool for diagnosing and resolving issues encountered with the mock HVAC board, as depicted in Figure 4.13. This guide outlined a systematic approach to troubleshooting, encompassing several key steps designed to equip participants with the skills needed to efficiently identify and address malfunctions:

1. Identify malfunctions by recognizing deviations from standard operations.
2. Gather information through readings to form an understanding of the issue.
3. Conduct visual inspection for visible issues or signs of faults.
4. Examine the thermostat for correct mode, display accuracy, and power.
5. Isolate functionality by deactivating certain components to narrow down the problem source, utilizing mode switches to test individual system parts.
6. Electrical inspection involved using a multimeter or tester to assess components, comparing findings against standard specifications to identify anomalies.
7. Review and document findings and components requiring repair.

In addition to the troubleshooting guide, participants received a **Comprehensive Guide to the Mock HVAC Workspace**, providing an in-depth look at the simulated HVAC system and its 13 key components. This guide served as an invaluable resource for understanding the mock board's functionality, further enabling participants to undertake effective troubleshooting, as illustrated in Figure 4.14.

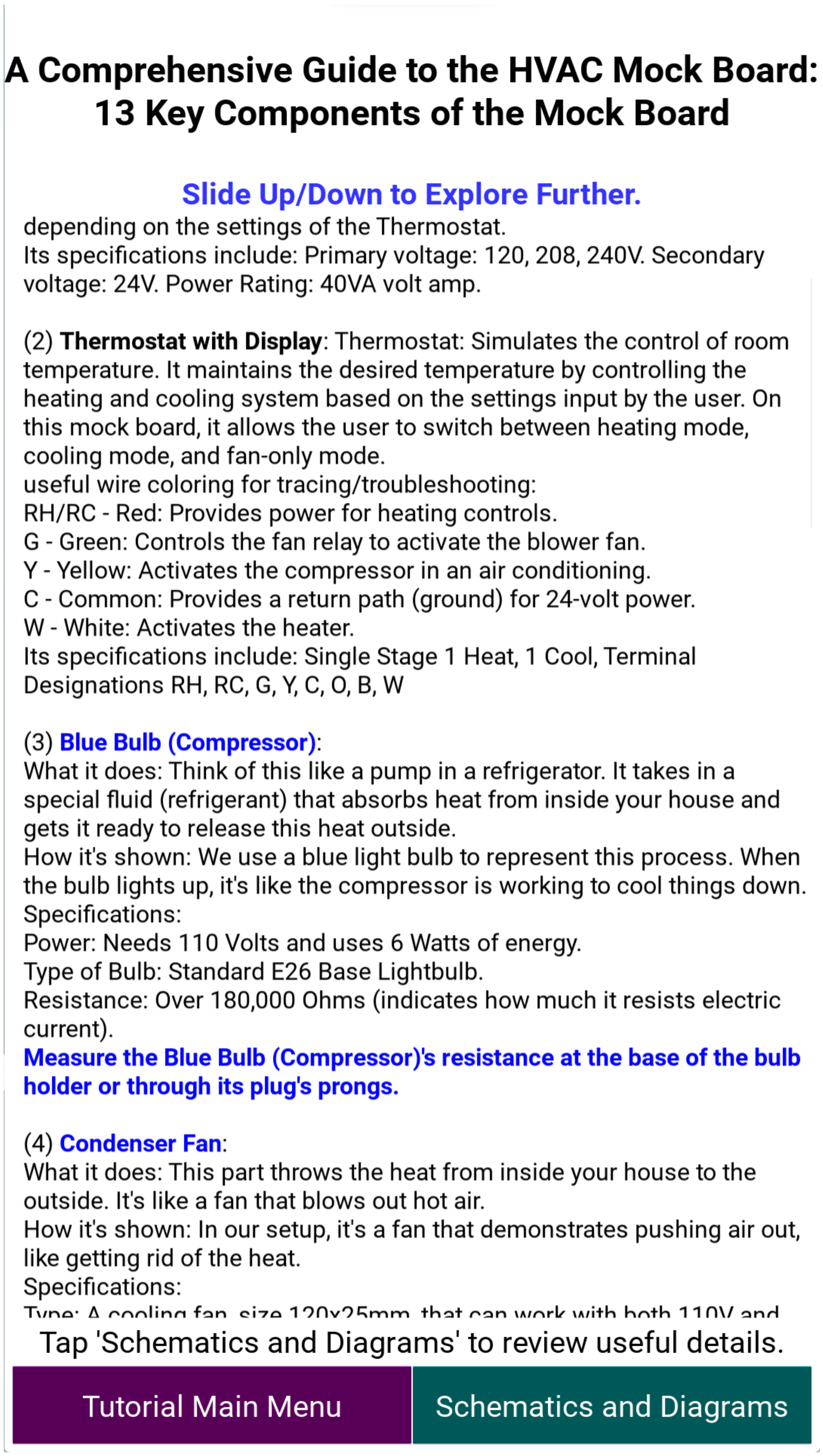

Figure 4.14: The Mock Board's 13 Components.

Essential Tools & Safety Equipment

Tool Usage and Safety Overview
This module will guide you through the proper and safe usage of essential tools and safety equipment.

Key Components:
- **Essential Tools:** Learn to use each tool with precision for various HVAC maintenance tasks.
- **Safety Equipment Adherence:** Gain knowledge on the protective gear that safeguards against potential hazards.

On the following screens, you'll find detailed information on each tool and piece of safety equipment. You will have the option to view demonstrations of their use. To reinforce learning, you're encouraged to practice using the tools as guided by the demonstrations.

Important Participant Instructions:
- After using any tool, please place it back in its original position and orientation. This is crucial for the workspace's order and functionality, as robotic systems may also interact with these tools.
- Always wear the provided safety gear when practicing and during actual maintenance tasks to prevent injury.

By following these practices, we maintain a safe, efficient, and robot-friendly learning environment.

Discover each tool for a comprehensive understanding...

BACK to Troubleshooting... | NEXT to Digital Multimeter

Figure 4.15: Introduction to Workspace and Tools.

The **Tool Usage and Safety Overview** module was a critical component of the study session, designed to educate participants on the correct and safe use of tools and safety equipment essential for HVAC maintenance. Participants were instructed to practice tool usage as demonstrated and to maintain workspace order by returning tools to their designated places after use. The emphasis on adhering to safety protocols during both practice and actual tasks was a key aspect of this module, ensuring participants understood the significance of safety in the maintenance environment, as illustrated in Figure 4.15.

Following the safety overview, the **Multimeter Usage Demonstration** provided participants with hands-on instructions on using the multimeter effectively for electrical troubleshooting tasks. This demonstration highlighted the proper techniques for connecting leads and setting the dial for various measurements, including DC voltage, AC voltage, resistance, continuity, and current. Key instructional points included:

- Ensuring correct lead placement and selecting appropriate dial settings.
- Following specific procedures for voltage, resistance, continuity testing (including touching probes together to test), and current measurement.
- Highlighting the importance of safety and precision.

These comprehensive instructions aimed to bolster participants' confidence and proficiency in using the multimeter, a pivotal tool in electrical troubleshooting. The guidance provided in this demonstration, along with the emphasis on safety and correct tool usage, was made available for participants to refer back to throughout the session, as depicted in Figure 4.16.

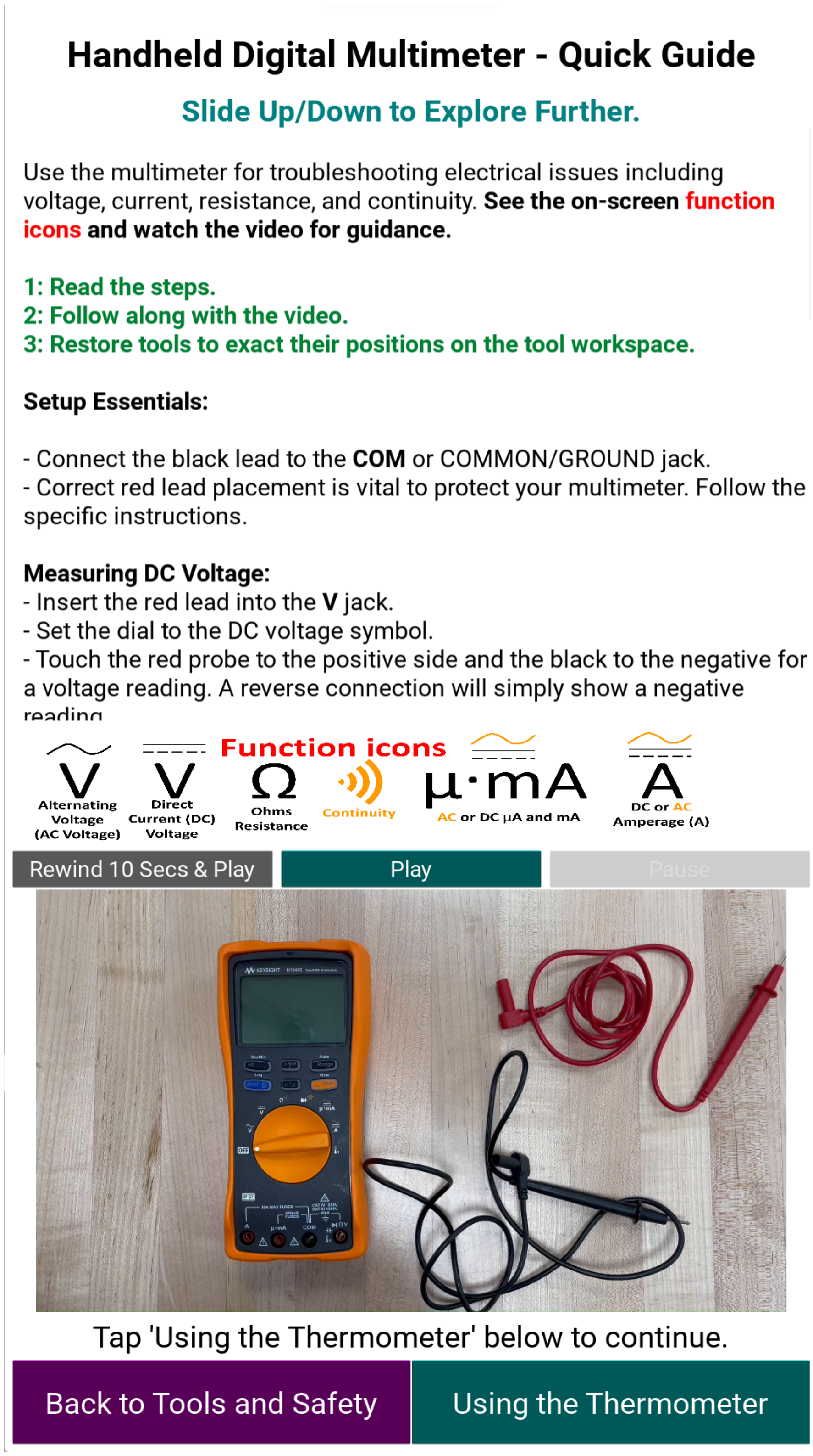

Figure 4.16: A Follow-Along Digital Multimeter Tutorial.

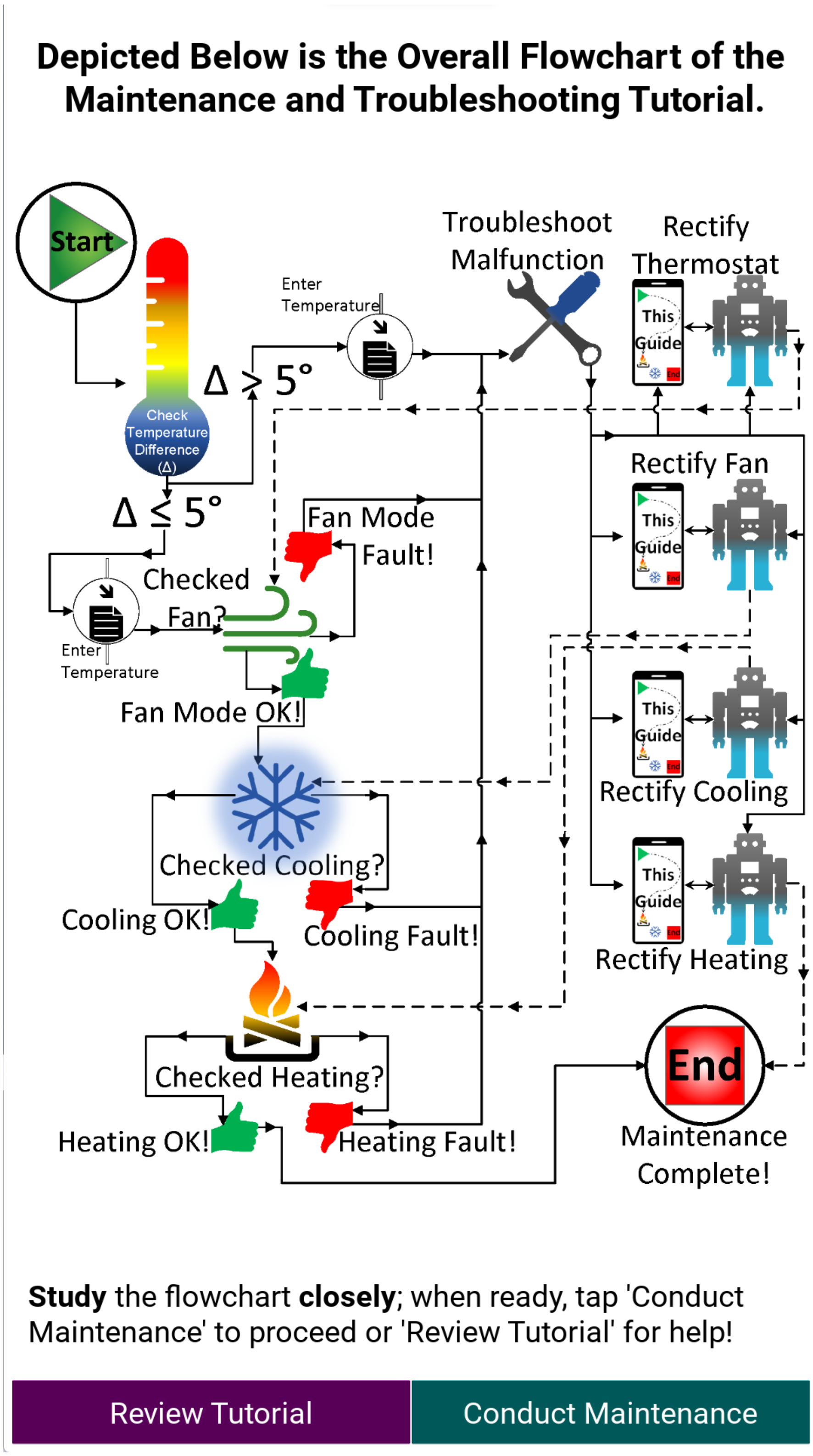

Figure 4.17: A flowchart depicting the whole maintenance task process.

The **Process Sequence and Interactive Flowchart Overview** module introduced participants to the ‘Process Sequence’ screen. This screen signified the commencement of the hands-on maintenance tasks, presenting the sequence of operations through an engaging flowchart format. Participants, upon viewing with this screen, were given an overview of the whole maintenance and troubleshooting process, as illustrated in Figure 4.17.

The **Interactive Flowchart Screen** further enhanced participants’ engagement by structuring their journey through the HVAC system evaluation. This interactive platform led participants from the initial step of identifying temperature discrepancies through detailed checks of the system’s fan, cooling, and heating operations. With tailored prompts and actions that adapted to participants’ real-time inputs, the flowchart served as a guide, facilitating a responsive and educational experience. This approach allowed participants to not only follow a structured sequence but also to receive specific guidance that informed their actions throughout the session, as depicted in Figure 4.18.

This combination of the Process Sequence screen and the Interactive Flowchart provided a comprehensive framework for participants to navigate the maintenance tasks. By integrating responsive guidance with a structured task sequence, the study session aimed to foster a deep understanding of HVAC system maintenance, enhancing participants’ technical skills and problem-solving abilities in a supportive, interactive environment.

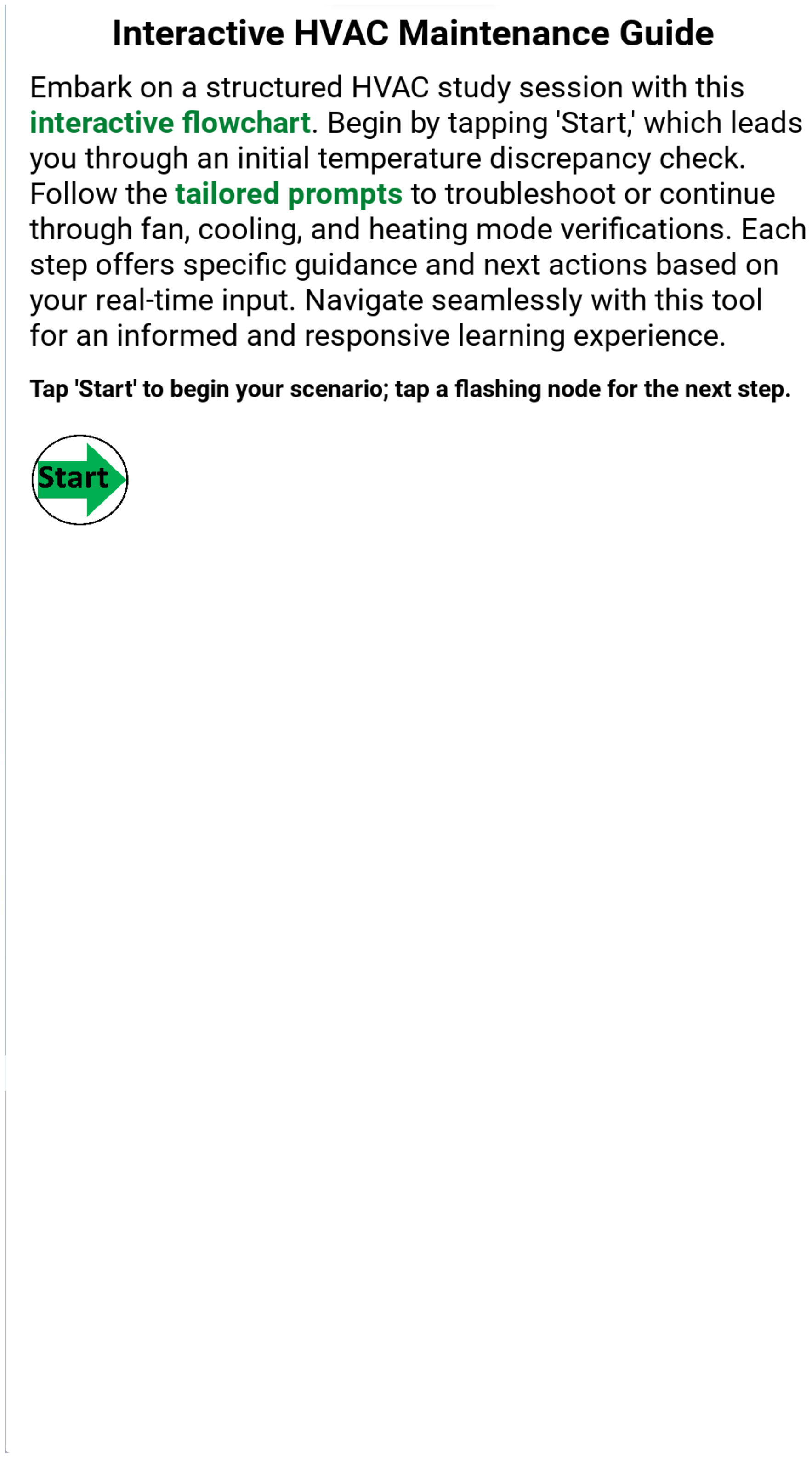

Figure 4.18: An adaptive flowchart, individualized to the participant.

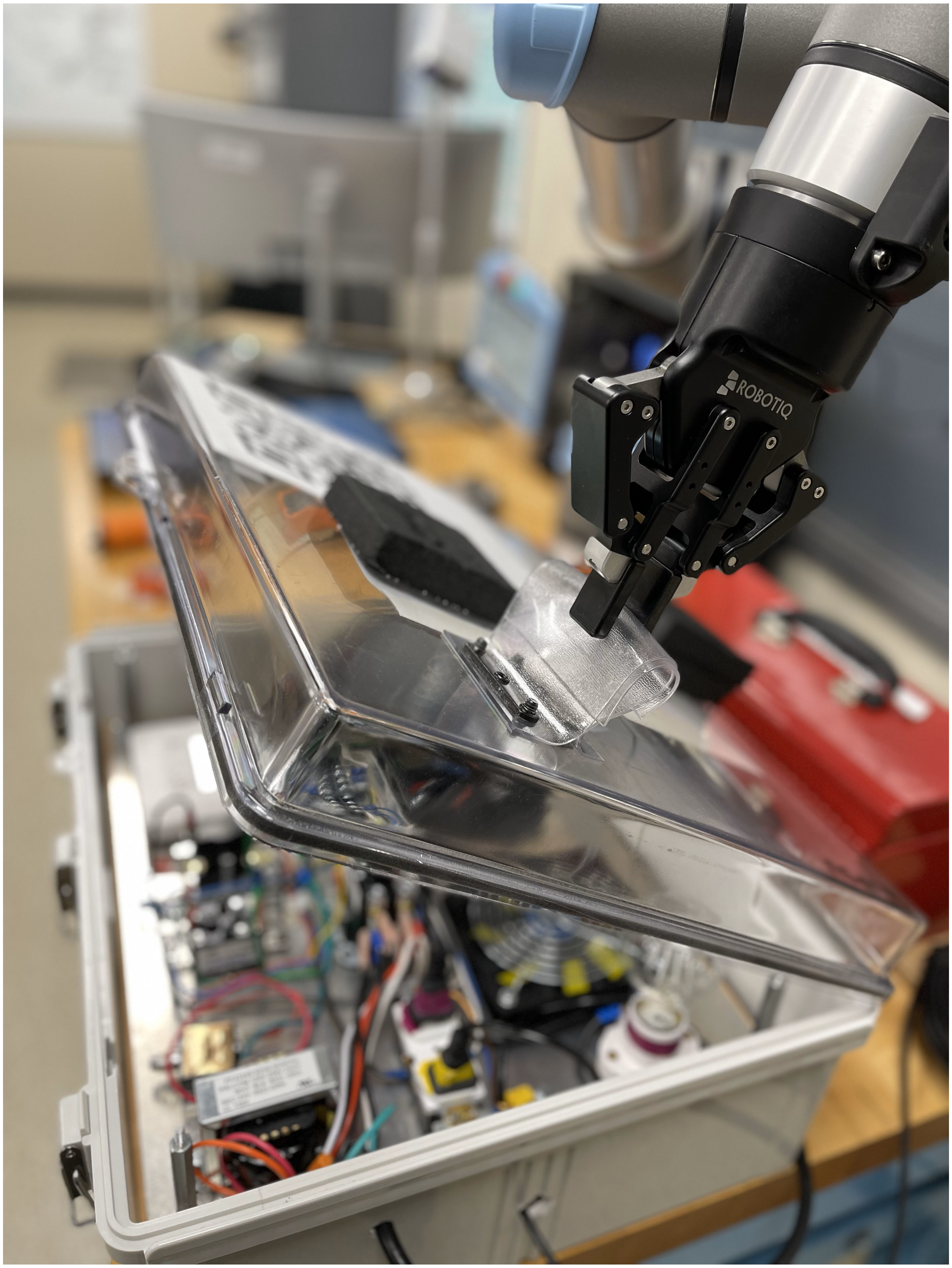

Figure 4.19: Robot opening the mock board for a participant to begin maintenance task. Participants begin by using the thermometer to take the temperature reading.

The **Interactive Guide and Robot's Role in Task Navigation** segment was integral to the HVAC maintenance study session, serving as a key resource for participants to effectively maneuver through the maintenance tasks. This guide offered structured prompts, guiding participants through critical stages of the maintenance process: temperature congruence, fan mode, cooling mode, and heating mode checks.

From the outset, the robot was essential in facilitating participant interaction with the guide. It introduced itself at the beginning, setting the tone for a collaborative session. Depending on the ongoing assessment of each participant's expertise, the robot either promptly provided access to the mock board, reinforcing task objectives, or offered additional guidance on safety and task procedures, as illustrated when the robot opened the Mock Board for a participant in Figure 4.19.

Adaptive Task Scenarios and Troubleshooting were tailored to the complexity level suited to each participant's experimental group—simpler or complex. In simpler scenarios, participants encountered malfunctions during the cooling mode, such as a defective condenser fan, followed by a compressor issue. The complex scenarios introduced a malfunction during the cooling mode check and another during the heating mode, challenging participants to apply their troubleshooting skills more extensively.

The robot and the interactive guide provided essential support in these scenarios, offering adaptive guidance tailored to the nature of the fault and the participant's skill level. This approach ensured that participants received the necessary information and assistance to effectively address the malfunctions. We depict a notional scenario where a participant identified a fault in the cooling mode in Figure 4.20.

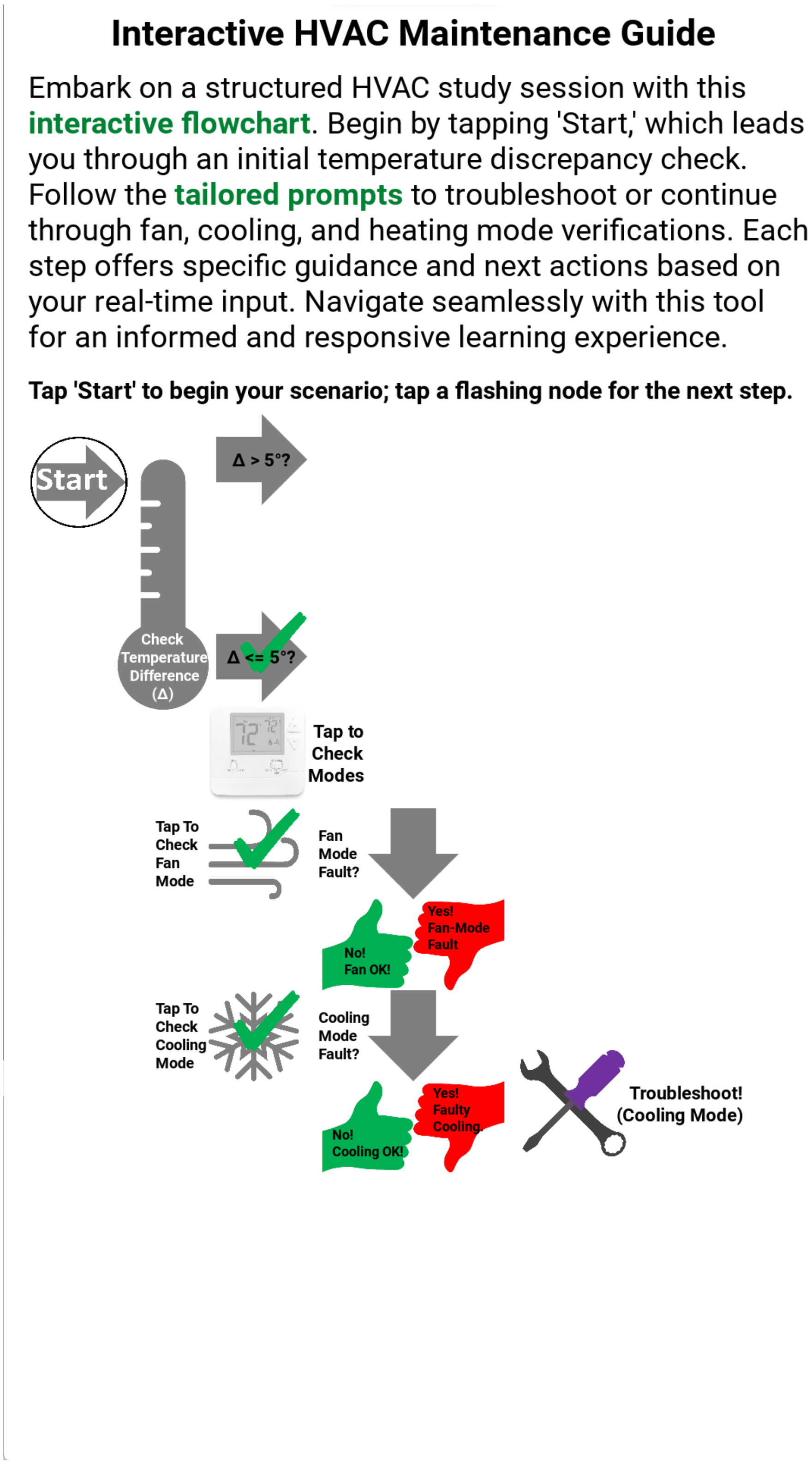

Figure 4.20: Participant indicating a Cooling Mode malfunction after having tapped on the red thumb-down button.

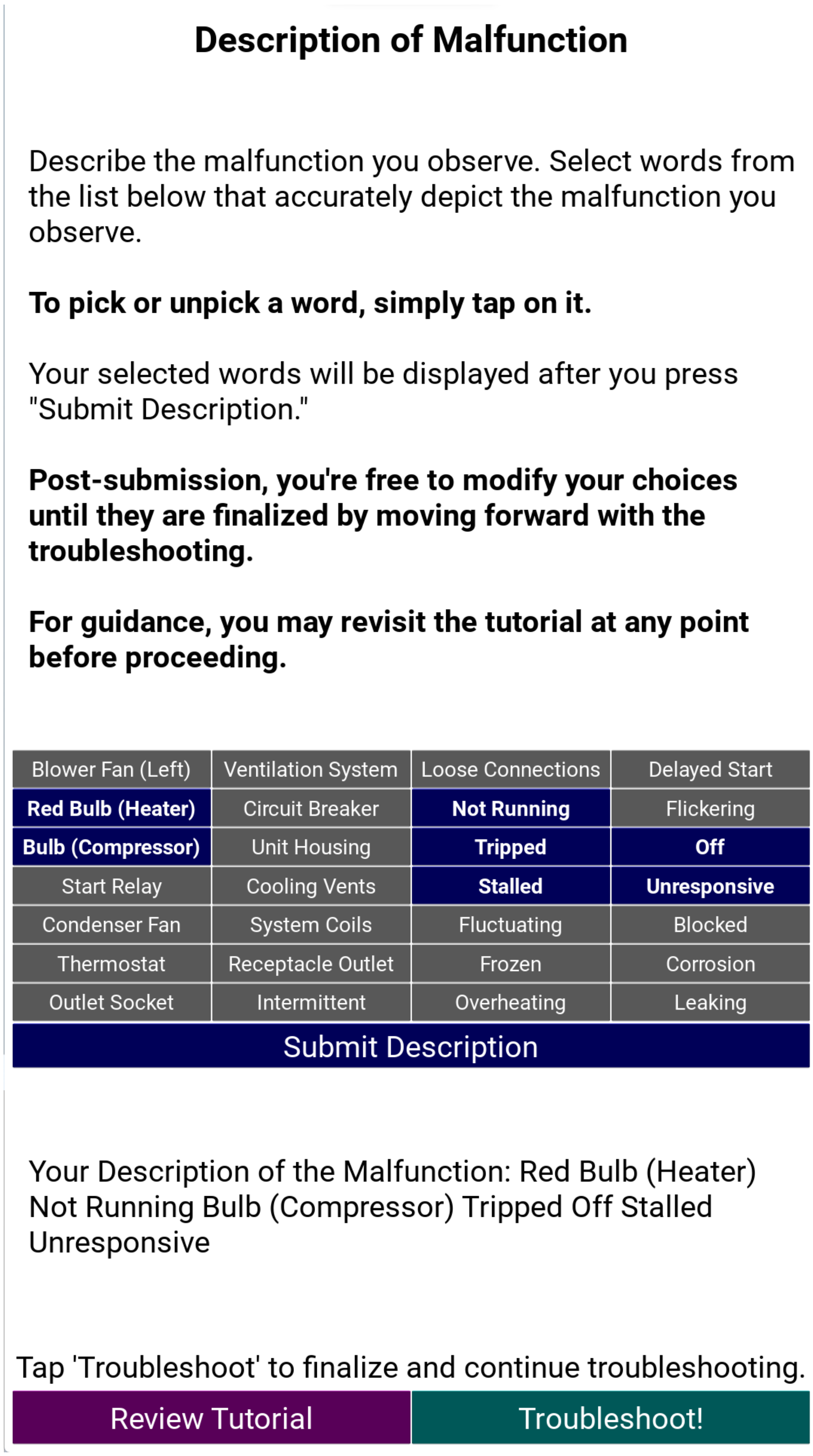

Figure 4.21: Participants Describe the Malfunction..

During the HVAC maintenance task, the interaction between participants and the robot was pivotal in identifying and addressing malfunctions. The robot not only signaled the detection of a malfunction but also took an active role in guiding participants towards the suspected issue, physically indicating the malfunctioning part on the mock board. This assistance aimed to direct participants' attention to potential problems, yet the onus was on the participants to verify and articulate the nature of the malfunction, reinforcing their engagement and analytical skills in the troubleshooting process.

Describing the Malfunction involved an exercise where participants used a list of descriptive words to articulate the malfunction they observed. This task encouraged a detailed examination of the issue, with participants tapping on words to accurately convey their observations. The flexibility to adjust their descriptions before final submission allowed for a reflective process, ensuring a thorough and precise communication of the malfunction. Moreover, participants were prompted to consult the tutorial as needed, ensuring they were well-supported in articulating their observations, as shown in Figure 4.21.

As depicted in Figure 4.22, an essential pause was introduced into the troubleshooting sequence, preventing participants from prematurely concluding the fault identification process. This mechanism ensured that participants engaged deeply with the troubleshooting process, compelling them to undertake a methodical examination of the mock board before indicating a finding of fact as to the specific fault. This step served as a **Troubleshooting Cue**, guiding participants to initiate troubleshooting, thereby enhancing the depth and effectiveness of their problem-solving approach.

Figure 4.22: Participants Identify the Malfunction.

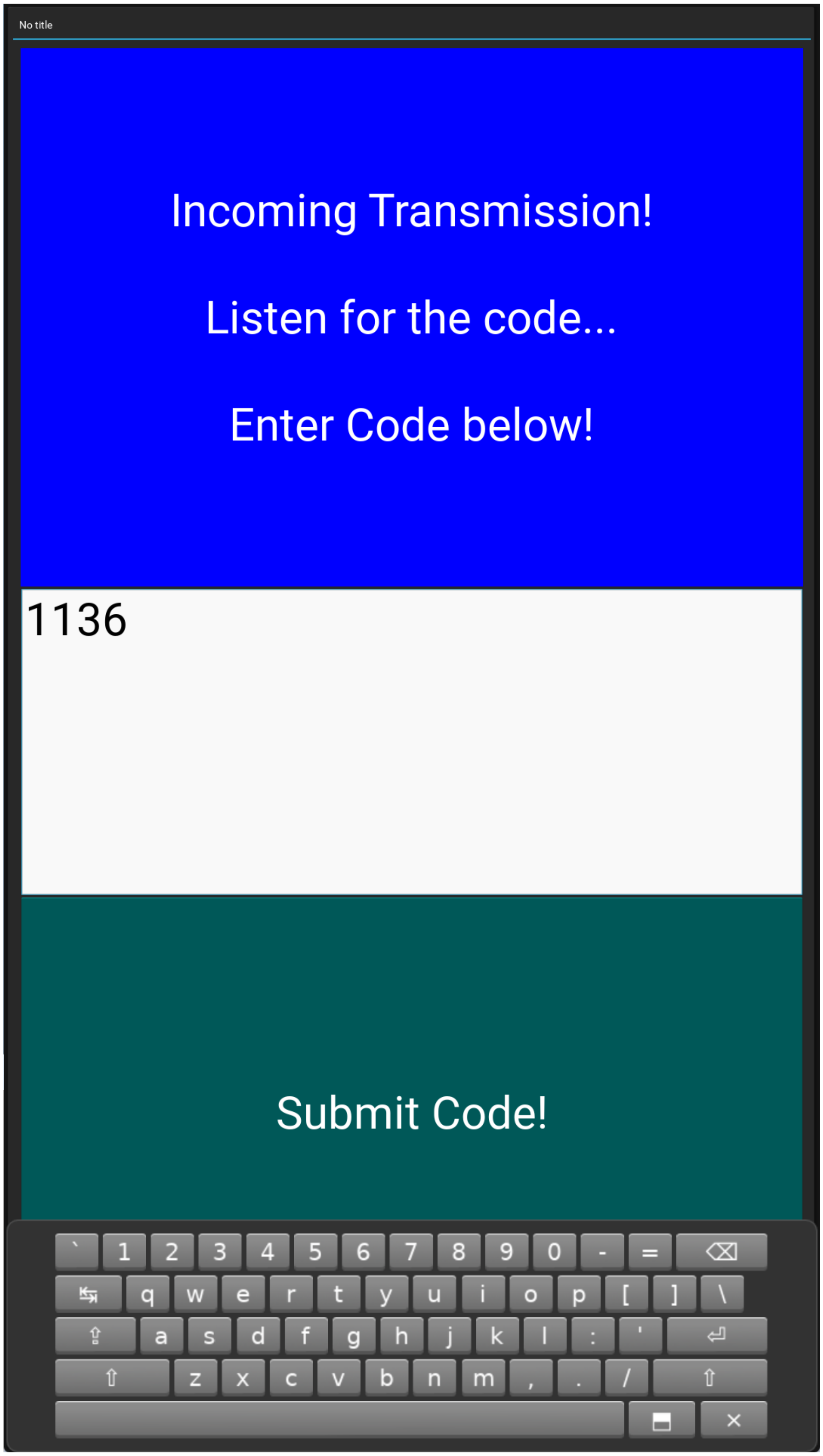

Figure 4.23: Interruptions Prompt Screen. listening for and following the instructions enables participants to handle the interruptive task during troubleshooting.

Depicted in Figure 4.23 is the study session's interface designed for managing interruptions, which occur during the participant's engagement with troubleshooting tasks on the mock HVAC board. These interruptions are crafted to mimic real-world distractions that technicians might encounter, requiring participants to momentarily shift their focus. Participants are tasked with listening to instructions and responding appropriately by entering a specified code, testing their ability to manage multitasking and maintain attention to detail under potentially disruptive conditions. The **Role of the Robot in Handling Interruptions** was strategic, enhancing the troubleshooting process's depth and realism. While the robot did not directly assist in managing the interruptions themselves, its role in facilitating the troubleshooting process was critical. As depicted in Figure 4.24, the robot actively contributes to the task environment by placing a digital multimeter within the participant's reach, signifying the instrument as the next necessary tool for the task at hand. This action by the robot serves as a crucial cue, subtly guiding the participant towards the correct course of action in the midst of troubleshooting activities.

Despite not intervening in the interruptions directly, the robot provided invaluable support once participants addressed the interrupting tasks. By offering step-by-step guidance tailored to the situation, the robot ensured that participants could efficiently resume their troubleshooting efforts with minimal disruption to their workflow. This dynamic interaction between the participant, the robot, and the interrupting tasks underscored the importance of adaptability, focus, and the effective use of **Environmental Cues** in maintaining progress and accuracy during technical maintenance activities.

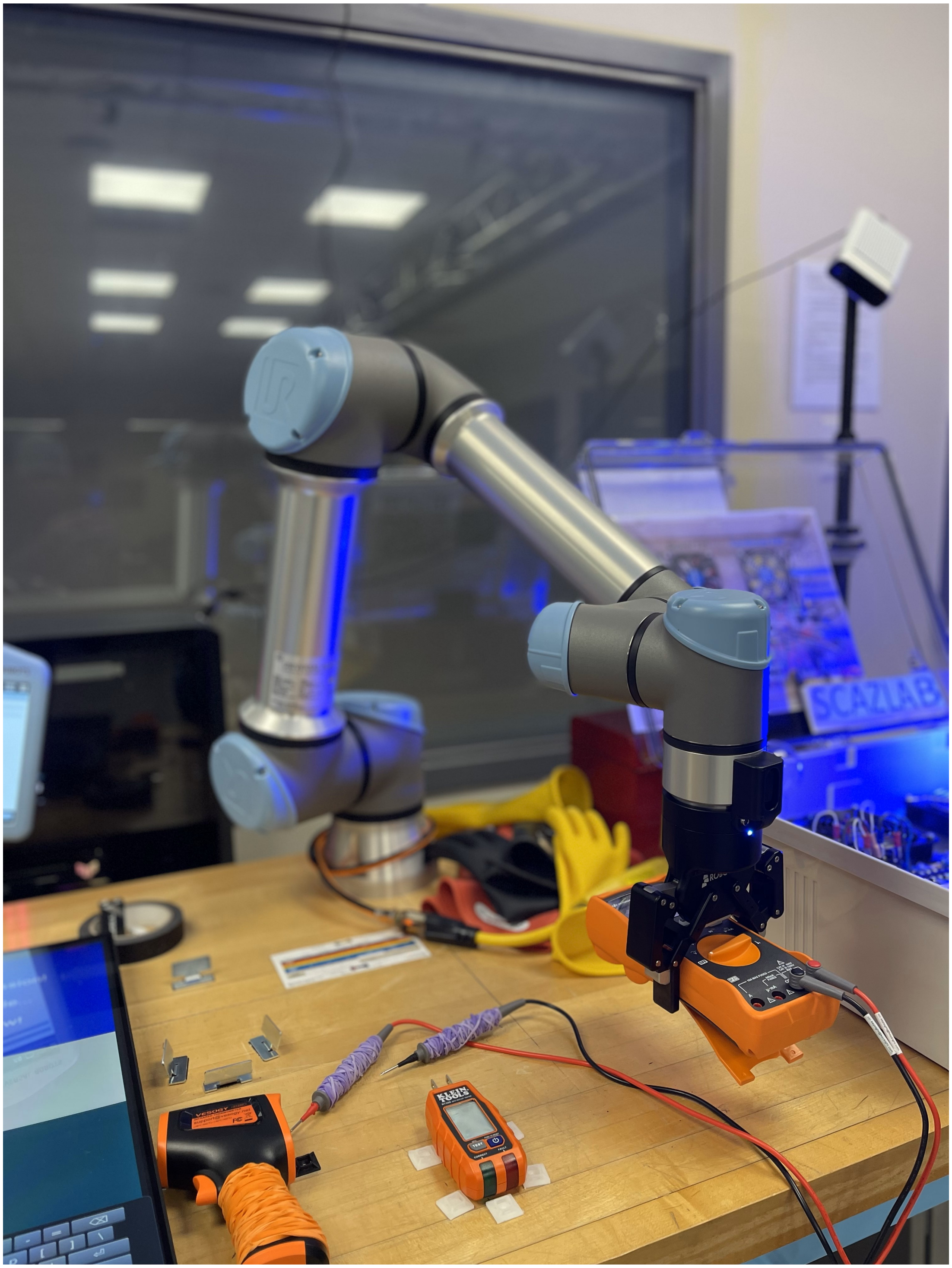

Figure 4.24: Robot in motion, placing a digital multimeter near the user as the correct and next-step tool during an interruption. A cue in the environment of the technician.

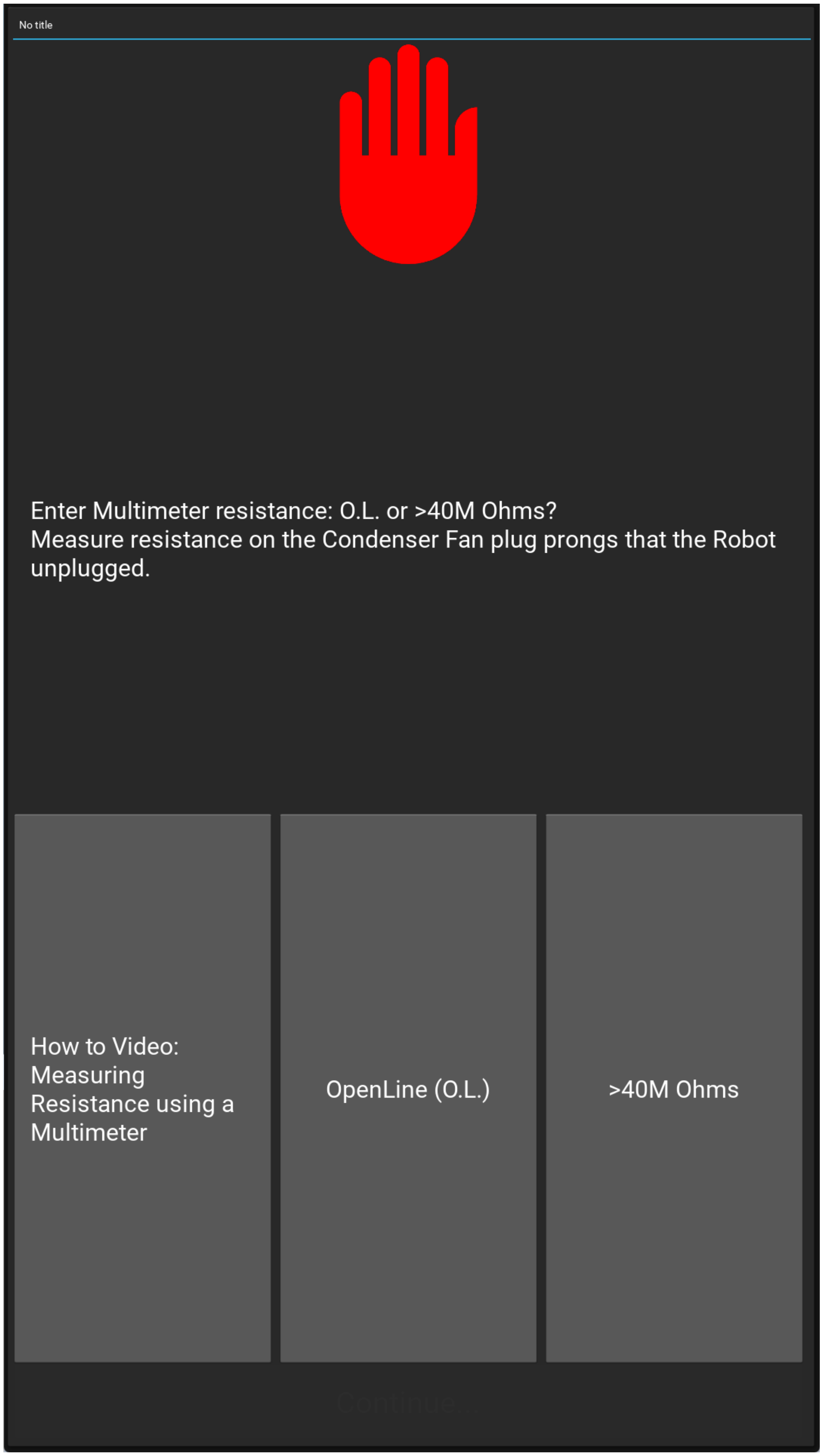

Figure 4.25: Instructions deliver by voice and on the screen assisting participants with troubleshooting faults in a malfunctioning mock HVAC workspace.

Simpler Scenario: Focused Approach to Component Testing: In these less complex scenarios, the robot's assistance was pivotal, yet straightforward, facilitating an easier navigation through the troubleshooting process for participants:

- Directing Attention: The robot effectively guided participants towards identifying potential issues by pointing out components likely to be faulty. This direct approach significantly streamlined the troubleshooting process, enabling participants to focus their efforts more efficiently.

- Manipulating Components: One of the robot's key roles was its physical interaction with the HVAC system, exemplified by actions such as unplugging the condenser fan, as shown in 4.26. This intervention allowed participants to perform specific tests, such as checking the condenser fan's resistance, without the need for intricate disassembly or reconfiguration of system components.

- Visual and Auditory Guidance: The troubleshooting experience was enriched by the robot's use of visual and auditory cues. Figure 4.25 illustrates how the robot not only vocalized instructions but also utilized the touchscreen interface to display pertinent information. This multi-modal approach to guidance provided participants with a comprehensive and accessible learning experience, catering to different learning preferences and enhancing the overall effectiveness of the troubleshooting process.

Through the integration of direct assistance, physical interactions with the system, and multi-modal guidance, the robot significantly contributed to simplifying the troubleshooting process in simpler scenarios.

Figure 4.26: Robot unplugs the plug for the compressor so that the participant can measure the participant can measure the resistance at the plug's prongs.

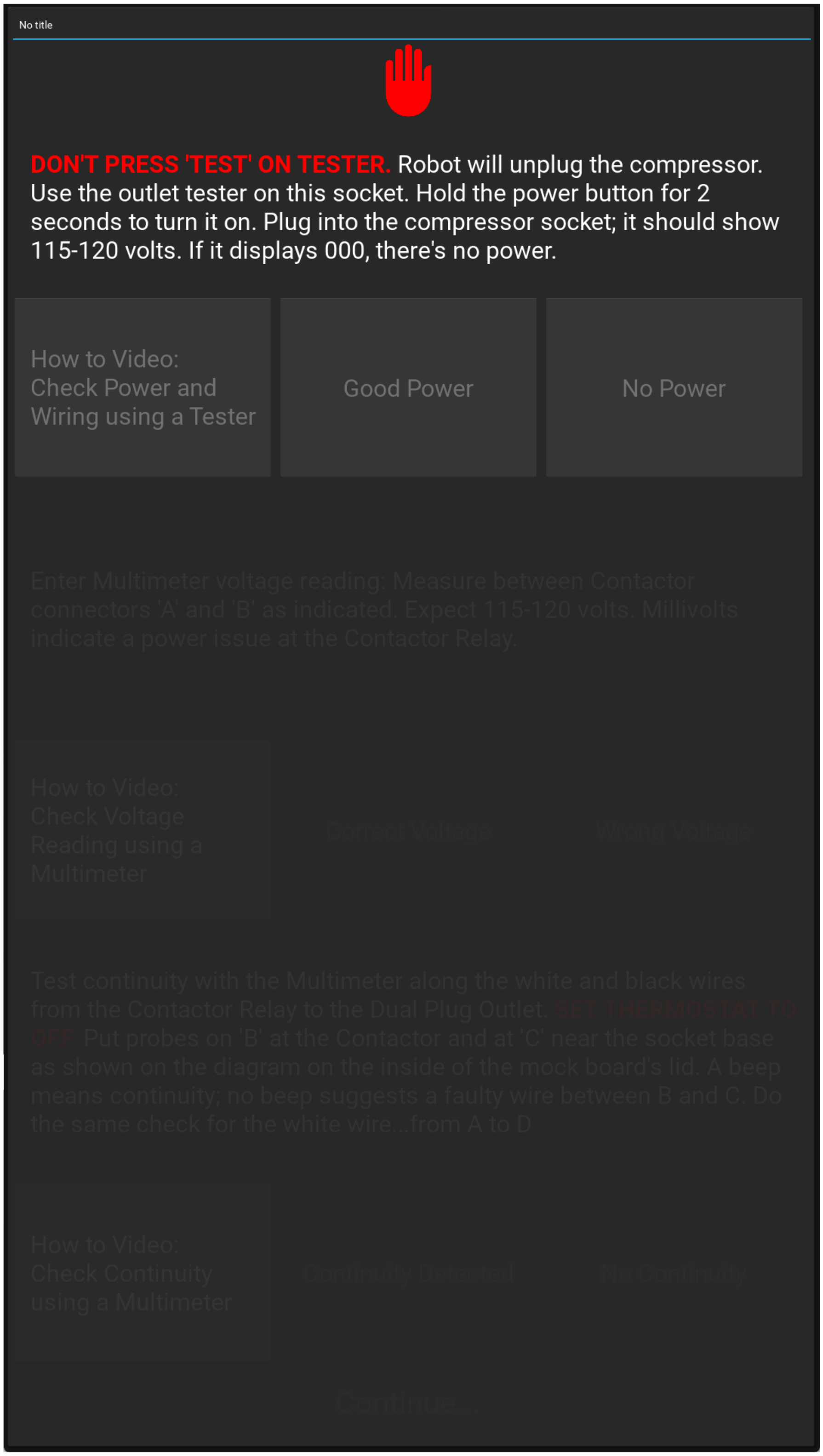

Figure 4.27: Robot unplugs the plug for the compressor so that the participant can measure the participant can measure for power at the open outlet.

In the **Complex Scenario: Extensive Troubleshooting Guidance**, participants were immersed in more complicated troubleshooting tasks that demanded a deeper engagement with the HVAC system's intricacies:

- Complex Component Checks: The act of physically unplugging components, such as the compressor, allowed participants to conduct thorough examinations of sockets, power relays, and wiring connections. This step was crucial for accurately identifying the power source, offering clear guidance for subsequent actions, and facilitating a deeper understanding of the troubleshooting process by isolating specific issues and enabling targeted diagnostics.

- Analytical Skill Integration and Responsibility: Despite the robot's guidance, the ultimate responsibility for identifying faults rested with participants. They needed to use their analytical skills to interpret the robot's advice and combine it with their observations for an accurate diagnosis. The robot's assistance, designed for both simple and complex scenarios, aimed to complement—not replace—the participants' analytical process. This approach fostered a learning environment where participants enhanced their problem-solving capabilities through exploration, analysis, and deduction.

Figure 4.27 showcases the robot offering complementary instructions on the touchscreen, which included not just procedural guidance but also recommendations for tool usage. Meanwhile, Figure 4.28 highlights the robot's action in identifying the specific socket for examination, aiding participants in pinpointing areas of interest during their troubleshooting efforts.

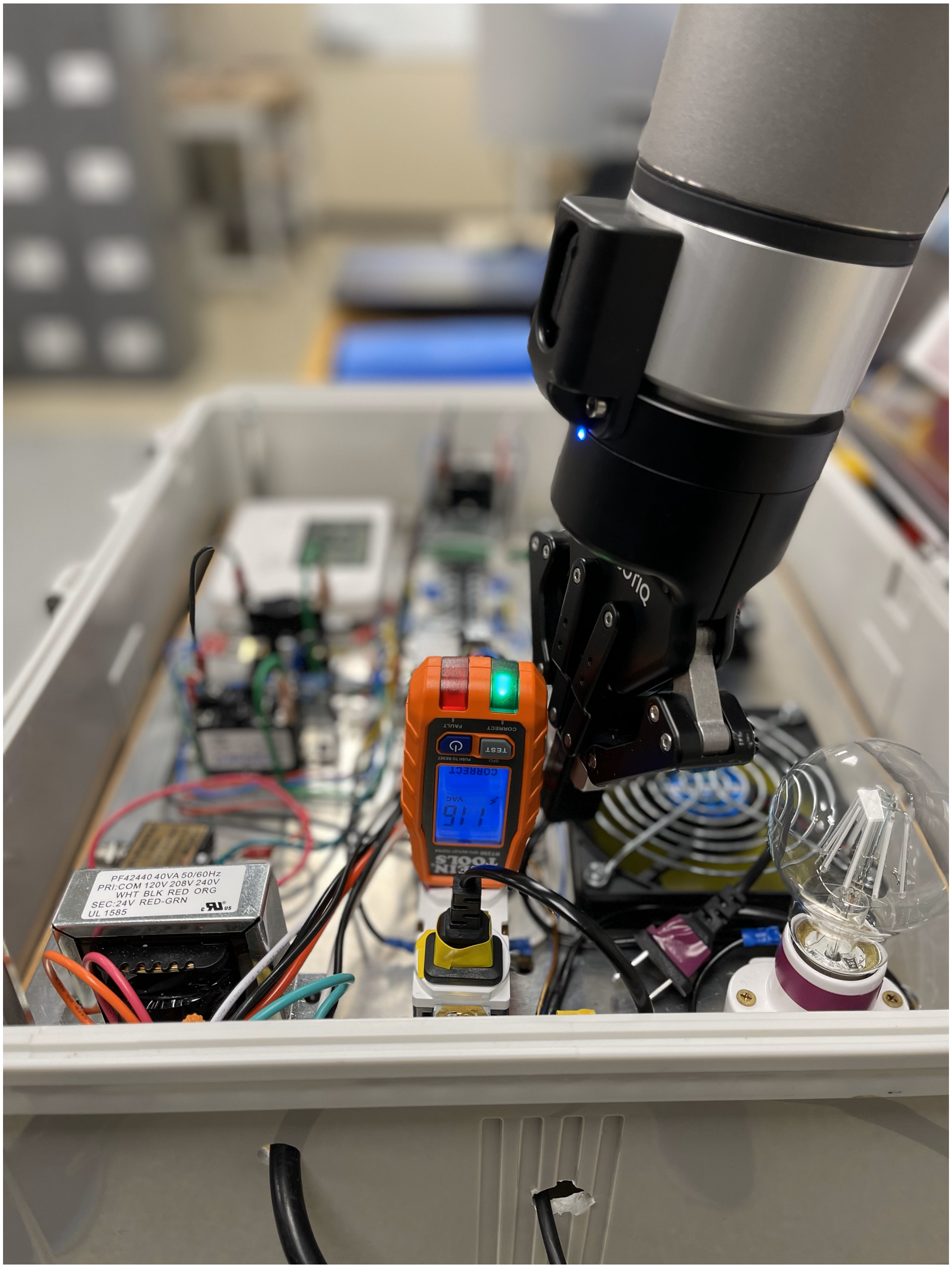

Figure 4.28: Robot pointing at the open outlet after having unplugged the component from the socket.

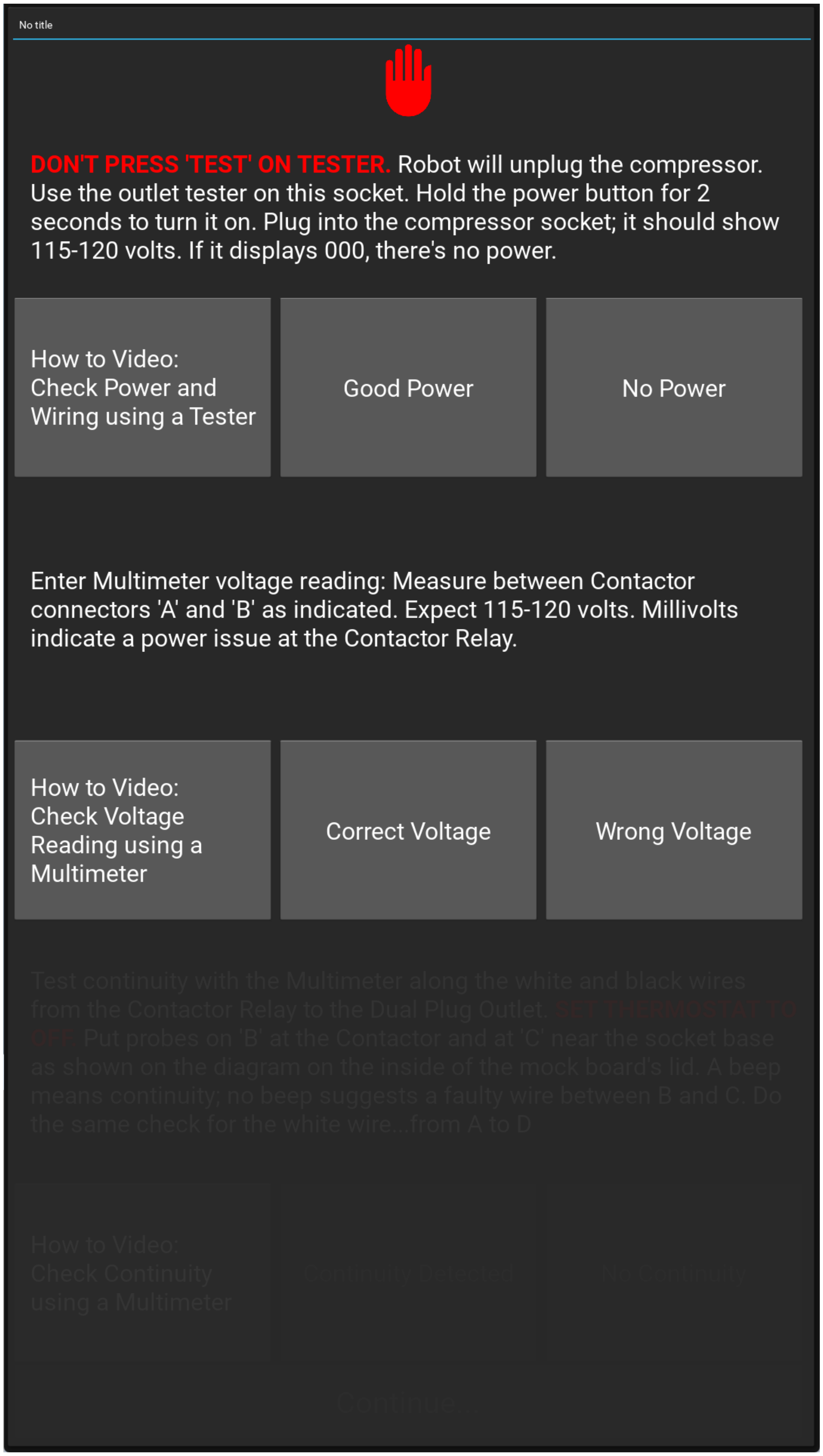

Figure 4.29: Robot unplugs the plug for the compressor so that the participant can measure the participant can measure for power at the open outlet.

In the progression of the HVAC maintenance study session, Figure 4.29 captures a critical juncture in the troubleshooting process, where the actions and guidance provided by the robot adapt based on the outcomes of the participant's investigative efforts. At this stage, the task at hand involves the measurement and reporting of voltage levels, a step crucial for determining the next step. This **Adaptive Guidance** is pivotal, as it ensures that participants receive support tailored to their current task state. Illustrated further in Figure 4.30 is the robot's role in guiding participants towards accurate tool usage. Here, the robot points out the specific contact point on the relay, which are key to powering the sockets connected to the potentially faulty compressor and condenser fan. This visual cue from the robot directs participants to use the multimeter and its leads for voltage measurements at these critical points, a step fundamental to diagnosing the issue accurately.

Complementing the robot's physical cues, the touchscreen interface offers comprehensive procedural guidance alongside tool usage recommendations. This digital guidance is further augmented by wiring diagrams located on the inside of the mock board's lid, providing participants with a visual reference that aids in understanding the system's electrical connections and configurations. This **Multi-Modal Approach** to instruction—combining visual indicators from the robot, digital guidance on the touchscreen, and supplementary wiring diagrams—ensures that participants have access to a rich array of information resources. These resources are designed to support participants in navigating the troubleshooting process effectively, fostering a deep engagement with the task and enhancing their technical troubleshooting skills.

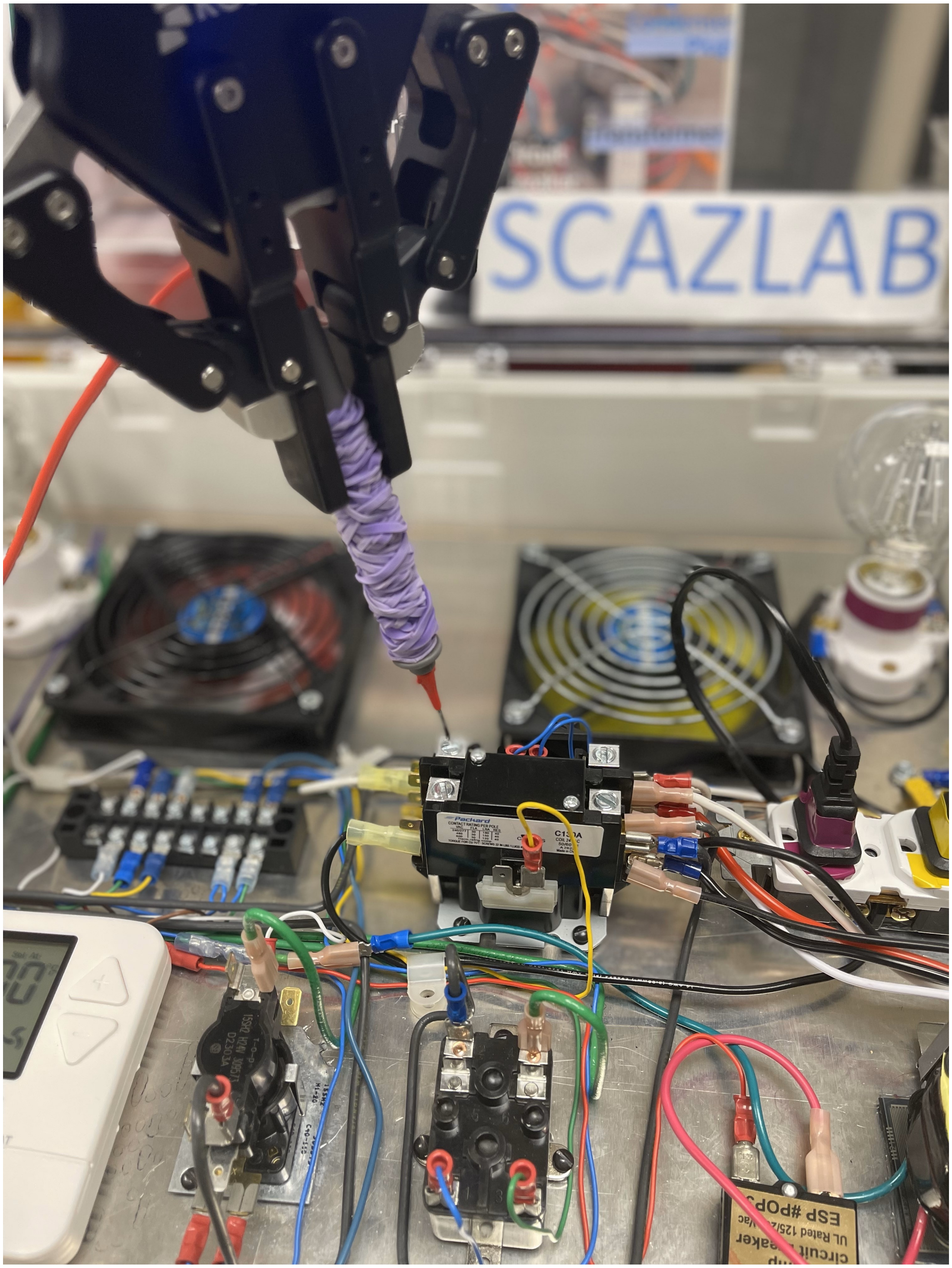

Figure 4.30: Robot pointing at the open outlet after having unplugged the component from the socket.

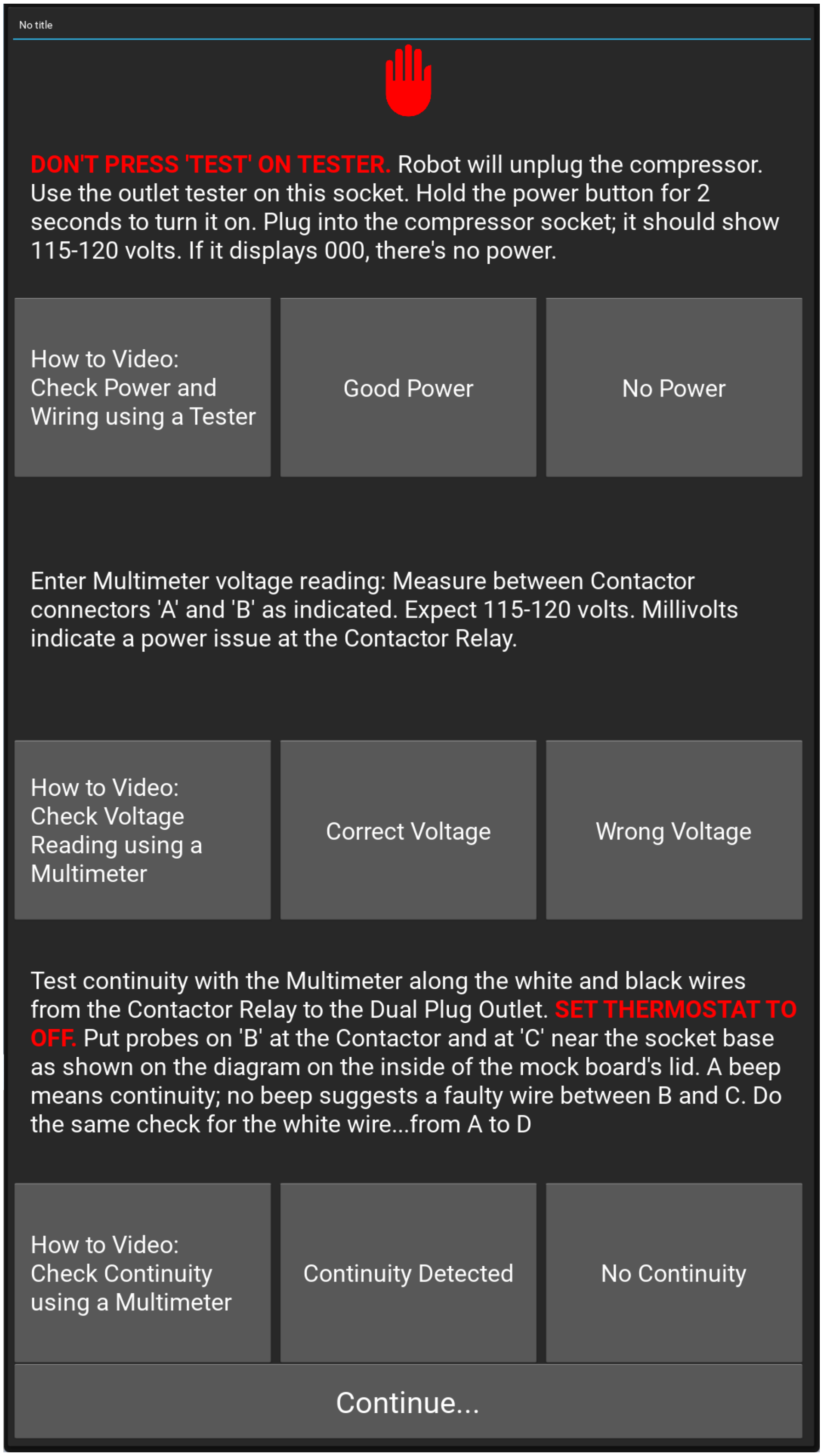

Figure 4.31: Continuity check instructions provided by voice, gestures, and in print.

In the process of troubleshooting within the complex scenario, **Robot-Assisted Continuity Testing** emerges as a critical phase, with the robot guiding participants through this precise diagnostic task. The robot's assistance is multifaceted, blending auditory instructions, text prompts on the touchscreen, and physical demonstrations to ensure a comprehensive understanding and execution of the continuity check.

As participants approach this pivotal step, they are first advised by the robot to set the thermostat to 'off', a necessary precaution to ensure accurate testing conditions. Figure 4.31 illustrates this initial instruction as displayed on the touchscreen, setting the stage for the continuity test.

The subsequent guidance focuses on the practical execution of the test. The robot directs participants to place the multimeter probes on specific **Points along the Circuit**: one probe at point 'B' on the Contact Relay and the other at point 'C' near the socket base, as visually indicated by the robot pointing at point 'C' in Figure 4.32. These critical points for the test are not only demonstrated by the robot but are also clearly detailed on the diagram inside the mock board's lid, ensuring participants have a clear visual reference to aid in probe placement.

In addition to directing the physical placement of the probes, the robot provides essential guidance on **Interpreting the Multimeter's Readings**. It explains that a continuity beep signifies a complete circuit between points 'B' and 'C', while the absence of a beep could indicate a potential fault in the wire connecting these points. This nuanced instruction extends to the continuity check along the white wire, recommending a similar test from point 'A' to point 'D'.

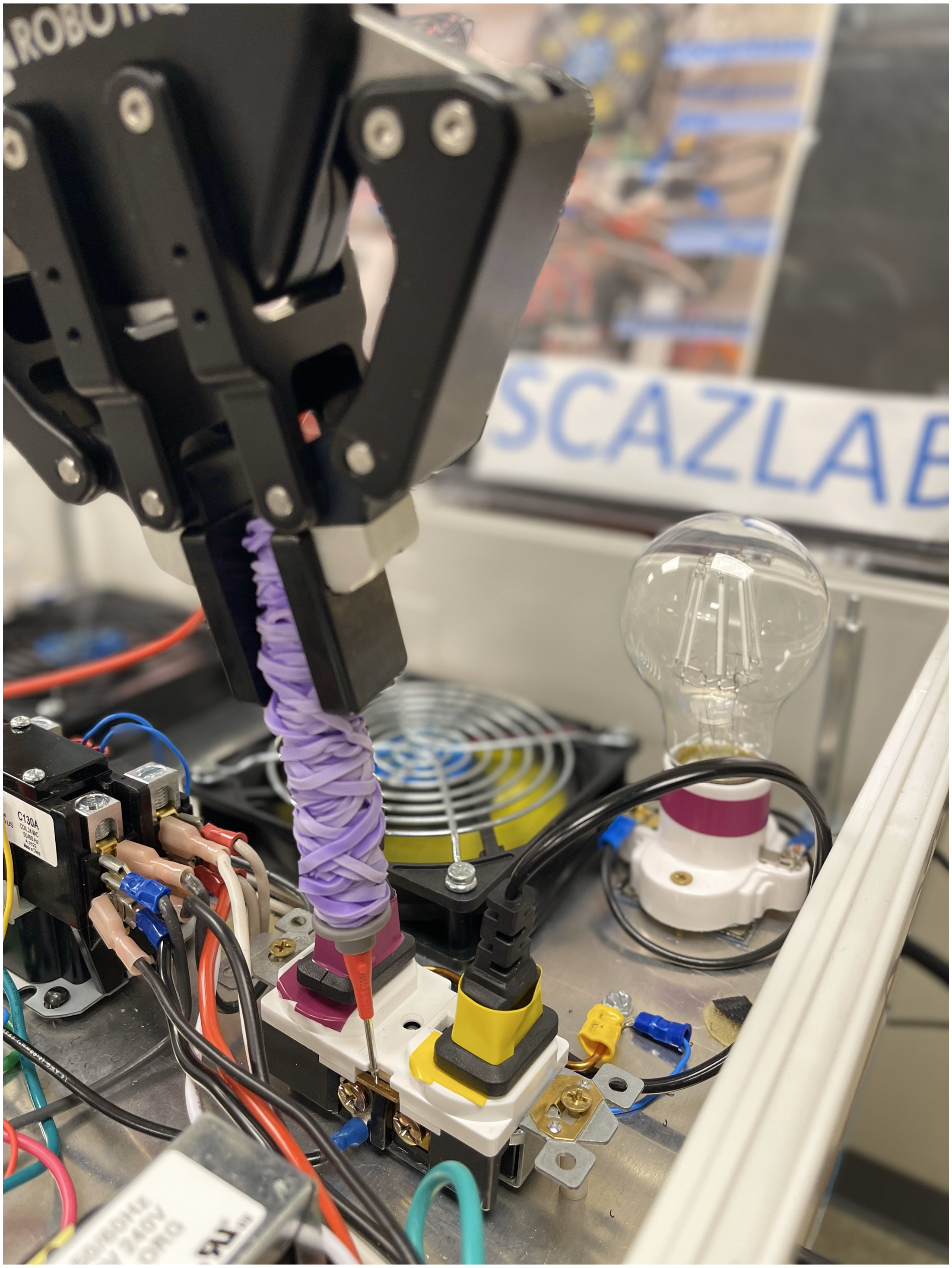

Figure 4.32: The robot point at point ‘C’ as depicted in the mock board diagram available on the inside of the mock board’s lid and in the tutorial materials.

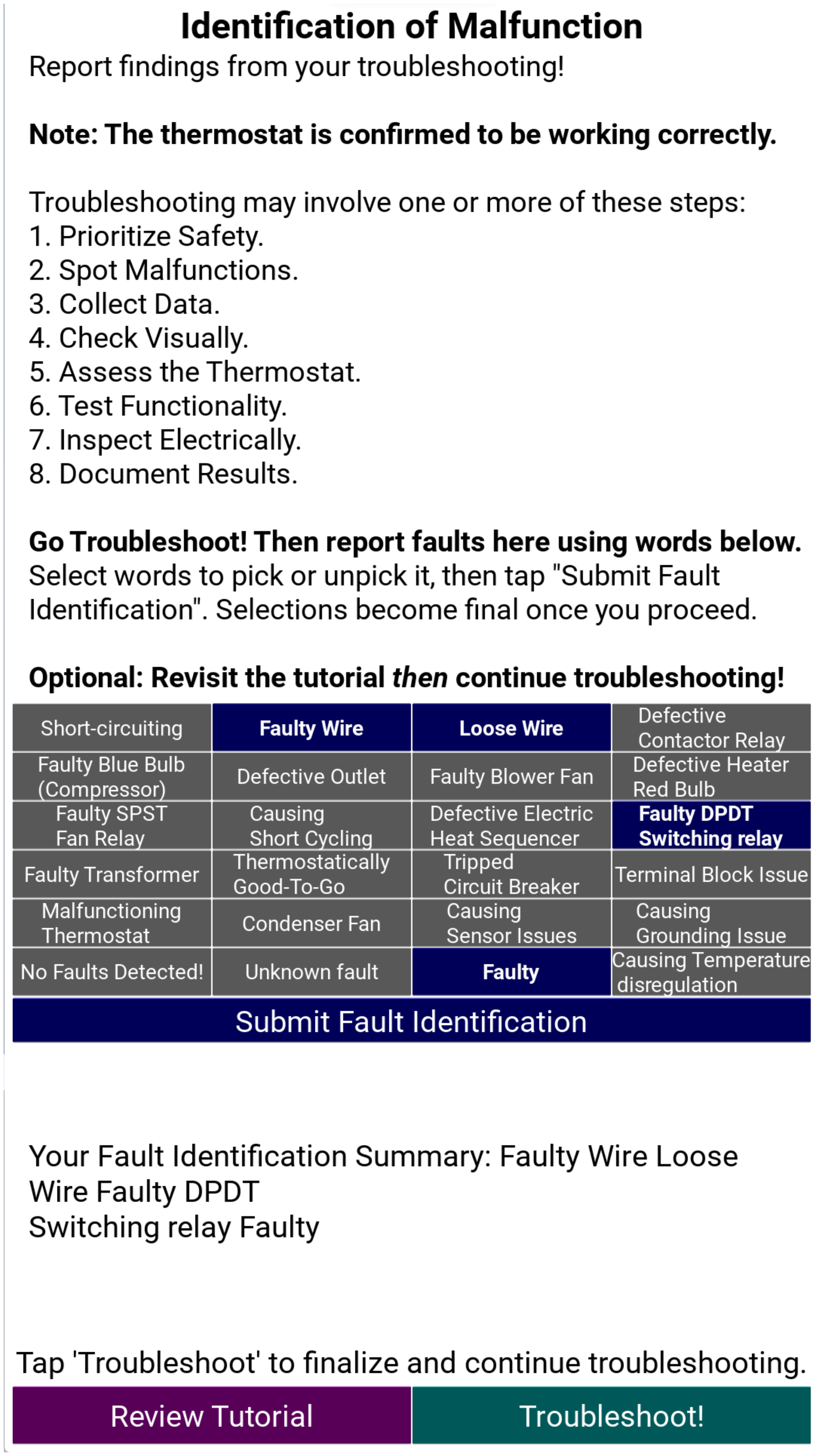

Figure 4.33: Participants report their results of troubleshooting at this screen.

Upon completing the troubleshooting process, participants are tasked with **Reporting their Findings**. This step is integral for summarizing their experiences and insights gained throughout the session.

Fault Reporting Instructions: At this juncture, participants are prompted to consolidate and report the faults they have identified. They do this by selecting the most accurate descriptive words from a provided list to articulate the nature of the faults found. This selection process culminates with the "Submit Fault Identification" action, at which point their choices become final, as illustrated in Figure 4.33.

Repair Strategy Formulation: Following the fault reporting, participants are guided towards formulating a repair strategy by translating diagnostic findings into actionable repair plans. Note: participants are not expected to execute the actual repairs; instead, the focus is on developing a theoretical strategy and useful technical skills.

Strategy Development: In developing their repair strategy, participants are tasked with outlining the necessary steps and identifying the required parts for the hypothetical repair. They finalize their strategy by selecting relevant terms that best describe their proposed approach and confirm their plan with the "Confirm Plan" action, solidifying their approach, as depicted in Figure 4.34.

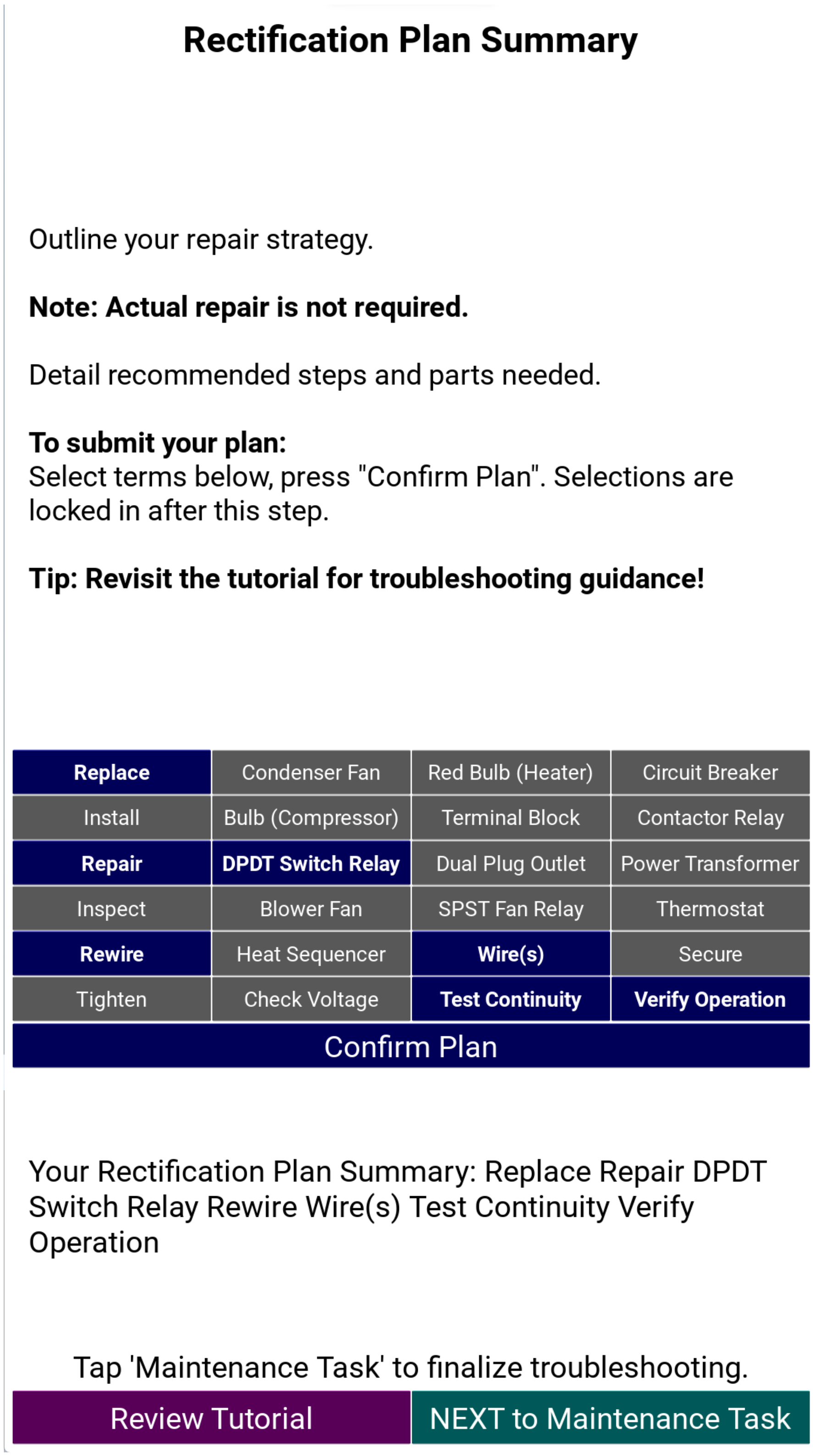

Figure 4.34: Participants proffer a plan of rectification. the plan should be effective at rectifying the identified fault.

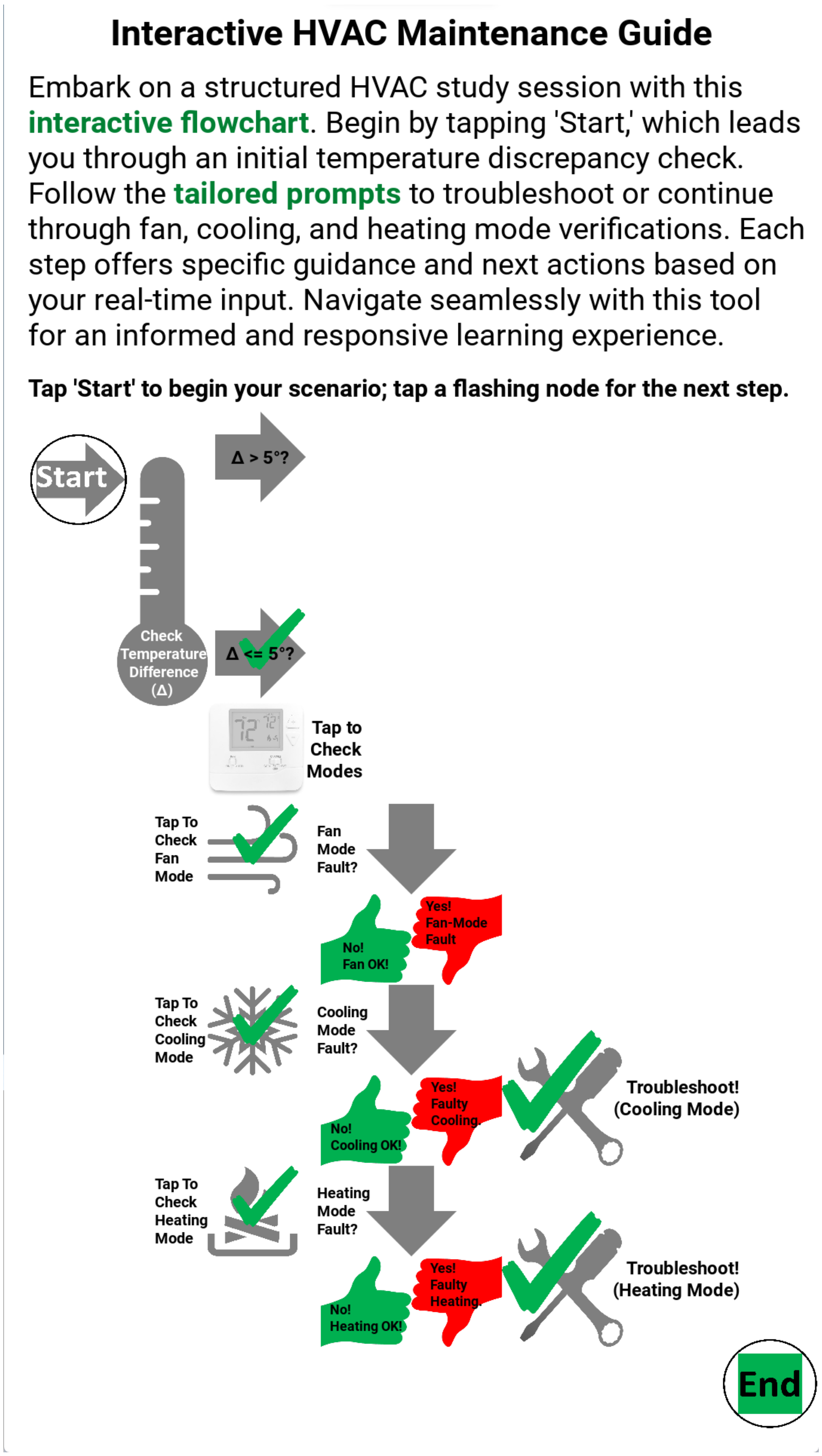

Figure 4.35: The participant's flowchart guiding them to the end to the session.

As participants navigated through the the maintenance session, culminating in the identification and troubleshooting of faults, as well as managing interruptions, their journey reached its conclusion as outlined in Figure 4.35. This figure symbolically represents the structured flowchart that guided participants toward the session's endpoint.

Upon reaching the **Completion of the Maintenance Session**, participants were warmly congratulated for their commitment and resilience demonstrated throughout the session. They were also reminded to verify that all components of the session had been addressed, ensuring a thorough and comprehensive engagement with the tasks at hand.

The **Final Steps and Outbrief** served as the session's capstone, where participants were tasked with restoring the mock HVAC board to its initial setup. This step was followed by an outbrief session with the facilitator, creating a reflective space for participants to share their experiences, insights gained, and provide feedback on the session. This closing dialogue offered valuable perspectives on the learning process and the application of skills in troubleshooting and maintenance tasks.

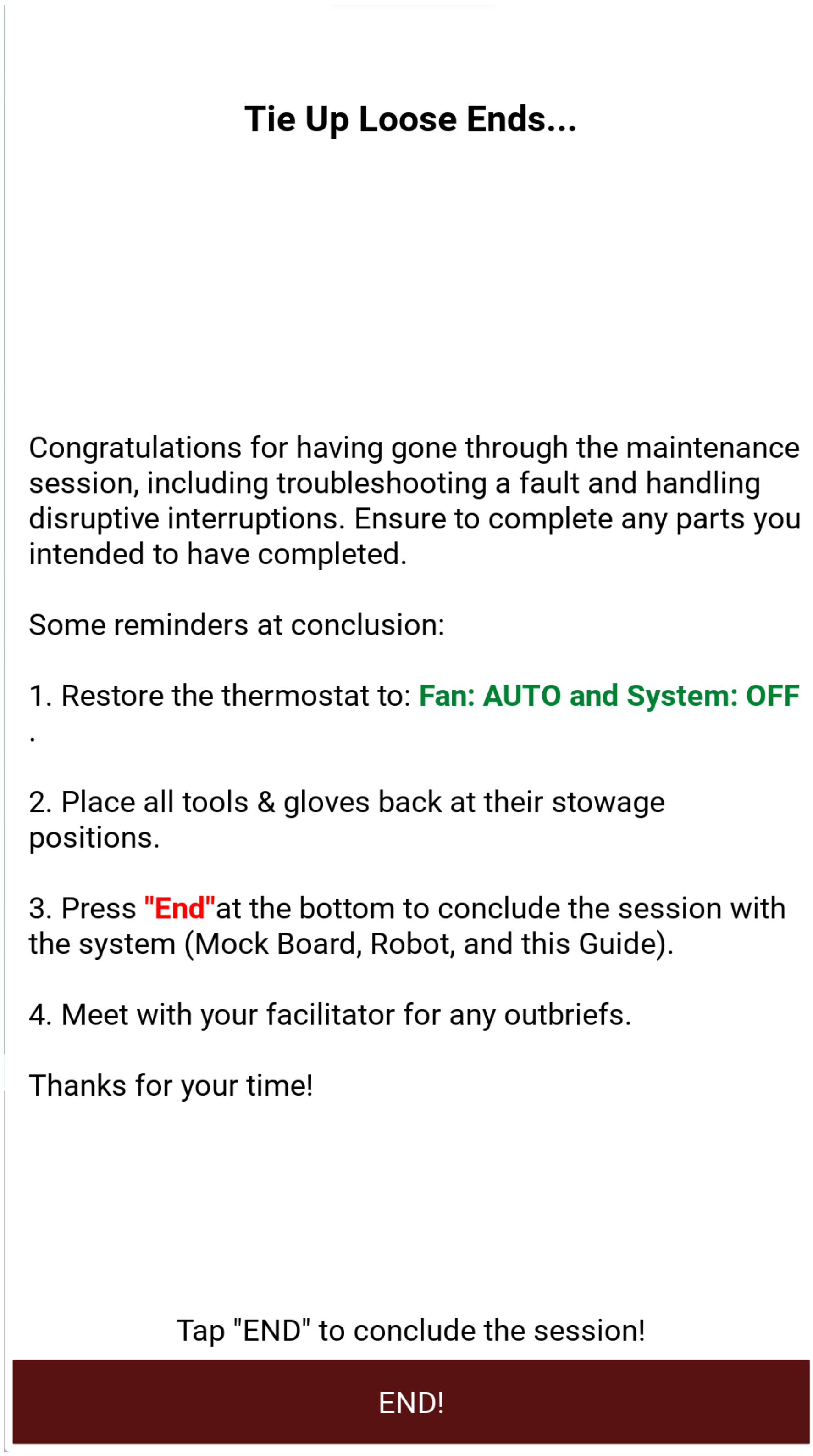

Figure 4.36: Participant is instructed to restore tools and the mock board to original states and to meet with their facilitator..

4.3.3 Hypothesis Testing and Metrics

The study tests a series of hypotheses pertaining to the impact of robotic assistance on task efficiency, interruption management, and error reduction. The primary hypothesis asserts that robotic assistance significantly enhances the efficiency of task performance in troubleshooting activities. This overarching hypothesis is further segmented into sub-hypotheses, each focusing on specific aspects of robotic assistance, including its effectiveness in managing interruptions, aiding in task resumption post-interruption, and influencing task efficiency and error rates. The metrics employed for hypothesis testing encompass:

- **Interruption Response Time:** This metric measures the duration taken by participants to address and conclude an interruption task, shedding light on the efficacy of robotic assistance in interruption management.

- **Task Resumption Time:** This metric gauges the time taken by participants to return to and recommence the primary troubleshooting task after an interruption, evaluating the proficiency of robotic assistance in ensuring a smooth transition back to tasks.

- **Task Efficiency:** The influence of interruptions on task efficiency is scrutinized by examining the resumption lag and time-on-task (TOT) (Magrabi et al., 2010). TOT represents the time expended in completing the maintenance task and serves to investigate any lingering effects of an interruption. This measure is especially pertinent in an educational milieu where technical tasks are undertaken under the pressure of time constraints. It is computed as follows:

$$TOT = T_{total} - T_{interruption} - T_{resumption}$$

where T_{total} is the Session Time, $T_{interruption}$ is the time dedicated to the interrupting task, and $T_{resumption}$ is the resumption lag.

- **Errors:** This metric records the frequency and types of errors made during task execution, comprising both errors of commission and omission. Specifically, errors are accrued in *one or both* of the following cases: when a participant neglects to perform a required action for a specific problem, or performs an action that is incorrect or unnecessary for the problem. Each error type is tallied and contrasted against an optimum benchmark, established based on expert performances at each level of task complexity. The computation of errors involves the following formula:

$$\text{Error} = \text{Participant's Errors} - \text{Optimal Number of Errors}$$

  In this context:

  - Participant's Errors refers to the number of errors made by a participant.
  - Optimal Number of Errors is the benchmark or the expected number of errors for a task, ideally the minimum or no errors.

Additionally, we measure interruption task performance times, encompassing interruption lag (time taken to attend to interruptions) and the time required to complete interruptive tasks. This measurement is crucial as literature suggests that participants may accelerate the completion of primary tasks if they perceive that excessive time has been devoted to interruptive tasks (Speier et al., 1999, 2003; Brumby et al., 2013). We expect this phenomenon to notably impact resumption lag, that is, the time taken to resume the primary task following an interruption, particularly after time-intensive interruptive tasks. Moreover, we anticipate an increase in errors consequent to the time cost imposed by such interruptive tasks. If these time-cost related errors are observed, our study design enables us to discern whether robotic assistance effectively ameliorates these errors and whether such effects vary across different levels of task complexity. Notably, in our study design, robotic assistance as an intervention always precedes the second occurrence of an interruption.

Hence, Hypothesis 1: Robotic assistance significantly enhances the efficiency of task performance in troubleshooting activities.

- H1.1: There is an inverse correlation between the time spent on interruption tasks and the subsequent resumption lag time, with longer interruptions leading to quicker resumption of primary tasks.

- H1.2: The imposition of a time cost by interruptive tasks leads to an increase in errors during the completion of primary tasks.

- H1.3: Robotic assistance effectively reduces the errors consequent to the time cost imposed by interruptive tasks.

- H1.4: The impact of robotic assistance on mitigating errors varies task complexity, with more complex tasks showing a greater benefit from robotic intervention.
- Hypothesis 1.5: Robotic assistance aids in quicker task resumption post-interruption.
- Hypothesis 1.6: Robotic assistance effectively manages interruptions.
- Hypothesis 1.7: Robotic assistance contributes to a reduction in error rates during task execution.
- Hypothesis 1.8: Robotic assistance positively influences Time-on-Task (TOT) efficiency, reducing the total time required for task completion.

  These hypotheses are key to assessing the role and efficacy of robotic assistance in technical education, offering insights into how robotics influences learning outcomes in relation to task complexity and learner's skill level.

4.3.4 Understanding Task Complexity Dynamics in the Mock Board HVAC System Troubleshooting.

In our experimental design, we distinguished two levels of task complexity in the simulated HVAC system, categorized as high and lower complexity. These levels were determined based on the intricacy of component interactions and the difficulty involved in diagnosing malfunctions. High-complexity tasks involved multiple informational layers, sequential steps, and a nuanced understanding of how various components interacted. The lower complexity tasks, while simpler, still presented significant challenges in troubleshooting. For each complexity level, our study had groups undertake two distinct tasks. These tasks, tailored to their respective complexity levels, were designed to be of similar difficulty within each category, ensuring a consistent challenge across both high and low complexity tasks. This approach allowed for a balanced evaluation of robotic assistance's impact on performance and learning outcomes. By analyzing how each group handled two tasks of a similar complexity level, we could more accurately gauge the influence of robotic assistance in fostering skill acquisition and enhancing problem-solving abilities in HVAC system maintenance and troubleshooting.

To participants, malfunctions might initially seem to occur in components like the condenser fan, compressor, or heater. However, the true faults were programmed into specific parts of the system. These included the condenser fan, compressor, the connecting wire from the Contactor Relay to the Dual Plug Outlet, and the Double Pole Double Throw (DPDT) relay. This deliberate focus was intended to steer participants towards recognizing common points of failure within HVAC systems. The system's complexity is further highlighted by the blower fan's configuration. Unlike more straightforward components, the blower fan, lacking conventional plugs, is designed to operate through a more complex setup involving two relays and a sequencer. This design choice not only underlines the intricate workings of HVAC components but also the depth of understanding required for effective troubleshooting. The blower fan's ability to be powered from multiple sources adds another layer of complexity to its operation, emphasizing the need for advanced troubleshooting skills to identify and resolve issues within the mock HVAC board's task scenarios.

Task Complexities: Simpler Task Scenarios

Task: Identify the fault causing the condenser fan to malfunction.

The simpler task generally involves the following steps:

1. Identifying deviations from the expected behavior of the mock board mode.

2. Identifying the component on the mock board that appears to be faulty.

3. Determining the range of potential faulty components on the mock board that could be the actual fault other than the ostensibly faulty component, which includes:

   - The power source to the apparently faulty component.

   - Components involved in power transmission, including for the cooling fault: Thermostat, Terminal Block, Contactor Relay, Duplex Outlet, Compressor, and Condenser Fan.

   - Identifying relevant components within this range that could cause the observed malfunction, thereby narrowing down the components to be checked.

     – The requisite knowledge and deduction to reduce the space of possibilities is to know that:

       (a) The Condenser Fan and Compressor share a common power source: Duplex Outlet.

       (b) The Compressor is functioning.

       (c) Since the Compressor is functioning, there is power at Duplex Outlet.

(d) Eliminate all other components as potential cause the observed malfunction as there is no other intervening component between the malfunctioning component (Condenser Fan) and its power source.

4. Selecting the correct tools/instruments to inspect the component.

5. Electrically inspecting the seemingly faulty component, i.e., the Condenser Fan.

6. Comparing the findings from the instruments with the expected specifications of the components.

7. Determining the likely faulty component based on discrepancies between the instrument readings and the expected specifications.

This procedure underscores the simplicity of the task through its structured, logical approach to identifying and replacing a malfunctioning condenser fan, reflecting clear, direct signs that unambiguously indicate the problem and mimic common troubleshooting scenarios essential for foundational learning and practical applications. This methodical troubleshooting approach is required of the second troubleshooting task: identifying the fault causing the compressor to malfunction.

Task Complexities: Complex Task Scenarios

Task: Identify Fault causing the condenser fan and compressor to malfunction.

The complex task involves a more intricate diagnostic process:

1. Identifying deviations from the expected behavior of the mock board mode.

2. Identifying the component on the mock board that appears to be faulty.

3. Determining the range of potential faulty components on the mock board that could be the actual fault other than the ostensibly faulty component, which includes:

    - The power source to the apparently faulty component.

    - Components involved in power transmission, including:

        - For the Cooling Mode fault:

            (a) Thermostat

            (b) Terminal Block

            (c) Contactor Relay

            (d) Duplex Outlet

            (e) Compressor

            (f) Condenser Fan

            (g) SPST Relay

            (h) Transformer

            (i) Circuit Breaker

        - For the Heating Mode fault:

            (a) Thermostat

            (b) Terminal Block

(c) DPDT Relay

(d) SPST Relay

(e) Heater

(f) Blower Fan

(g) Transformer

(h) Circuit Breaker

(i) Sequencer

- Identifying relevant components within this range that could cause the observed malfunction, thereby narrowing down the components to be checked.
  - The requisite knowledge and deduction to reduce the space of possibilities is to know that:

    (a) The Condenser Fan and Compressor share a common power source: Duplex Outlet.

    (b) Since the neither is functioning, there might be no power at the Duplex Outlet.

    (c) The Duplex Outlet is possibly the first common source of malfunction that immediately precedes the malfunctioning components.

    (d) Follow schematics/wiring diagrams to determine signal lines and power lines to get power at Duplex Outlet.

    (e) Disregard distractions: the Blower fan's behavior is complicated

      i. It stays on for five minutes if it was on as a result of being activated in the cooling mode

ii. It is delayed in its activation, but only in the heating mode.

(f) Exclude the SPST Relay, Circuit Breaker, and Transformer as the Blower Fan is functioning; the transformer transmits power through the circuit breaker to the SPST relay onward to the Blower Fan. If the SPST relay were faulty, the blower fan will not function properly in the cooling mode.

(g) Exclude the Thermostat as specified in the instructions.

4. Understanding the behaviors and specifications of the remaining (included) intervening and terminal components.

5. Examining the connections/wiring between remaining intervening and terminal components.

6. Selecting the correct tools/instruments to inspect the remaining components within the suspected fault area.

7. Isolating functionality by electrically inspecting each component, starting upstream (first common potentially faulty components (Duplex Outlet)) and moving toward downstream (terminal components) if the Duplex Outlet is powered, or upstream, to the source of power to the Duplex Outlet.

8. Methodically traverse the circuitry, electrically inspecting connections and components.

9. Comparing the findings from the instruments with the expected specifications of the components.

10. Determining the likely faulty component based on discrepancies between the instrument readings and the expected specifications.

This detailed diagnostic approach highlights the complexity of the task, necessitating a comprehensive understanding of HVAC system electrical wiring, the effective use of diagnostic tools, and accurate interpretation of results. It simulates advanced technical challenges encountered by professionals, thereby testing and enhancing deep analytical and problem-solving skills. This methodical troubleshooting approach is required of the second troubleshooting task: identifying the fault causing the heater to malfunction.

4.3.5 Task Selection

In line with our established performance metrics, we selected tasks that not only embody typical cognitive demands in various work settings but also facilitate measurement of these metrics. Participants were engaged with an electrical HVAC mock board, a detailed simulation of a standard household heating, ventilation, and air conditioning system, as elaborated on in Section 4.3.4.

Maintenance Tasks:

The participants' primary objective was to ensure the efficient operation of our mock board HVAC system through systematic checks:

1. **Ensure Ambient Temperature Congruence:** Participants verified the ambient temperature reading of the Thermostat on the Mock Board using an

infrared thermometer.

2. **Test Fan Mode Operation:** The thermostat was set to operate the fan continuously, independent of the heating or cooling systems.

3. **Test Cooling Mode Operation:** Here, participants engaged the cooling systems on-demand via the thermostat, alongside fan operation.

   Troubleshooting Tasks:

   (a) Simpler:

      i. Identify Fault causing the condenser fan to malfunction.

      ii. Identify Fault causing the compressor to malfunction.

   (b) Complex:

      i. Identify Fault causing the condenser fan and compressor to malfunction.

4. **Test Heating Mode Operation:** This task involved activating the heating systems on-demand with fan operation through the thermostat.

   Troubleshooting Tasks:

   (a) Complex:

      i. Identify Fault causing the heater to malfunction.

These tasks were chosen for their prevalence in household HVAC operations and the relative ease of identifying malfunctions by participants. They demand substantial cognitive resources for precise information processing and retention, especially when interrupted (Altmann and Trafton, 2002; Anderson and Douglass, 2001; Altmann and Hambrick, 2017). Moreover, these tasks serve as a platform to introduce technical HVAC concepts, aiming to enhance participants' understanding and troubleshooting skills in such systems — competencies they are expected to develop through the training sessions with our ensemble setup.

From our perspective, competency in technical fields like HVAC systems needs to be developed over time through education, training, and experience. Notably, only a few of our participants possessed the requisite competency in HVAC systems at the outset. While most participants had education up to the 12th grade level, almost none had all three components of the competency related to HVAC systems. This reality underscored the need for a carefully designed educational intervention, such as the one provided by our experimental setup.

Interruptions:

To mimic real-world scenarios, we introduced two types of interruptions, each varying in difficulty and cognitive load:

- **Routine Audio Interruption:** This involved an audio cue resembling a 1970s telephone ring, followed by voice instructions. Participants responded by entering a specific code on the touchscreen.

- **Audio-Math Question:** This interruption required participants to solve a basic arithmetic problem and input the answer on the touchscreen. It was designed to engage them in analytical and numerical thinking, akin to typical professional interruptions.

These interrupting tasks were strategically employed to challenge the participants' focus and mental effort, inducing attention shifts and heightening the cognitive load on their working memory (Altmann and Trafton, 2020; Trafton et al., 2003). This approach aligns with the objectives outlined in Section 4.3.4, offering a framework for evaluating cognitive engagement and learning in technical tasks.

4.3.6 Participant Selection and Grouping

To facilitate a comprehensive analysis of the impact of robotic assistance and task complexity on task performance, we implemented a controlled experimental design. This design divided participants into four distinct groups based on two key criteria: the presence of robotic assistance and the complexity of the tasks to be performed.

The grouping is organized as follows: two main categories were established based on whether participants receive robotic assistance during the tasks. Within each of these main categories, participants were further divided based on the complexity of the tasks they are assigned—either simpler or more complex troubleshooting tasks. This division allows for comparative analyses across different dimensions, including task performance, response to interruptions, and error rates between groups.

For those groups designated to receive robotic assistance, it is important to note that the robot's support was provided exclusively during the first of the two assigned troubleshooting tasks. This approach enables the study to assess the specific contributions of robotic assistance to task performance and to examine how participants manage subsequent tasks independently.

This structured grouping and the experimental setup are crucial for exploring the interactions between task complexity, the presence of robotic assistance, and their collective impact on participant performance, as detailed in the study design illustrated in table 4.1.

4.3.7 Materials, Instruments, and Data Collection

The study leveraged a variety of materials and instruments, each playing a crucial role in the experimental setup and data collection process. The following components were integral to the study:

1. **Azure Kinect DK Cameras:** These cameras captured participant activity for image classification and object detection. The visual data collected were crucial for monitoring participant behavior during the session.

2. **Force Resistance Sensors:** Installed beneath key components on the mock board, these sensors detected physical interactions by participants, such as pressing, turning, or attaching tools. Each time a participant manipulated a part of the board, these sensors recorded the force applied, providing insight into how participants engaged with the equipment. This allowed for tracking of actions on the mock board.

3. **Arduino Modules:** Arduino boards placed under the mock board collected signals related to mode selections and operational commands. These signals were essential for understanding how participants navigated through different

operational modes of the HVAC system. These modules served as intermediaries for data collection, facilitating the recording of participant choices and interactions with the HVAC system.

4. **Experimental Application:** The study's application played a key role in gathering data on participants' actions. This included inputs regarding their self-assessed technical expertise, choices made during the troubleshooting process, and interaction patterns with the tutorial and guide.

Data was collected throughout the experimental trials, including task completion times, resumption lag times, error rates, physical interactions with the mock board, mode selection choices, and application interactions. This comprehensive collection of data from the various instruments and interactions provided a dataset for analyzing the impact of robotic assistance on task performance and learning outcomes.

4.3.8 Recruitment and Screening

The recruitment process for our study was initiated with careful prescreening of potential participants. Our focus was on enlisting adults who were fluent in English and had not previously been involved in our studies. In order to ensure unimpaired interaction with the study materials and maintain the integrity of the results, individuals with medical conditions that could potentially affect their comprehension or interaction, such as color blindness or auditory impairments, carefully excluded from participation.

Additionally, in line with our objective to assess the impact of the ensemble —

consisting of the robot's assistance and its complementary tutorial and guide application — on the learning of technical subjects, we screened out participants possessing specific knowledge of HVAC systems. Therefore, all participants were novices with regard to the intricacies of HVAC circuitry and systems.

Power Analysis and Participant Recruitment

A power analysis was conducted to determine the necessary sample size for assessing the effects of robotic assistance and task complexity on task performance. Drawing on empirical benchmarks from relevant literature, we estimated a large effect size ($f = 0.40$), in line with Cohen's conventions for ANOVA. The analysis utilized the F-test for ANOVA, with the following parameters: a significance level (α) of 0.05, a desired power ($1 - \beta$) of 0.80, and four groups corresponding to our experimental design. Employing the `statsmodels.stats.power` Python package, our calculations indicated the requirement for approximately 72 participants per group.

Our study engaged a cohort of 76 adults. While 11 participants were excluded based on predefined criteria, resulting in a final dataset comprising 65 participants, with a demographic composition of 55 males and 10 females. Our sample population reflects the ratio of the cadet student body and the population of the US Military Academy, where the study sessions were conducted.

Methodology for Group Allocation:

1. Group Assignment: Participants were randomly assigned to one of four groups (Groups 1-4), ensuring an unbiased distribution across the study's different

conditions. This randomization was crucial for maintaining the integrity of the data collection process.

2. Uniform Expertise Level: Since all participants had a similar level of expertise, extensive rebalancing for skill disparities was not necessary. This uniformity in expertise allowed for a more straightforward analysis of the impact of robotic assistance and task complexity, without the confounding factor of varying participant skill levels.

3. Division Based on Experimental Conditions: The participants were categorized into four groups based on two primary criteria:

   (a) The presence of robotic assistance.

   (b) The complexity of the tasks assigned.

   The groups were structured as follows:

   (a) Group 1: Received robotic assistance and assigned simpler tasks.

   (b) Group 2: Received robotic assistance and assigned more complex tasks.

   (c) Group 3: Did not receive robotic assistance and assigned simpler tasks.

   (d) Group 4: Did not receive robotic assistance and assigned more complex tasks.

4. Controlled Application of Robotic Assistance: For groups 1 and 2, robotic assistance was provided only during the first of the two assigned troubleshooting

tasks. This controlled use of robotic assistance allowed for a focused analysis of its impact on task performance and independent task management by participants in subsequent tasks.

This methodology, alongside the controlled experimental setup, was key in exploring how robotic assistance and task complexity interact and affect participant performance. The study design, as detailed in Table 4.1, is tailored to capture these dynamics effectively.

4.4 Results

Our analysis hinged on the application of Analysis of Variance (ANOVA), employing both repeated measures and mixed-model methodologies to dissect the dynamics within our dataset. To fulfill the assumptions of normality, we analyzed our data using Q-Q plots and conducted Shapiro-Wilk tests (Shaphiro and Wilk, 1965). The independence of observations was stringently maintained within and across the different groups, and dependent variables were quantified at the interval level, allowing for meaningful and nuanced comparisons.

In our effect size calculations, we used a methodological approach that mirrored the complexity inherent in our data. For Mixed-Model ANOVA, the traditional computation of Cohen's d was adopted. In contrast, for repeated measures ANOVA, our approach was tailored to resonate with the paired nature of our data. We utilized Cohen's d_z specifically for paired samples (Goulet-Pelletier and Cousineau, 2018).

4.4.1 Overall Effects and Their Interactions

We used a Mixed Linear Model to capture the correlations of observations within individual subjects. Moreover, the incorporation of random effects within the model was strategic, accommodating the spectrum of individual variability and infusing an additional layer of analytical depth into our study.

4.4.2 Resumption Lag:

The mixed linear model's analysis of resumption lag, evaluated at different stages, brought to light key findings. The baseline resumption lag, as indicated by the model's intercept, was 11.133 seconds, underscoring a significant inherent challenge in task resumption (statistically significant compared to zero, $p < 0.001$).

The analysis considered the main effects and two-way interactions between Task Complexity and Robot Assistance, with the point of assessment for measuring resumption lag serving as a fixed effect to represent distinct measurement stages. The results are summarized below:

- **Task Complexity Effect:** The influence of task complexity on resumption lag was not significant ($\beta = 0.426$, $p = 0.790$), indicating that the complexity level of the task did not have a considerable impact on the time taken to resume tasks.

- **Robot Assistance Effect:** The presence or absence of robot assistance did not significantly influence resumption lag times ($\beta = 0.836$, $p = 0.607$), suggesting that the impact of robot assistance on task resumption was not statistically significant.

- **Assessment Point Effect:** There was a notable reduction in resumption lag at the second assessment point compared to the first ($\beta = -3.432$, $p < 0.001$), pointing to a significant decrease in resumption lag over the course of the study.

- **Interaction Effects:** The interaction between Task Complexity and Robot Assistance was not significant ($\beta = -2.700$, $p = 0.243$), indicating that the combined effect of these variables on resumption lag was minimal.

In summary, the initial resumption lag was significant, with a notable decrease observed at the later assessment point. The lack of significant influence from Task Complexity and Robot Assistance suggests that these factors, either individually or combined, did not substantially affect resumption lag within the context of this study.

4.4.3 Interruption Task Completion Time:

The mixed linear model's analysis of interruption task completion time, assessed at different points, revealed significant insights. The model's intercept was set at 16.868 seconds, indicating a baseline completion time for interruption tasks that is statistically significant compared to zero ($p = 0.001$). This highlights the inherent challenge in completing interruption tasks.

The analysis incorporated the main effects and two-way interactions between Task Complexity and Robot Assistance, with 'Assessment Point' as a fixed effect to represent distinct measurement stages. Key findings from the model are summarized below:

- **Task Complexity Effect:** The impact of task complexity on interruption task completion time was not statistically significant ($\beta = -5.853$, $p = 0.394$), suggesting that the complexity level of the task did not notably affect the time taken to complete interruption tasks.

- **Robot Assistance Effect:** The influence of robot assistance on the completion time of interruption tasks was not statistically significant ($\beta = 4.442$, $p = 0.525$), indicating that the robot assistant's impact on these tasks was not substantial.

- **Assessment Point Effect:** A significant increase in interruption task completion time was observed at the second assessment point compared to the first ($\beta = 20.422$, $p < 0.001$), indicating an escalation in the time required to complete interruption tasks over the course of the study.

- **Interaction Effects:** The interaction effect between Task Complexity and Robot Assistance on interruption task completion time was not significant ($\beta = 0.186$, $p = 0.985$), suggesting that the combined effect of these variables on this metric was minimal.

In summary, while the baseline time for completing interruption tasks was significant, an increase in this metric was observed at the later assessment point. However, neither Task Complexity nor Robot Assistance, either individually or combined, substantially influenced the completion time of interruption tasks within the context of this study.

4.4.4 Error Metric Analysis:

The mixed linear model's evaluation of error rates in task execution offers vital insights into how task complexity, robot assistance, and assessment points influence performance. The model, based on 130 observations, utilizes an error definition where errors are the difference between a participant's errors and the optimal number of errors, effectively quantifying deviation from the ideal performance. Here are the model's findings:

- **Baseline Error Rate:** The intercept, set at 1.795, represents the average error rate when other variables are at their baseline (reference) levels. This rate is statistically significant ($p = 0.021$), indicating a general level of error present across all participants irrespective of the task complexity or robot assistance. Essentially, this baseline rate reflects the average deviation from optimal performance across all participants.

- **Task Complexity Effect:** The beta coefficient for 'Task Complexity' being 'Complex' is 3.448 ($p = 0.001$), signifying that as tasks become more complicated, the average count of errors increases. Participants engaged in more complicated tasks tend to deviate more from the optimal number of errors compared to simpler tasks.

- **Robot Assistance Effect:** The coefficient for robot assistance is -0.433 ($p = 0.690$), though not statistically significant.

- **Assessment Point Effect:** The coefficient for the second measurement point is 4.077 ($p < 0.001$), indicating that the deviation from optimal performance increases significantly during the performance of the second troubleshooting activities. This suggests that errors tend to increase as participants progress in the task, potentially due to factors like fatigue, reduced concentration, or the absence of robot assistance during later stages.

- **Interaction Effects:** The significant interaction effect ($\beta = 5.090$, $p = 0.001$) between Task Complexity and Robot Assistance implies a combined influence on error counts. Specifically, in the context of complex tasks without robot assistance, the average count of errors increases more than in other scenarios.

In summary, the analysis shows a consistent level of error across all participants, with more complicated tasks leading to a higher count of errors. The absence of robot assistance is suggested to possibly increase errors, particularly in more complicated tasks. Over time, there is a trend of increasing errors, and the interaction between task Complexity and robot assistance is notably significant, emphasizing their combined impact on task performance.

4.4.5 Total Time on Task (TOT) Analysis:

The mixed linear model's evaluation of the Total Time on Task (TOT) metric, conducted with 65 observations.

- **Baseline TOT:** The model's intercept was established at 1429.401 seconds, suggesting a significant baseline TOT ($p < 0.001$). This indicates a substantial inherent time spent on tasks by participants before considering the effects of task complexity and robot assistance.

- **Task Complexity Effect:** The effect of 'Task Complexity' being 'complex' on TOT was significant ($\beta = 553.490$, $p = 0.013$). This implies that participants spend more time on complex tasks compared to simpler ones.

- **Robot Assistance Effect:** The absence of robot assistance had a significant impact on TOT ($\beta = 799.155$, $p < 0.001$), indicating that tasks performed without robot assistance are associated with an increased TOT. This highlights the role of robot assistance in reducing the time spent on tasks.

- **Interaction Effects:** The interaction between Task Complexity and Robot Assistance was significant ($\beta = -1134.513$, $p < 0.001$). This significant interaction suggests that the combined effect of higher task complexity and the absence of robot assistance leads to a substantial reduction in TOT. This finding could indicate that the absence of robotic assistance in Complex tasks does not increase TOT as much as would be expected based on the individual effects of Complex tasks and the absence of assistance. That is, while both Complex tasks and the absence of robotic assistance tend to increase TOT, their combined effect is less than the sum of their separate impacts, suggesting some form of interaction that mitigates the expected increase in TOT for Complex, unassisted task performances.

- **Group Variability:** The random effects, indicated by Group Variance, were estimated to be 215031.059 minutes^2. This suggests considerable variability in TOT across different groups, highlighting the diversity in how participants approach tasks.

In summary, the analysis indicates that participants, on average, spend a significant amount of time on task. The presence of robot assistance and the complexity of tasks significantly influence the TOT. Particularly, the assistance is more beneficial in reducing time spent on more complex tasks, as evidenced by the significant interaction effect between task complexity and robot assistance.

4.4.6 Resumption Lag and Interruption Task Time effect on Errors:

Given initial analyses and their potential implication, we check whether Resumption Lag and Interruption Task Time affect Error in our analysis. We expand the existing mixed-effects model for Error to include these two variables as predictors. This will allow us to assess the impact of Resumption Lag and Interruption Task Time on Error, while controlling for the effects of Task Complexity, Robot Assistance, and Measurement Point. Below is a detailed breakdown of these results:

- **Intercept:** The intercept is near zero and not statistically significant ($\beta = 0.062$, $p = 0.949$). This suggests that when all other variables are at their reference level, the average error is close to zero, but this finding is not statistically significant.

- **Task Complexity Effect:** The effect of 'Task Complexity' being 'complex' remains significant ($\beta = 3.308$, $p = 0.001$), indicating that complex tasks are associated with an increased count of errors.

- **Robot Assistance Effect:** The effect of robot assistance (absence) is not statistically significant ($\beta = -0.527$, $p = 0.612$), suggesting that the presence or absence of robot assistance does not significantly alter the error count.

- **Assessment Point Effect:** The second measurement point continues to show a significant increase in errors ($\beta = 4.902$, $p < 0.001$), indicating that errors increase as the study progresses.

- **Interaction Effects:** The interaction between Task Complexity and Robot Assistance is significant ($\beta = 5.558$, $p < 0.001$), indicating a notable combined effect of the absence of Robot Assistance and a Complex Task on error rates.

- **Resumption Lag Effect:** The Resumption Lag shows a significant positive effect on errors ($\beta = 0.173$, $p = 0.005$). This implies that longer resumption lags are associated with an increase in the count of errors, suggesting that as participants take more time to resume tasks, they tend to make more errors.

- **Interruption Task Time Effect:** The effect of Interruption Task Time on errors is not significant ($\beta = -0.011$, $p = 0.356$). This indicates that the duration spent on interruption tasks does not significantly impact the count of errors.

In summary, the expanded model reveals that Resumption Lag has a significant impact on error rates, with longer lags leading to more errors. However, the time spent on interruption tasks does not significantly affect errors. The interaction between complex tasks and the absence of robot assistance remains a significant factor worth investigating, particularly as it pertains to the different levels of tasks toward the latter part of the study. Further, errors tend to increase as the study progresses.

4.4.7 Interruption Task Time affects Resumption Lag:

As a consequence of the preceding analyses indicating Resumption Lag's effect on Errors, and the potential implication, we check whether Interruption Task Time affects Resumption Lag in our analysis. The model, based on 130 observations, indicates significant findings as outlined below:

- **Intercept:** The baseline Resumption Lag is 9.454 seconds, significantly different from zero ($\beta = 9.454$, $p < 0.001$), indicating the average lag when all other variables are at their reference levels.

- **Task Complexity Effect:** The complexity of the task ('complex') does not significantly affect Resumption Lag ($\beta = 1.009$, $p = 0.439$).

- **Robot Assistance Effect:** Robot assistance does not have a significant influence on Resumption Lag ($\beta = 0.394$, $p = 0.766$).

- **Assessment Point Effect:** A significant decrease in Resumption Lag is observed at the second measurement point ($\beta = -5.464$, $p < 0.001$), suggesting faster task resumption as the study progresses.

- **Interaction Effects:** The interaction between Task Complexity and Robot Assistance is not statistically significant ($\beta = -2.718$, $p = 0.148$), indicating a combined effect of the absence of Robot Assistance and a Complex Task on Resumption Lag.

- **Interruption Task Time Effect:** A significant positive effect of Interruption Task Time on Resumption Lag is observed ($\beta = 0.099$, $p < 0.001$). This suggests that longer interruption times lead to longer delays in resuming the main task.

- **Group Variability:** The random effects ($Group\,Variance = 3.412$ seconds^2) indicate variability in Resumption Lag across different participant groups.

In summary, this analysis reveals that Interruption Task Time significantly impacts Resumption Lag, with longer interruptions leading to longer lags in task resumption. Other factors, such as Task Complexity and Robot Assistance, do not exhibit a significant impact on Resumption Lag in this model.

4.4.8 Subgroup Analysis: Effect of Robot Assistance on Error Rates

Since Interruption Task Time affects Resumption Lag, and Resumption Lag in turn affects error rates, there appears to be a cascading effect where longer interruptions not only delay the resumption of work but also potentially degrade the quality of work due to increased errors. However, there also seems to be a persistent impact of robot assistance on errors particularly when the task is complex and participants are more prone to make errors. Hence, we check whether the effect of Robot Assistance on Errors varies based on Task Complexity. We conduct an interaction analysis examining the interaction term between Robot Assistance and Task Complexity in relation to Error rates. This analysis helps understand if the impact of Robot Assistance on Errors is different for simpler tasks compared to more complex ones.

Model for Simpler Tasks

- **Intercept**: Significant at 3.833 errors ($p < 0.001$), indicating the baseline error rate for simpler tasks without robot assistance.

- **Robot Assistance Effect**: The effect of Robot Assistance in the scenario where there was no Robot Assistance is not statistically significant ($\beta = -0.433$, $p = 0.443$). This suggests that robot assistance does not significantly impact error rates in simpler tasks.

- **Group Variability**: $Group Variance = 0.000 \text{errors}^2$, indicating low variability in error rates across different participant groups in simpler tasks.

Model for Complex Tasks

- **Intercept**: Significantly higher at 7.281 errors ($p < 0.001$), indicating a higher baseline error rate for complex tasks.

- **Robot Assistance Effect**: The absence of Robot Assistance in the scenario where there were complex tasks results in significantly increased errors ($\beta = 4.656$, $p = 0.001$). This suggests that robot assistance is particularly beneficial in reducing errors in more complex tasks.

- **Group Variability**: $GroupVariance = 3.403$ errors^2, suggesting higher variability in error rates across different participant groups in complex tasks.

The subgroup analysis confirms that the role of robot assistance in reducing errors is much more critical in complex tasks than in simpler ones. This understanding can guide the effective application of robot assistance, especially in environments where task complexity varies.

4.4.9 Robotic Assistance Differentially Impacts Errors According to Skill Levels Influenced by Task Complexity:

The mixed linear model's analysis of error rates across all tasks, with a focus on the influences of Task Complexity and Robotic Assistance, offers insightful findings. This model, based on 130 observations, sought to unravel how these factors, along with proficiency points, contribute to error rates. The baseline error rate, as shown by the model's intercept, was 6.371, indicating a significant initial level of errors (statistically significant compared to zero, $p < 0.001$).

The analysis explored the main effects and interactions between Task Complexity, Robot Assistance, and Proficiency Points. The results are as follows:

- **Task Complexity Effect:** There was a significant increase in error rates for complex tasks ($\beta = 6.532$, $p = 0.001$), demonstrating that increased task complexity contributes to higher error rates.

- **Robot Assistance Effect:** The absence of robotic assistance did not significantly affect error rates across all tasks ($\beta = -1.996$, $p = 0.338$), suggesting that robotic assistance, in general, does not have a marked impact on error rates.

- **Interaction Effects:** The interaction between Task Complexity and Robot Assistance was significant ($\beta = 10.553$, $p < 0.001$), indicating a substantial increase in errors for complex tasks without robotic assistance.

- The influence of Proficiency Points and its interactions with Task Complexity and Robot Assistance showed mixed results. The interaction involving all three factors was significant ($\beta = -0.470$, $p = 0.044$), suggesting a nuanced relationship between proficiency levels, task complexity, and robotic assistance in influencing error rates.

In summary, this analysis highlights the significant role of task complexity in influencing error rates, particularly when combined with the absence of robotic assistance. The interaction effects involving proficiency points indicate a complex interplay of skill level, task complexity, and the presence or absence of robotic assistance in determining error rates across various tasks.

4.4.10 Learning and Skill Retention: Influence of Robotic Assistance and Task Complexity on Proficiency Carryover

The mixed linear model's examination of proficiency carryover effects, considering the impact of Task Complexity and Robotic Assistance, offers crucial insights into learning and skill retention across tasks. Analyzing data from 65 participants, the model explored how proficiency achieved with robotic assistance in the first measure influenced performance in the second measure conducted without such assistance. The analysis also factored in the participants' baseline proficiency levels. Key findings from the model are as follows:

- **Baseline Proficiency Effect:** Baseline proficiency significantly predicted proficiency in the second measure ($\beta = 1.081$, $p = 0.015$), indicating that participants with higher self-professed initial skill levels tended to maintain higher proficiency without robotic assistance.

- **First Measure Proficiency Effect:** A significant positive correlation was observed between proficiency scores in the first and second measures ($\beta = 0.410$, $p < 0.001$). This finding suggests a notable carryover effect; participants who demonstrated higher proficiency with robotic assistance continued to show higher proficiency when the assistance was removed.

- **Task Complexity Effect:** Task complexity negatively impacted proficiency in the second measure ($\beta = -2.372$, $p = 0.026$). This result implies that participants engaged in more complex tasks experienced a decrease in proficiency scores in the subsequent unassisted task.

- **Robot Assistance Effect:** The absence of robotic assistance did not show a significant impact on second measure proficiency ($\beta = 0.211$, $p = 0.847$), suggesting that the direct effect of robotic assistance on subsequent independent task performance was not substantial.

In summary, this analysis highlights the importance of initial skill levels and the potential benefits of robotic assistance in enhancing proficiency. The significant carry-over effect observed suggests effective skill acquisition and retention from the assisted to the unassisted phase. However, the challenge posed by task complexity significantly affects proficiency, particularly in more demanding tasks. The findings indicate a complex interplay of individual skills, task demands, and the role of assistance in learning and performance.

4.5 Discussion and Implications

Direct Impact of Resumption Lag on Error Rates

The significant impact of Resumption Lag on error rates underscores the intricate relationship between task interruption and performance quality, highlighting a multifaceted issue. Analysis reveals that longer resumption lags after an interruption are correlated with an increased likelihood of errors, potentially due to cognitive overload or memory challenges. This direct and significant correlation can be attributed to a combination of cognitive factors exacerbated by interruptions.

Interruptions impose an additional cognitive load on individuals, consuming mental resources needed for the primary task. This reallocation challenge increases cognitive strain, particularly in tasks requiring high concentration or complex problem-solving, leading to errors. Additionally, resuming a task necessitates recalling where one left off and the nuances of the task status. Longer resumption lags may lead to a decay in short-term memory retention of task-related details, resulting in critical omissions or mistakes due to forgotten or misremembered information.

The process of shifting attention between an interruption and the primary task also plays a role. Longer lags exacerbate the difficulty of this shift, leading to a fragmented focus and potential overlooking of important task aspects. Moreover, prolonged delays can disrupt the flow state or deep engagement with a task, making it challenging to re-establish focused attention and leading to a slower, more error-prone resumption process.

Emotional responses, such as stress and frustration induced by prolonged interruptions, further impair cognitive function. This impairment particularly affects executive processes responsible for planning, decision-making, and error detection, thereby increasing the likelihood of errors.

The direct impact of Resumption Lag on error rates is rooted in a complex interplay of cognitive load, memory challenges, attentional shifts, mental engagement, and emotional responses. Effectively managing these aspects is crucial for maintaining high-quality performance, especially in environments where interruptions are frequent.

Impact of Interruption Task Time on Resumption Lag

The significant positive correlation between Interruption Task Time and Resumption Lag is a critical element in understanding task management and cognitive functioning. Analysis shows that longer interruptions typically result in extended delays when resuming the primary task. This relationship stems from a variety of factors involving cognitive processes and task management. Longer interruptions necessitate a more substantial cognitive shift when transitioning back to the primary task. This shift, involving a change in mental context, becomes increasingly demanding and time-consuming with the length of the interruption. The brain must deactivate the cognitive schema of the interrupting task and reactivate that of the main task, a process that grows more complex as the interruption extends. Additionally, after prolonged interruptions, individuals may require extra time for memory refreshing. This phase, essential for effective task resumption, involves recalling and reassessing the primary task's objectives, status, and next steps, consequently adding to the overall Resumption Lag. The need for reorientation also grows with longer interruptions. This process might include reviewing previous work, understanding the context anew, and planning forthcoming steps, all contributing to the delay in resumption.

Attentional inertia is another factor to consider. The longer one is engaged in a task, the harder it becomes to disengage from it. Thus, extended interruptions may create inertia, hindering the swift shift of attention back to the primary task. Emotional and motivational factors also influence the pace of resuming the primary task. Lengthy interruptions can lead to feelings of frustration or demotivation, slowing down the resumption process. Finally, environmental and contextual factors impact this dynamic. For instance, interruptions that involve moving to a different location or a significantly different activity may necessitate additional time for physical and mental realignment before returning to the primary task.

The impact of Interruption Task Time on Resumption Lag is a complex interplay of cognitive, emotional, and environmental factors. These insights highlight the importance of effective interruption management and task design to minimize cognitive shifts and enable quicker task resumption.

Combined Effect on Task Performance

The analysis of task performance in the context of interruptions uncovers a cascading effect where the duration of interruptions and the subsequent Resumption Lag collectively influence the overall quality of work. This interconnected relationship highlights several key aspects of task management and cognitive efficiency.

Extended interruptions often lead to increased Resumption Lag, which in turn correlates with higher error rates. This pattern indicates that longer interruptions not only disrupt workflow but also negatively affect the quality of work upon resumption. The more extended the interruption, the more challenging it becomes for individuals to transition back to their primary tasks smoothly, leading to an increased likelihood of errors.

Cognitive discontinuity is another significant consequence of prolonged interruptions. A break from a task can disrupt the cognitive flow of work, impairing the ability to maintain a consistent thought process or strategy. Consequently, this leads to mistakes or oversights when the task is resumed, as the brain's capacity to 'pick up where it left off' diminishes with longer interruptions.

After an interruption, there is a need to reallocate cognitive resources back to the primary task. If the interruption is prolonged, these resources may be more significantly depleted, requiring more effort and time to rebuild the mental model of the task. Inefficient reallocation can result in poorer task execution and an increase in errors. Understanding the cascading effect of interruptions on task performance is vital for task and workflow design. Minimizing interruption duration, providing cues for quick resumption, and maintaining cognitive continuity can significantly improve performance quality, especially in high-stakes environments where errors can have serious consequences. Furthermore, training individuals to handle interruptions effectively and increasing awareness about their effects can mitigate the negative impact on task performance. Techniques for rapid task resumption and cognitive realignment, along with a mindful approach to work disruptions, can enhance performance despite interruptions.

The combined effect of interruption duration and Resumption Lag on task performance emphasizes the importance of effective interruption management strategies. By addressing both the interruption duration and the challenges of resuming tasks, it is possible to maintain higher levels of accuracy and work quality.

Impact of Robot Assistance on Complex Tasks

This study underscores the significant role of robot assistance in enhancing the execution of complex tasks, particularly those that demand high cognitive effort. This beneficial impact is rooted in several key functionalities provided by robot assistance.

First, Robot assistance in complex tasks can offer step-by-step guidance, helping participants navigate through intricate procedures. This assistance is invaluable in ensuring critical steps are not overlooked and in reducing the cognitive burden of remembering and sequencing task components.

Second, Robot assistants can play a crucial role in maintaining or refocusing attention on critical aspects of a task. This support is particularly valuable in tasks requiring sustained concentration or those with a high risk of distraction.

Third, robotic systems are capable of detecting potential errors in real-time and alerting participants for immediate correction. This feature is essential in complex tasks where errors can lead to significant consequences.

Fourth, Robot assistance can be designed to adapt to a participant's performance, offering varying levels of support as needed. This adaptability ensures that assistance is rendered in the most effective manner for each specific task.

In educational or training contexts, robot assistance in complex tasks can expedite skill acquisition and improve skill retention. Learners benefit from immediate feedback and guidance, which accelerates the learning process.

Proficiency Carryover and the Role of Robotic Assistance

A key finding of our study is the carryover effect of proficiency from tasks performed with robotic assistance to subsequent tasks performed independently. This result suggests that skills acquired or honed with the aid of technology are not merely situational but are internalized by learners to a degree that positively influences their subsequent task performance. This observation underscores the potential of robotic assistance not just as a tool for immediate task facilitation but as a catalyst for longer-term skill development.

Educational and Training Implications

The study's results have several implications for the design and implementation of educational and training programs:

- **Blended Learning Approaches**: Combining robotic or technological assistance with traditional hands-on methods might be the most effective way to ensure both immediate performance enhancement and long-term skill retention.
- **Gradual Increase in Task Complexity**: Educators and trainers should consider progressively increasing task complexity, aligning it with the learner's growing proficiency to maximize learning outcomes.
- **Assessment-Driven Personalization**: Initial assessments should be used to personalize learning experiences, ensuring that learners are neither underchallenged nor overwhelmed.
- **Focus on Active Learning**: To complement the benefits of technological assistance, educational strategies should emphasize active learning that engages learners in the process more deeply.

Implications for Design and Application

The positive impact of robot assistance on complex tasks carries significant implications for the design and application of robotic systems. It indicates that robot assistance should be thoughtfully integrated into cognitively demanding tasks, ensuring that it enhances human performance without adding complexity or creating dependency. This insight is crucial for developing robotic systems capable of providing context-sensitive support, dynamically adapting to the user's needs and the specific challenges of the task.

Potential for Targeted Interventions

The insights from our study on the dynamics of task interruptions, resumption lags, and error rates pave the way for targeted interventions. These interventions can be strategically designed to enhance task performance in environments where interruptions are frequent. The following areas are key targets for such interventions:

- Focusing on strategies to reduce the time needed to resume tasks after interruptions is crucial. This could involve training in quick mental refocusing techniques, implementing structured pause-and-resume protocols, or utilizing technology aids like automated reminders or contextual cues.

- Managing the duration of interruptions is vital for minimizing their impact. Strategies could include establishing guidelines for the allowable length of interruptions or creating systems that postpone non-urgent interruptions to a more suitable time.

- Altering the nature of interruptions to make them less disruptive is another effective approach. This might entail changing the mode of interruption delivery (e.g., using visual instead of auditory cues) or ensuring that interruptions are relevant and require minimal cognitive shift.

- Customizing interventions based on the complexity of tasks is important, as the impact of interruptions varies with task complexity. For more complex tasks, a greater focus on tools and techniques that support cognitive continuity and error reduction is beneficial.

- In contexts where robot assistance is employed, optimizing this assistance based on the task's nature and typical interruption patterns can be effective. This might involve programming the robot assistant to offer more targeted support during and after interruptions, particularly in complex tasks.

- Developing training programs that focus on interruption management can provide individuals with the skills to more effectively handle interruptions. These programs could cover cognitive strategies for task resumption, stress management techniques, and efficient use of technology aids.

- Implementing feedback mechanisms for monitoring and improving interruption management strategies can be beneficial. Regular reviews and adjustments based on employee feedback can help refine these interventions for greater effectiveness.

Summary

In this chapter, we explored the impact of interruptions on task performance, the potential of robot assistance as a mitigating factor, and the role of targeted interventions and in managing these challenges. The insights garnered from our study not only illuminate the complexities inherent in task interruptions and resumption but also chart a path forward for effectively countering their adverse effects.

We have explored how interruptions, a seemingly inevitable aspect of modern work environments, can significantly prolong resumption lags and elevate error rates, thereby impacting overall task performance. In response, we have highlighted the potential of robot assistance as a buffer against these effects, particularly in complex tasks where precision and focus are paramount.

Furthermore, the chapter has underscored the importance of designing targeted interventions to specifically address different facets of interruption impacts. These interventions range from training programs and workflow adjustments to the integration of technology tools designed to facilitate quick task resumption and effective interruption management. By customizing these interventions to individual needs and task complexities, we can significantly enhance task performance and reduce error rates.

A significant takeaway from our investigation is the affirmation of a proficiency carryover effect. This effect, observed from tasks performed with robotic assistance to those undertaken independently, highlights the potential of such technologies to not only aid in immediate task execution but also to facilitate lasting skill acquisition. The implication here is significant, suggesting that robotic assistance, when properly integrated into learning environments, can serve as a powerful tool in the educational toolkit, one that extends its utility beyond immediate task facilitation to long-term skill development.

In conclusion, this chapter contributes to a deeper understanding of the dynamics of task interruptions and lays the groundwork for innovative strategies to mitigate their impact. The integration of robotic assistance, targeted interventions, and privacy-centric technology design offers a comprehensive approach to enhancing task performance in interruption-prone environments.

Chapter 5

Social Robot Design: Fostering Trust with Integrated Privacy and Ethics

In the dynamic landscape of technological advancement, the broader implementation of robotics is not just a testament to human ingenuity but also a reflection of our relentless pursuit of innovation. As these robotic systems become increasingly interwoven into the fabric of our daily lives, spanning domains from healthcare to home assistance, the urgency to confront the growing concerns related to ethics and privacy escalates. Chapter 5 of this dissertation explores these pivotal issues, shedding light on the multifaceted factors that influence the adoption of robots while emphasizing the paramount importance of privacy and ethical design in their seamless integration. Drawing on the seminal works of Dwork and Roth (2014) and Rueben et al. (2018), we seek to construct an understanding and strategic approach to these evolving challenges.

The advent of robotics has opened new horizons, redefining how we interact with machines and envisage our future. Yet, this progression is intertwined with its own set of complexities. As robots evolve to assume increasingly intricate roles, navigating through a vast sea of data, the spotlight on individual privacy and the ethical implications of data usage intensifies. The discourse on the ethical facets of data handling in robotics, as explored in Schafer and Edwards (2017), offers valuable insights into this relationship between technology and ethics.

A key aspect of this exploration lies the concept of differentially private algorithms, an innovation in the realm of privacy-preserving technology. These algorithms represent more than a technological breakthrough; they symbolize a paradigm shift in how we approach data analysis. By introducing a measure of 'noise' into the data or the queries made on the data, these algorithms veil individual contributions, safeguarding privacy without substantially compromising the integrity of the analysis. This methodology paves the way for informed decision-making, leveraging collective insights while staunchly defending the sanctity of individual data subjects' privacy. The potential of differentially private reinforcement learning in complex scenarios, as highlighted by Zhou (2022), further amplifies the significance and applicability of these advanced techniques. The incorporation of these algorithms into robotic systems is supports harnessing the power of data-driven technologies and upholding protections for individual privacy, a balance emphasized by the findings of Rueben et al. (2018) and Zhou (2022).

5.1 The Need for Privacy in Robotics

Robotic systems, equipped with advanced sensors and data processing capabilities, are capable of gathering a vast array of personal and sensitive information. This data spectrum includes visual and audio recordings, location tracking, biometric data, and detailed insights into personal habits and preferences. The collection, processing, and potential dissemination of such data raise profound privacy concerns, necessitating a careful examination of data storage and usage practices (Eick and Antón, 2020).

The significance of privacy in robotics is further accentuated when considering the operational environments of these systems. Robots often operate in intimate proximity to humans, whether in healthcare settings, where they may handle sensitive patient information, or in homes, where they could observe private family interactions. This close interaction necessitates robust privacy measures to prevent misuse, unauthorized access, or inadvertent privacy breaches (Priyadarshini, 2018).

Addressing privacy in robotics transcends technical solutions. The responsibility to protect individual privacy is a collective one, encompassing designers, manufacturers, those who deploy them as well as those who interact with them. Moreover, the public's trust and acceptance of robotic systems are significantly influenced by privacy and ethical considerations. Privacy concerns can markedly impact individuals' willingness to adopt and interact with robotic technologies, making it essential to address these issues to build trust and foster positive human-robot interactions (Priyadarshini, 2018; Kok and Soh, 2020).

A key challenge in the realm of privacy in robotics is balancing the protection of privacy with the utility of data. Robotic systems rely on data to function effectively, and overly restrictive data practices could hinder their performance. Striking an optimal balance is crucial, and this section will explore strategies to achieve this, including the adoption of 'Privacy by Design' principles, the use of anonymization and data minimization techniques, and the implementation of privacy-preserving technologies such as differentially private algorithms. These strategies aim to create robotic systems that respect privacy while fulfilling their intended purposes (Eick and Antón, 2020).

As we navigate the intricate landscape of privacy in robotics, it becomes clear that addressing privacy concerns is not just a technical endeavor but also an ethical and societal necessity. By proactively engaging with these challenges, we can protect individual rights and foster the trust and acceptance needed for the harmonious integration of robotics into society, setting the stage for a future where technology and privacy coexist in harmony (Hale et al., 2019).

5.2 The Anonymity Assessment method: Application in AI and Robotics

The "Anonymity Assessment" method delineated Kolain et al. (2021) offers a framework for evaluating the anonymity of datasets within the context of GDPR compliance, with a particular emphasis on the realm of smart robotics. This approach merges legal and technical insights to ascertain if data processing aligns with the GDPR's definition of anonymity, facilitating a robust assessment of data anonymization and pseudonymization processes.

The methodology introduces two pivotal metrics: the Objective Anonymity Score (OAS) and the Subjective Anonymity Score (SAS), which collectively forge a dual-faceted lens through which the anonymity of data is scrutinized. The OAS quantifies the risk of re-identification through statistical analysis, leveraging data characteristics and processing context to gauge the probability of individual identification. Concurrently, the SAS delves into the subjective considerations of data controllers or processors, evaluating the feasibility of re-identification in terms of required resources, efforts, and associated costs. This metric reflects an assessment of re-identification risks, acknowledging the diverse capabilities and motivations that may influence such endeavors.

By amalgamating these metrics, the Anonymity Assessment method provides a tool for assessing data anonymity. The OAS and SAS, in concert, offer an evaluation that not only quantifies re-identification risks but also contextualizes these risks within the practical realities of data handling. This synergy between objective statistical measures and subjective practical assessments ensures an adaptive approach to data anonymity, aligning closely with the GDPR's requirements for data protection and privacy.

This method highlights the interdisciplinary collaboration necessary to navigate the complexities of GDPR compliance, particularly in technologically advanced areas such as AI and robotics. By translating legal mandates into quantifiable, actionable metrics, the Anonymity Assessment method bridges the gap between theoretical legal standards and the practical challenges of ensuring data anonymity in an era of rapid technological advancement. It underscores the importance of a flexible, informed approach to data protection, advocating for continuous adaptation to technological innovations and their implications for data privacy.

5.3 Ethical Considerations in Robotic Data Handling

This section explores the ethical issues surrounding robotic data handling, concentrating on foundational principles such as transparency, accountability, and respect for individual autonomy. Transparency stands as a cornerstone ethical principle in the realm of robotic data handling. It encapsulates the imperative of lucidly communicating to users the modalities of data collection, processing, and utilization by robotic systems. The essence of transparency lies in nurturing trust and ensuring that users are not only cognizant of but can also meaningfully consent to the data practices entwined with their interaction with robots.

The design of robotic systems should prioritize user access to comprehensible and transparent information regarding their data practices. This encompasses illuminating the spectrum of data being amassed, the objectives of its utilization, and the safeguards in place for its protection. Transparency further extends its reach, necessitating that users are furnished with insights into the decision-making mechanisms of robots, particularly when these decisions bear significant implications for individuals.

Accountability in robotic data handling denotes the onus placed on the shoulders of designers, manufacturers, and operators of robotic systems to ensure ethical and regulatory-compliant data management. Robotic systems ought to be crafted and deployed with mechanisms that facilitate the traceability and auditing of data handling processes. Such mechanisms ensure that should issues emerge, they can be accurately traced to specific entities or actions, enabling the implementation of corrective measures. Accountability also mandates the establishment of coherent policies and procedures to adeptly respond to privacy breaches, encompassing the notification of affected individuals and the initiation of harm mitigation strategies.

Respect for individual autonomy in robotic data handling is about acknowledging and venerating individuals' sovereignty over their personal information. Robotic systems must be architected to gather and utilize data in a manner that honors the preferences and decisions of individuals. This entails securing explicit consent for data collection and empowering users with the autonomy to regulate the scope of their data's utilization. Moreover, robotic systems should eschew manipulative or coercive tactics in data collection and usage. Upholding respect for autonomy acquires heightened significance in sensitive domains such as healthcare, education, or personal assistance, where the data involved is inherently intimate and carries significant implications for individuals' lives.

5.4 Regulatory and Legal Frameworks for Privacy in Robotics

The legal environment that envelops privacy in robotics is a mosaic of laws and regulations, each distinct in its scope and application, varying significantly across regions and domains Malchik and Feigenbaum (2022). While certain jurisdictions have enacted specific privacy laws that directly addresses data collection and usage by robotic systems, others rely on broader data protection statutes like the General Data Protection Regulation (GDPR) in the European Union to scaffold privacy protections in the context of robotics (Adéníran, 2021).

These laws contain key provisions like data minimization, purpose limitation, consent, transparency, and robust security measures. For manufacturers and operators of robotic systems, navigating these legal currents is not an option but a mandate. Compliance is not merely a legal obligation but a cornerstone for maintaining reputation and trust. Non-compliance, conversely, can lead to severe repercussions, including hefty penalties and reputational damage.

The legal and regulatory tapestry directly influences the deployment of differentially private algorithms in robotics. These algorithms, by their very design, provide a mechanism to analyze data in a manner that respects and protects individual privacy, aligning seamlessly with legal mandates for privacy and data security (Malchik and Feigenbaum, 2022).

Employing differentially private algorithms enables robotic systems to adhere to legal stipulations regarding data minimization and purpose limitation. By ensuring that data collection and usage are confined to what is strictly necessary, and by safeguarding individual privacy, these algorithms also support compliance with transparency and consent directives, rendering data privacy protections both clear and comprehensible (Adéníran, 2021).

Staying abreast of legal developments and proactively adapting privacy-preserving methodologies will be paramount for the robotics community. This proactive stance ensures that as robotic technologies continue to advance and permeate more deeply into our societal fabric, they do so in a manner that is not only legally compliant but also ethically sound and socially responsible.

5.5 Design Principles for Privacy-Aware Robotics

The inception of privacy-aware robotics necessitates a principled design approach that embeds privacy considerations inherently within the system development process. This section outlines pivotal design principles that should be at the forefront of the creation of privacy-conscious robotic systems, complemented by real-world applications and illustrative examples that demonstrate the potential application of these principles across diverse robotic applications.

Principle 1: Privacy by Design

Privacy by design champions the proactive embedding of privacy into the design and architecture of robotic systems from the very beginning. It advocates for the concept of privacy as a default setting and integral component of system development, incorporating data minimization, clear purpose specification, and privacy-by-default settings.

Real-World Application - The Whiz in Retail: Rindfleisch et al. (2022) provides a detailed case study of a robot's deployment in a Japanese retail chain, Daiei. The Whiz, an AI-enabled vacuum cleaning robot, not only enhances store hygiene but also engages in subtle promotional activities. Importantly, the case study highlights the robot's design and operational protocol that prioritizes customer privacy. The Whiz operates autonomously, minimizing interaction with customers and ensuring that no sensitive personal data is collected during its cleaning or promotional tasks. This adherence to the 'Privacy by Design' principle is instrumental in maintaining the trust of both customers and employees, as indicated by the positive feedback received.

Insights into Practical Deployment and Challenges: Deploying the Whiz in Daiei stores offered valuable insights into the practical implementation of privacy-aware robotics in a retail environment. While the robot's design ensures minimal invasion of customer privacy, the case study also discusses challenges such as navigating complex store layouts and avoiding disruptions during peak hours. Addressing these challenges required continuous refinements in the robot's operational algorithms, showcasing the dynamic nature of integrating privacy-aware principles with practical robotic functionality. The success of the Whiz robot in Daiei stores exemplifies how privacy considerations can be seamlessly integrated into robotic technology, striking a balance between operational efficiency and ethical considerations.

Principle 2: Transparency and User Consent

Transparency regarding data processing activities and the securing of informed user consent are foundational to fostering trust. Users should be adequately informed about the nature of data collection, its usage, and sharing provisions. Consent must be explicit, well-informed, and unequivocally given.

Real-World Application - Transparent Data Acquisition with Robots in Healthcare: A study by Boumans et al. (2019) provides an insightful exploration into the use of social robots for collecting patient-reported outcome measurements among older adults. The research demonstrates a novel use of the Pepper robot in a clinical outpatient setting to autonomously administer patient-reported outcome measurements questionnaires to older adults, a process traditionally conducted by healthcare professionals. This application highlights the robot's role in transparently acquiring health data while respecting the autonomy and privacy of the individuals involved.

The Pepper robot, designed to interact in a human-like manner, ensured that participants were informed about the nature of the data collection process. Participants were given clear instructions and dialogue options displayed on the robot's screen, allowing them to provide data in a controlled and consensual manner. The study found that the interaction with the robot was well-received by participants, indicating a positive perception of transparency and user consent in the data collection process.

Furthermore, the robot's ability to complete interviews autonomously in most cases (92.8% of interactions) while maintaining data quality comparable to that obtained by healthcare professionals showcases the potential of robotic systems to support healthcare services transparently and effectively. Participants' feedback on the acceptability of using the robot for clinical interviews further emphasizes the importance of user consent and comfort in the adoption of such technologies (Boumans et al., 2019).

This real-world application underlines the significance of integrating transparency and user consent into the design and operation of privacy-aware robotic systems, especially in sensitive settings such as healthcare. The study's findings reinforce the notion that with clear communication and consent protocols, robots can play a pivotal role in data acquisition, contributing to efficient healthcare delivery while respecting patient privacy and autonomy.

Principle 3: Data Security and Anonymization

Robust data security protocols and anonymization techniques are imperative for safeguarding the data collected by robots. This involves the application of encryption, secure data storage solutions, and sophisticated anonymization procedures to prevent the re-identification of individuals. The intricate balance between data utility and privacy is eloquently addressed by Kolain et al. (2021) through their pioneering approach of Anonymity Assessment, which merges legal and technical perspectives to enhance data protection in the field of smart robotics.

Real-World Application - Anonymity Assessment in Smart Robotics: The study by Kolain et al. (2021) proposes a comprehensive Anonymity Assessment method, laying out a dual framework with the Objective Anonymity Score (OAS) and the Subjective Anonymity Score (SAS) to evaluate the degree of privacy protection in data sets. This method is not only pivotal in evaluating the anonymity of data but also serves as a tool for navigating the complex landscape of cross-national legal regimes (Adéníran, 2021), thereby ensuring global compliance with varying legal standards related to data privacy and security.

In a scenario where a robotic system operates across international jurisdictions, the Anonymity Assessment becomes a critical tool. It enables developers and legal practitioners to quantify the risk of re-identification, thereby operationalizing the legal concept of anonymization in a technical format. This approach not only enhances the data security and anonymization capabilities of robotic systems but also ensures that these systems are designed and operated in compliance with international privacy regulations, fostering trust among users and stakeholders.

For example, a healthcare robot collecting patient data can employ this methodology to ensure that the data it processes is sufficiently anonymized, meeting the standards of the GDPR while also being adaptable to other international legal frameworks. This adaptability is crucial in a global context where data protection laws may vary significantly from one country to another.

By integrating the Anonymity Assessment methodology into the design and operation of robotic systems, developers can navigate the intricate matrix of data privacy laws and technical challenges. This comprehensive approach, as suggested by Hanneke et al. (2023) ensures that robotic systems not only respect privacy but also maintain data utility, paving the way for international deployment and acceptance.

Principle 4: Accountability and Compliance

In the realm of privacy-aware robotics, engineering systems with accountability mechanisms is paramount to ensure strict adherence to prevailing privacy laws and frameworks. This principle is particularly crucial when robotics systems operate across different national jurisdictions, each with its distinct legal requirements related to data privacy and security. The pioneering work by Kolain et al. (2021), along with insights into the intricacies of cross-national legal regimes by Adéníran (2021), provides a comprehensive framework for embedding accountability and compliance into the fabric of smart robotics.

Real-World Application - Enhanced Compliance in International Robotic Operations: Consider the case of a robotic delivery service that operates globally, navigating the complex web of international data protection laws. Employing the Anonymity Assessment methodology allows the service to systematically assess and quantify the risk of data re-identification through the Objective Anonymity Score (OAS) and the Subjective Anonymity Score (SAS). This assessment ensures that the data processed by the robotic system meets the high standards of anonymity required by GDPR and other stringent data protection laws.

Moreover, understanding the complexities of cross-national legal regimes is instrumental for the robotic service to dynamically adapt its data handling practices and privacy measures to comply with the specific legal requirements of each jurisdiction it operates in. This adaptive compliance strategy not only safeguards the privacy and security of the data but also fortifies the robotic service's position as a trusted entity, capable of maintaining high standards of accountability across international borders (Khattar, 2023).

In addition to proactive compliance measures, the robotic delivery service implements a comprehensive incident response plan, drawing upon best practices and legal guidelines from various jurisdictions (Khattar, 2023). This plan delineates clear protocols for prompt and effective action in the event of a data breach, ensuring that potential damages are minimized and the trust of users and stakeholders is preserved.

By integrating advanced methodologies like Anonymity Assessment and adapting to the multifaceted nature of international privacy laws, the robotic delivery service exemplifies the essence of Principle 4. This approach not only ensures robust data privacy and security but also underscores the commitment of the service to uphold the highest standards of accountability and compliance in an increasingly interconnected and legally diverse world.

Principle 5: User Empowerment and Control

User empowerment concerning personal data is a pivotal aspect of privacy-aware robotics, especially in the context of social robots that interact closely with individuals in sensitive settings. Social robots, like Robbie, are designed to engage with users in a personalized manner, making it essential that they provide accessible tools for users to review, modify, and delete their personal information, and maintain autonomy over the decision-making process regarding data use. This principle is crucial in realizing the concept of Privacy-Sensitive Empowerment (PSE) in technology-assisted care, as discussed by Welsch and Buhr (2022), which calls for a harmonious balance between empowering individuals and safeguarding their privacy.

Real-World Application - Empowerment and Privacy in Dementia Care with Social Robots: In the specific case of dementia care, social robots like Robbie present a unique set of opportunities and challenges. The role of Robbie as a Monitoring and Assistive System (MAS) in care settings involves a delicate interplay between providing support, enhancing safety, and maintaining the privacy and dignity of people with dementia. The concept of PSE, as introduced by Welsch and Buhr (2022), emphasizes the integration of empowerment strategies with a deep respect for the bodily-topological and intimacy-decisional dimensions of privacy in the use of such technologies.

For example, Robbie may offer functionalities to assist people with dementia in their daily activities and promote social interaction. However, it is crucial that Robbie also upholds the principles of PSE by ensuring that any data collection and processing activities are transparent, consensual, and respect the informational, topological, and decisional dimensions of privacy. This means that Robbie should be equipped with interfaces that allow people with dementia or their authorized caregivers to easily understand, control, and manage the extent of data collection and usage, aligning with their preferences and consent.

In practice, designing Robbie and similar social robots to embody the principle of

PSE involves a user-centric approach. This approach respects the relational aspects of care, ensuring that the technological functionalities of the robot do not overshadow the importance of human dignity, autonomy, and intimacy. It fosters an environment where technology serves as an enabler of better care, rather than a source of intrusion or discomfort.

By emphasizing User Empowerment and Control, and incorporating the understanding of PSE, social robots like Robbie can navigate the complex landscape of dementia care. This ensures that while these robots provide valuable assistance and companionship, they also staunchly uphold the values of privacy, autonomy, and respect that are fundamental to ethical care practices.

In this section, we have navigated the critical design principles essential for fostering privacy-aware robotics. These principles—Privacy by Design, Transparency and User Consent, Data Security and Anonymization, Accountability and Compliance, and User Empowerment and Control—serve as the foundational pillars for integrating ethical and privacy considerations into the fabric of robotic systems.

Through the exploration of real-world applications and illustrative examples, we have demonstrated the practical implications and the paramount importance of these principles. From ensuring data security through Anonymity Assessment to navigating the complexities of cross-national legal frameworks, and empowering users with control over their personal data in sensitive environments, these principles collectively guide the responsible development and deployment of robotics.

The application of these principles goes beyond mere compliance with legal standards; it is about embedding ethical values into the core of robotics technology. By adhering to these principles, robotic systems can not only enhance operational efficiency but also champion the rights and dignity of individuals, earning trust and acceptance from users and society at large.

In traversing the landscape of design principles for privacy-aware robotics, we have uncovered the pivotal role these principles play in weaving privacy into the very fabric of robotic systems. Principles such as Privacy by Design, Transparency and User Consent, Data Security and Anonymization, Accountability and Compliance, and User Empowerment and Control are not standalone concepts but are deeply interconnected, each reinforcing the others to create a comprehensive approach to privacy. These principles, when implemented, address the challenges and fulfill the requirements discussed in earlier sections, bridging the gap between theoretical ethics, practical functionality, and legal compliance.

However, the journey of integrating these principles into the design and operation of robotics is marked by complexities and continuous evolution. As we look to the future, the field of privacy-aware robotics is poised for further innovation and transformation. Emerging technologies, evolving design methodologies, and shifts in regulatory landscapes will undoubtedly shape how these principles are actualized in practice. The insights and applications discussed here lay a strong foundation, but they also invite ongoing dialogue, reflection, and collaboration among technologists, legal experts, ethicists, and the broader community. As we advance, the commitment to privacy-aware design in robotics will remain a guiding beacon, ensuring that as robotic technologies progress, they do so with respect for privacy, ethical integrity, and societal trust at their core.

5.6 Differentially Private Algorithms: An Approach to Enhancing Privacy in Robotics

Differential Privacy (DP) is a system for safeguarding individual information within data sets. DP is a mathematical framework employed to enhance the privacy of algorithms. It does this by adding controlled noise, that is carefully calibrated to balance privacy with data utility, to data queries. DP therefore prevents the precise inference of individual information from aggregated data, ensuring that the risk of identifying an individual is minimally impacted by their data's inclusion or absence. This makes it ideal for organizations needing to analyze sensitive data without revealing personal information. This approach is vital for government agencies handling sensitive information, as it allows for the extraction of meaningful insights without compromising individual privacy. Essentially, DP maximizes query accuracy from statistical databases while minimizing identification risks. It ensures that the addition or removal of a single item in a database has a negligible effect on analysis outputs, safeguarding individual data privacy. This preservation of privacy fosters trust in technology, as users are assured of their information's confidentiality.

Definition 1 (ϵ-differential privacy, Dwork and Roth (2014):) A randomized mechanism M gives ϵ-differential privacy if, for all neighboring datasets D, D', and all events $S \subset \text{Range}(M)$,

$$P(M(D) \in S) \leq e^{\epsilon} P(M(D') \in S).$$

Depending on the context, two datasets are called neighboring if one could be obtained from the other by (Drechsler, 2023):

(a) adding or removing a single record (*unbounded DP*), or

(b) changing the values of one record, while keeping the size of the database fixed (*bounded DP*).

An adaptation of the underpinnings of DP is Local Differential Privacy (LDP), which takes this a step further by randomizing data directly on a user's device, offering immediate data protection before it is even shared or analyzed. This method is particularly useful for apps or services where user trust is paramount. There is subsequent implementation of the underpinnings of DP, i.e., CDP. Central Differential Privacy (CDP) contrasts with LDP by centralizing data processing. Here, data is collected in its original form and then anonymized in a central location. This approach is often used by larger organizations or researchers who need more precise data analysis while still maintaining privacy.

In the comparative analysis of LDP and CDP, Bernau et al. (2021) highlight key differences. LDP, with its data randomization at the user's device, offers strong privacy protection but can lead to reduced data accuracy. This makes LDP ideal for scenarios where user privacy is paramount. CDP, conversely, provides better data accuracy since the noise addition happens after data aggregation, making it suitable for situations where detailed, accurate data analysis is required. However, this can sometimes result in slightly weaker individual privacy protections compared to LDP. While LDP can lead to reduced data accuracy and CDP offers better data accuracy, the trade-offs are more nuanced and depend on specific implementation and context. Bernau et al. (2021) emphasizes these trade-offs, suggesting the choice between LDP and CDP depends on the specific privacy and data utility requirements of the application.

The paper by Erlingsson et al. (2019) transitions from Local Differential Privacy (LDP) to Central Differential Privacy (CDP) through shuffling. LDP protects data at the source by randomizing it on the user's device. Shuffling further anonymizes this data, effectively blending individual contributions before analysis to prevent specific user linkage. This technique significantly enhances privacy by reducing the privacy budget, a measure of privacy loss, thereby offering stronger protections than LDP. The paper outlines an algorithmic approach for processing data under LDP and transitioning to CDP through shuffling, demonstrating how this method acts as a bridge between LDP and CDP to enhance data privacy in differential privacy models. This approach is particularly beneficial for researchers seeking data and participants providing data, ensuring greater privacy protection. In scenarios involving robots that capture and process information for researchers, the transitioning from LDP to CDP through shuffling can be a technique for ensuring privacy in robotics. The clarity of privacy, particularly on the part of the user may contribute to improved public perception of robotics and user privacy.

5.7 Community Engagement and Public Perception

The acceptance and success of privacy-aware robotic technologies are heavily influenced by public perception and community engagement. This section discusses the crucial role these factors play in the development and deployment of robotic systems that prioritize privacy, drawing insights from Schulz and Herstad (2018). Understanding and actively engaging with public concerns and perceptions can significantly impact the adoption and trustworthiness of these technologies.

Public perception of robotic technologies is shaped by a variety of factors, including media portrayal, personal experiences, cultural attitudes, and awareness of privacy issues. Negative perceptions, often stemming from concerns about privacy, security, and the potential misuse of data, can hinder the acceptance and widespread adoption of robotic technologies. Conversely, positive perceptions, fostered by transparency and demonstrations of privacy protection, can enhance trust and acceptance.

Educational initiatives and public awareness campaigns play a significant role in shaping perceptions by providing accurate information about the capabilities and privacy safeguards of robotic technologies. These efforts help demystify the technology and address common misconceptions, as highlighted in the sociotechnical approach (Malchik and Feigenbaum, 2022).

Community engagement involves actively involving stakeholders, including potential users, privacy advocates, and regulatory bodies, in the development and deployment process of robotic technologies. This engagement can take various forms, such as public consultations, collaborative design processes, and pilot programs. Engaging with communities allows developers to understand and address the specific privacy concerns and needs of different groups. It also provides an opportunity to demonstrate the practical benefits and privacy protections of the technology, fostering a sense of ownership and acceptance among the community.

Successful examples of community engagement initiatives demonstrate their effectiveness in building trust and acceptance. For instance, a pilot program for a robotic delivery service in a residential area might involve community meetings to discuss privacy and safety concerns, demonstrations of the technology, and a feedback mechanism for residents to share their experiences and suggestions. Similarly, collaborative design processes for educational robots can involve teachers, students, and parents in decision-making, ensuring that the final product aligns with the privacy expectations and educational needs of the community.

Looking forward, the landscape of community engagement and public perception will continue to evolve, influenced by advancements in technology, shifts in societal values, and changing privacy landscapes. Developers and manufacturers of robotic systems must remain agile and responsive to these changes, continuously seeking to understand and address the concerns of the community while fostering an environment of trust and acceptance. The insights and strategies discussed here provide a foundation for navigating these complex dynamics, but they also highlight the need for ongoing dialogue, collaboration, and adaptation as we strive to ensure that robotics technologies are not only technologically sophisticated but also socially embraced and ethically aligned, as underscored by the principles and approaches in (Schulz and Herstad, 2018) and (Malchik and Feigenbaum, 2022).

5.8 Summary and Reflections

This chapter has explored the challenges and opportunities presented by the integration of privacy and ethics in the field of robotics. As robotics continue to evolve and become more ingrained in our everyday lives, the importance of addressing these issues becomes increasingly apparent.

5.8.1 Summary of Key Points

- **The Need for Privacy in Robotics:** We discussed the privacy challenges inherent in robotic data collection and processing and the impact of public perception and legal frameworks on the adoption and use of robotics.

- **Differentially Private Algorithms:** The use of differentially private algorithms, especially the transition from LDP to CDP via shuffling, can be useful. These algorithms balance user privacy with robotic functionality. Robots often collect sensitive data, and these algorithms ensure this data is handled responsibly, maintaining privacy without compromising the robots' operational efficiency. Implementing such privacy-centric approaches in robotics not only bolsters user trust but also aligns with ethical standards for data handling, fostering a more responsible and trustworthy environment in data-sensitive robotic applications.

- **Ethical Considerations:** We examined the ethical implications of data handling by robots, emphasizing the importance of principles like transparency, accountability, and respect for individual autonomy.

- **Regulatory and Legal Frameworks:** The analysis of the legal and regulatory environment related to privacy in robotics underscored its implications for the use of differentially private algorithms and the design of privacy-aware systems.

- **Design Principles for Privacy-Aware Robotics:** This section presented key design principles essential for privacy-aware robotics. To illustrate their application in real-world settings, we delve into a more detailed hypothetical scenario where a robotic system undergoes a privacy impact assessment. This process identifies potential privacy risks and implements design solutions such as encrypted data storage, user-accessible privacy settings, and automated consent protocols. For instance, a robotic system developed for retail inventory management could use encrypted communications to safeguard data about customer purchasing trends and store layouts. It could also feature a user interface that allows store employees to control what data is shared with corporate analytics departments, ensuring that privacy is maintained at both the customer and employee levels.

- **Community Engagement and Public Perception:** The importance of public perception and community engagement in the acceptance of privacy-aware robotic technologies was discussed, highlighting the need for educational initiatives and collaborative design processes.

5.8.2 Recommendations for Future Research

- **Advanced Privacy-Preserving Techniques:** Continued research into advanced privacy-preserving techniques, such as differentially private algorithms, is essential. This includes exploring their application in more complex and diverse robotic scenarios.

- **Interdisciplinary Approaches:** Future research should adopt interdisciplinary approaches, combining insights from technology, law, ethics, and social sciences, to address the multifaceted nature of privacy and ethics in robotics.

- **Human-Centric Design:** Emphasis should be placed on human-centric design principles that prioritize user needs, preferences, and privacy concerns in the development of robotic systems.

- **Legal and Regulatory Evolution:** Research should also focus on the evolution of legal and regulatory frameworks to keep pace with technological advancements in robotics, ensuring adequate protection of privacy and ethical standards.

- **Community Engagement and Education:** Further exploration of methods for effective community engagement and public education about privacy-aware robotics is needed to enhance public trust and acceptance.

The exploration of privacy and ethics in robotics, as discussed in this chapter, underscores the multifaceted and dynamic nature of this field. The integration of privacy-aware design principles, the adoption of advanced privacy-preserving techniques, and the commitment to ethical considerations represent not just responses to technological challenges but also a societal imperative for the responsible use of robotics. The interconnectedness of technical, ethical, legal, and societal aspects demands an interdisciplinary approach and a global perspective, acknowledging the diverse implications across different cultures and jurisdictions.

As we stand at the intersection of rapid technological advancements and evolving societal expectations, the field of privacy and ethics in robotics requires adaptive and forward-looking strategies. The recommendations for future research provide a roadmap for navigating this complex landscape, emphasizing the need for advanced privacy-preserving techniques, interdisciplinary collaboration, human-centric design, adaptive legal frameworks, and proactive community engagement. Emerging technologies and trends, such as AI and autonomous systems, further accentuate the importance of staying vigilant and responsive to the changing dynamics of privacy and ethics in robotics.

The journey of integrating privacy and ethics into robotics is ongoing, marked by continuous learning, innovation, and collaboration. As we move forward, it is imperative to embrace this journey with a commitment to creating robotic systems that are not only technologically advanced but also ethically sound, legally compliant, and socially accepted. The future of privacy-aware robotics is not just a reflection of our technological capabilities but also a testament to our collective values, vision, and responsibility towards society.

Chapter 6

Synthesis and Future Directions

6.1 Introduction

This chapter aims to integrate and synthesize the findings of this dissertation, drawing connections between the varied yet interconnected themes.

To set the stage for this comprehensive synthesis, let us briefly recapitulate the primary focus and findings of each chapter:

1. Chapter 2: Interruption Management and Cognitive Resilience: This chapter explores into the domain of interruption management, presenting empirical evidence on the effectiveness of structured, practice-based training interventions in enhancing individuals' ability to manage interruptions. It emphasizes the importance of cognitive resilience in dynamic workplace environments. The chapter confirms the efficacy of these training methods and their potential for broader application across various operational contexts, integrating cognitive psychology, pedagogical theory, and practical application. It highlights how structured training can improve individual performance and catalyze organiza-

tional transformation, enhancing efficiency and safety. The insights and findings are intended to inspire further research and practical implementation in the field, particularly focusing on developing more resilient, efficient, and safer work environments. The chapter sets the stage for innovative applications in interruption management and cognitive resilience training, paving the way for targeted interventions for diverse populations, including individuals with Autism Spectrum Disorder (ASD) in the next chapter.

2. Chapter 3: Social Robotics and Autism Spectrum Disorder: This chapter presents a comprehensive exploration of how social robotics can enhance the employability and daily living conditions of individuals with Autism Spectrum Disorder (ASD). It details the project, highlighting the transformative impact of combining advanced technological solutions with an understanding of specific user needs. The successful implementation of ISTAR, evidenced by its positive reception and the notable improvements in participants' abilities to handle workplace interruptions, demonstrates the efficacy of this innovative approach. The insights obtained from the ISTAR project offer practical strategies for developing inclusive and supportive technologies, emphasizing the broader societal benefits.

3. Chapter 4: Chapter 4 explores the critical issue of task interruptions, a common occurrence in today's fast-paced work scenarios, which can significantly hinder task performance by prolonging task resumption times and increasing error rates. It presents robotic assistance as an innovative solution to buffer these ef-

fects, particularly in tasks demanding high precision and focus. Through maintaining continuity and reducing cognitive overload, robotic assistance emerges as a valuable tool in enhancing task performance. The chapter emphasizes the importance of designing targeted interventions, including training programs, and technology tools integration, tailored to individual needs and task complexities. Furthermore, it underscores the necessity of privacy-conscious technology design, advocating for the ethical handling of user data to build trust and ensure a respectful technological environment.

The interplay between task complexity and learner proficiency is examined, stressing the need for personalized learning approaches that calibrate technological aids to match learners' capabilities. This balance is essential in creating educational interventions that cater to individual skill levels, ensuring effective learning outcomes.

4. Chapter 5: Privacy and Ethics in Robotics: This chapter explores the challenges and opportunities of integrating privacy and ethics in the rapidly evolving field of robotics. As robotics become increasingly integral to our daily lives, addressing privacy and ethical issues is crucial. The chapter discusses the privacy challenges associated with robotic data collection and processing, emphasizing the impact of public perception and legal frameworks on the adoption and usage of robotics. It highlights the importance of differentially private algorithms in balancing privacy protection with the functional needs of robots.

   In terms of ethical considerations, the chapter examines the implications of data handling by robots, stressing the need for principles like transparency, accountability, and respect for individual autonomy. It also analyzes the current legal and regulatory environment related to privacy in robotics, focusing on its implications for the use of differentially private algorithms and the design of privacy-aware systems. One of the key discussions is the presentation of essential design principles for privacy-aware robotics. The chapter illustrates these principles through real-world scenarios, such as a robotic system in retail inventory management using encrypted communications and user-accessible privacy settings to safeguard data.

Additionally, the chapter underscores the importance of community engagement and public perception in the acceptance of privacy-aware robotic technologies. It advocates for educational initiatives and collaborative design processes to foster a more informed and accepting public view.

6.2 Integration of Findings

The collective examination of these chapters yields several key insights:

1. **Enhanced Capability and Skill Development through Robotics:** Robotics is increasingly playing a pivotal role in enhancing human capabilities and skills. This is evident from its application in cognitive resilience training, skill acquisition, and assistance to individuals with specific needs, such as those with Autism Spectrum Disorder. Robotics is transforming from a tool for industrial applications to a versatile aid in personal, educational, and therapeutic

contexts.

2. **Complex Interplay of Robotics, Learning, and Task Performance:** The chapters underscore a complex dynamic between robotic assistance, human learning processes, and task performance. This includes how robotic assistance can facilitate skill transfer and retention, and the impact of task complexity on learning outcomes. It highlights the evolving relationship between humans and robots, where robots are not just tools but also partners in learning and cognitive development.

3. **Integration of Ethics and Privacy in Robotic Design:** A crucial insight is the increasing importance of integrating ethical considerations and privacy concerns into robotic design. As robotics becomes more ingrained in everyday life, addressing these ethical and privacy challenges is essential for responsible and socially accepted technological advancement.

4. **Adaptation to Technological Advancements:** There is a continuous adaptation process between the rapid advancements in robotics and how humans integrate these technologies into their lives. This adaptation is bidirectional; technology shapes human behavior, while human needs and societal norms influence technological development.

These integrated findings highlight the multifaceted impact of robotics in human-technology synergy. They emphasize a future where robotics is intricately linked with human needs, societal challenges, skill development, and ethical considerations, necessitating a comprehensive approach to understanding and advancing the field of robotics.

6.3 Future Research Directions

6.3.1 Emerging Areas

As the field of robotics and human-technology synergy continues to evolve, new avenues for research are emerging that promise to further deepen and broaden our interaction with technology. Building on the insights from this dissertation, key areas for future research include:

1. **Enhancing Cognitive Resilience and Skill Development:** Future research can explore the development of robotic systems and technologies aimed at further enhancing cognitive resilience and skill development. This includes investigating how robotic assistance can be optimized for different learning environments and individual needs, especially in educational and workplace settings.

2. **Personalized Robotics in Therapeutic and Supportive Roles:** Building on the insights from working with individuals with Autism Spectrum Disorder, there is an opportunity to expand research into the use of personalized robotics for a wider range of therapeutic and support roles. This can encompass mental health, emotional support, and addressing specific needs of diverse populations.

3. **Balancing Ethical and Privacy Considerations in Robotics:** As robotics becomes more integrated into daily life, a key area of research will be to develop

and refine ethical guidelines and privacy-preserving technologies in robotics. This includes examining the implications of data handling, user consent, and the overall impact of robotics on privacy and ethical norms.

4. **Robot-Assisted Task Management:** Investigating the role of robotics in assisting with task management, particularly in understanding and mitigating the impacts of task interruptions, presents a significant area for research. This includes exploring the synergy between human cognitive processes and robotic assistance to optimize task performance and learning outcomes.

5. **Interdisciplinary Approaches to Technical Education:** Future research should continue to adopt interdisciplinary approaches, combining insights from technology, psychology, education, law, and ethics, to address the multifaceted nature of robotics and its societal impact.

6. **Interactive Task Learning Robots:** Socially Collaborative Robots (SCRs) excel in mastering tasks through real-time interactions with humans by learning from and appropriately interrupting users to optimize task execution. These robots intelligently ascertain the most opportune moments for targeted assistance or feedback, tailored to their human partners' immediate task requirements and context by leveraging insights from ongoing interactions and their partners' responses (Fitzgerald et al., 2022). This methodology not only fosters deeper engagement but also ensures the alignment of task strategies with individual preferences and progress levels. SCRs continuously refine their learning and interrupting techniques based on this input, guaranteeing that their inter-

ventions are both relevant and timely. By integrating technology with interactive learning techniques, SCRs serve as dynamic partners in both learning from and assisting humans, offering highly personalized task learning experiences. They emerge as crucial instruments in adaptive, personalized, and interactive task learning and execution. SCRs are further explored in Appendix C.

These research directions are informed by the findings of this dissertation and point towards a future where robotics is not only technologically advanced but also ethically sound, personalized for specific needs, and integrated into a wide range of human activities, enhancing our interaction with technology and contributing to societal development.

6.3.2 Refining Interaction for Interruptive Learner Robots

Allowing Socially Collaborative Robots (SCRs) to ask questions and initiate interruptions can greatly improve their learning efficiency, effectiveness, and personalization. This enhances human-robot collaboration and learning outcomes through active learning and interaction. Actively seeking clarifications helps SCRs focus on uncertainties, aligning with active learning principles for more efficient knowledge acquisition. By understanding human intentions better, SCRs enhance their collaboration abilities, akin to improving Theory of Mind (ToM). Real-time adjustments through interruptions for clarifications adapt their learning to feedback, fostering adaptability. Bidirectional communication enhances engagement and data quality, while personalization addresses individual teaching preferences, improving learning effectiveness.

Active questioning reduces errors from ambiguous human instructions, ensuring more accurate behavior learning, which is critical in Human-in-the-Loop Machine Learning (HIL-ML) systems (Cui et al., 2021). These measures aim to make SCRs supportive and minimally disruptive, enhancing human-robot interaction by ensuring interruptions are both productive and well-received, thus maintaining a productive flow of interaction without overly disrupting human tasks.

SCRs as learner-interruptors are pivotal for enhancing learning, safety, and collaboration with humans. Their interruptions—ranging from clarifications, specific instructions, performance feedback, confirmations, expressing uncertainties, highlighting errors or safety issues, to suggesting more efficient alternatives—demonstrate a proactive approach to understand human intentions and optimize task execution (Fitzgerald et al., 2019; Norton et al., 2022). These varied interactions, whether questioning decisions, seeking precise guidance, evaluating actions, or proposing knowledge-based improvements, underscore the SCRs' dedication to comprehensively engage in and improve human-robot collaboration.

Goal: balancing interruptions against its disruptions involves:

1. **Minimizing Disruption:** SCRs are to implement non-intrusive interruptions, carefully timed and possibly conveyed through non-verbal signals or during natural task pauses. This approach minimizes interference with the human partner's workflow or concentration, underlining the robot's dual role as a considerate partner and an effective learner.

2. **Maximizing Information Gain:** The SCR's interruptions must be meticulously designed to gather essential information, asking targeted questions to obtain comprehensive insights from the human partner. This precision supports the SCR's learning process, emphasizing its role as both an inquirer and a collaborator keen on enhancing task understanding.

3. **Learning Through Interruptive Interaction:** Each interruption is intentionally used by the SCR to refine its understanding of the task at hand and the human partner's strategies, directly benefiting the SCR's learning curve. This process exemplifies the SCR's active role in learning from the human partner while simultaneously striving to improve collaborative efficiency.

4. **Valuable Interruption Design:** The SCR crafts interruptions to be clearly beneficial, articulating its needs for information and demonstrating how these interruptions can positively impact task performance or safety. This strategy aims to position the SCR as a valuable contributor to the task, actively learning and assisting its human partner.

5. **Adapting to Human Feedback:** Enable SCRs to adjust interruption strategies based on feedback, learning from their interactions with humans while also increasing their own effectiveness and reducing their disruption to the human.

When an SCR Should Interrupt

In the dissertation chapters that examine the timing and strategy of interruptions, key findings are as follows:

1. **Pedagogical Interventions:** As detailed in Section 2.5, interrupting during periods of low cognitive load significantly minimizes disruption. This strategy is most effective when guided by insights into the user's behavior, ensuring both timeliness and relevance of the interruptions.

2. **Interruptive Robot (ISTAR):** Section 3.4.3 highlights the importance of customizing interruptions to align with the user's current task and social context. Customization enhances the relevance and consistency of the interruptions, making them more beneficial.

3. **Technical Robot Assistance:** According to Section 4.4.9, strategic use of interruptions for error prevention, clarification, and guidance is crucial during pivotal learning moments. Such targeted interruptions significantly contribute to the learning process, making them a valuable tool for enhancing learning outcomes.

Key strategies for when SCRs should interrupt include:

1. **Strategic Timing for Task Complexity:** In managing task complexity, Section 4.4.9 suggests that as tasks increase in difficulty, and users' skill levels may not suffice for optimal performance, error likelihood rises. It is recommended that SCRs fine-tune the timing of their interruptions based on real-time assessments of potential performance penalties or errors. This adjustment is crucial when an interruption's timing could exacerbate errors. SCRs can detect errors by monitoring for discrepancies between the expected skill level and actual performance, as well as deviations from established common ground knowledge.

2. **Strategic Timing for Different Task Types:** Optimal interruption timing by SCRs is influenced by the user's cognitive state and level of task engagement, with behavioral indicators pinpointing the most opportune moments for intervention. Our findings in Section 2.4.6 reveal that interruptions, strategically placed based on the nature and phase of the task, can be advantageous even amidst accruing errors. For strategic problem-solving tasks with Markovian properties—where the optimal next substep is independent of previous ones—interruptions facilitate cognitive regrouping, allowing users to reassess and potentially enhance approaches to the ongoing task's subsequent substeps. In tasks that demand significant memory effort, SCRs act as external aids, providing cues for forthcoming substeps or reinforcing the memory of ones already completed, thus supporting accurate task continuation. This proactive interruption strategy, detailed in Section 4.3.2, employs environmental cues to aid memory and learning, preemptively addressing potential disruptions caused by the SCR's interruption and enabling a more effective resumption of the task.

3. **Customization and Adaptation:** Drawing from Sections 3.4.3 of our interruptive robot study and 4.4.7 of our technical robot assistant study, the timing of interruptions by SCRs can affect the duration required for users to resume their original tasks. Thus, it is crucial for interruptions to be closely aligned with the user's current activities, preferences, and context, especially when an interruption is likely to cause a specific user to experience a delay in resuming the task. SCRs should leverage personal data to continually refine and person-

alize interruption strategies, ensuring they evolve over time to meet the user's needs more effectively. This approach helps minimize disruption and facilitates a smoother transition back to the task, enhancing both user experience and task performance.

These approaches aim to make SCR interruptions timely, relevant, and minimally disruptive, thus improving human-robot collaboration.

How SCRs should interrupt

Given their dual role as both learners and interrupters, SCRs must employ strategies that enhance learning while minimizing disruption. Three key approaches, supported by our research, are critical for balancing these objectives:

1. **Personalized Interruptions Based on User Adaptation:** Based on insights into the generalizability of training effects and the need for tailored intervention strategies (Section 2.5), SCRs should customize their interruptions. By analyzing the user's current tasks, cognitive load, and interaction history, SCRs can determine the optimal moments for interruption, ensuring minimal disruption and maximum learning efficacy.

2. **Predictive and Adaptive Interruption Timing:** Highlighted by our research on reducing interruption and resumption lags in Section 3.4.3, SCRs must employ predictive modeling and real-time data to finely tune interruption timing and content. This capability ensures interruptions are well-suited to the urgency of the task and the human partner's engagement level, showcasing the

SCR's adaptability in its learner and interrupter roles.

3. **Leveraging Human Feedback for Strategy Refinement:** Insights from our investigation into robot-assisted technical education (Section 4.5) highlight the value of SCRs adapting based on user feedback. This iterative feedback process allows SCRs to refine their approaches, ensuring interruptions contribute positively to the collaborative experience and learning outcomes.

These strategies enable SCRs to navigate their unique position effectively, improving their function as collaborators and learners.

Minimizing the Impact of SCR Interruptions:

To further minimize disruptions and enhance the efficacy of SCRs' interruptions, we emphasize:

1. **Pedagogical Training Integration:** This strategy aligns with our study on tailored intervention strategies, with emphasis on pedagogical interventions enhancing interruption management (See Section 2.6). The study demonstrated that training could significantly improve how individuals manage and adapt to interruptions, suggesting SCRs could be programmed to use insights from these pedagogical interventions to better manage their interruption strategies.

2. **Contextual Adaptation:** The importance of adapting interruption strategies to the user's current context is supported by our interruptive robot study in Secion 3.4.3, which showed different types of interruptions (environmental, social, task) and have varying impacts on user engagement and task resumption.

This underscores the need for SCRs to adapt their interruptions based on the context to minimize disruptiveness.

These focused measures aim to refine the interruption strategy of SCRs, ensuring they support the user efficiently while maintaining minimal disruption to their workflow.

6.3.3 Potential Challenges and Opportunities

The landscape of future research in robotics and human-technology synergy is marked by a range of challenges and opportunities:

1. **Technological Challenges:** These encompass ensuring the reliable and robust performance of robotics in diverse environments, overcoming current technical limitations, enhancing AI interpretability, and developing technologies that can adapt to varied and complex human behaviors and learning processes.

2. **Ethical and Legal Challenges:** As robotics becomes more integrated into various aspects of society, ethical and legal complexities will intensify, especially regarding privacy, data security, and the autonomy of robotic systems. This includes addressing the ethical implications of robot-assisted learning and cognitive training, as well as managing the balance between technological innovation and privacy concerns.

3. **Societal Opportunities:** Robotics presents vast opportunities to address societal challenges across various sectors, including healthcare, education, environmental conservation, and workplace optimization. Future research can explore

these applications, focusing on how robotics can enhance human capabilities, facilitate skill development, and improve cognitive resilience in real-world settings.

4. **Inclusivity and Accessibility:** Ensuring that robotics technology is inclusive and accessible to all segments of society is a critical area for exploration. This entails developing robotic systems that can cater to a diverse range of needs, including those of individuals with special needs, and ensuring equitable access to these technological advancements.

5. **Human-Centered Design and Adaptation:** A key opportunity lies in furthering human-centered design approaches in robotics, emphasizing the adaptation of technology to human cognitive patterns, educational needs, and ethical standards. This includes research on how robotic systems can be designed to align more closely with human behavior, societal norms, and ethical considerations.

The future of robotics and human-technology synergy, therefore, entails navigating these challenges and capitalizing on these opportunities to advance the field in a way that is technologically innovative, ethically responsible, socially beneficial, and inclusive.

6.3.4 Long-Term Implications

The long-term implications of continued advancements in robotics and technology are vast and multifaceted, shaping the future of human-technology synergy in significant ways:

1. **Transformation of Social Norms and Human Interaction:** Robotics and advanced technology have the potential to significantly alter social norms, interpersonal interactions, and daily routines. This can lead to a society that is deeply integrated with technology, where human-robot collaboration becomes commonplace in personal, educational, and professional contexts.

2. **Impact on Employment, Skills, and Education:** The continuous advancement of robotics will transform the job market, necessitating shifts in skill sets and potentially leading to new forms of employment. This includes the need for education systems to adapt, preparing individuals for a future where robotic assistance and AI are integral to various job roles.

3. **Enhancing Quality of Life and Cognitive Resilience:** Robotics holds the potential to significantly enhance quality of life, offering innovative solutions to challenges in healthcare, education, accessibility, and cognitive resilience. The integration of robotics in these areas can lead to improved therapeutic outcomes, more effective learning processes, and enhanced daily living for diverse populations.

4. **Ethical and Societal Evolution:** As society adapts to these advancements, there will be a continuous evolution of ethical standards and societal norms. This reflects the growing integration of robotics into human life and underscores the importance of responsible and ethical technological development, with a focus on privacy, accessibility, and inclusivity.

5. **Advancements in Cognitive and Educational Technologies:** The development of robotics and AI will also have significant implications for cognitive training, skill acquisition, and educational methodologies. This includes exploring how robotic systems can aid in cognitive resilience, personalized learning, and the management of learning environments.

In conclusion, the future of robotics and human-technology synergy is a landscape ripe with opportunities for groundbreaking research, innovations, and societal impact. This dissertation has laid a foundation, but the journey ahead is vast and open for exploration and discovery. As we venture into this future, the continuous and responsible advancement of robotics will play a pivotal role in shaping human experiences, societal structures, and ethical paradigms.

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Contents

Appendix A

Detailed Description of the Mock HVAC Workspace

The mock Heating, Ventilation, and Air Conditioning (HVAC) board serves as a pivotal educational tool, designed to closely simulate the functioning of real-world HVAC systems for training and research purposes. It provides an immersive, hands-on learning experience through its comprehensive assembly of 13 essential components, each contributing to the system's overall functionality and the learners' understanding of HVAC operations. Below is a detailed rundown of these components and their specifications:

1. Power Transformer: Supplies two power circuits with 24V to the Thermostat, Relays, and Sequencer, actuating the 120V circuit for components based on the Thermostat settings. Specifications: Primary voltage of 120, 208, 240V; Secondary voltage of 24V; Power Rating of 40VA.

2. Thermostat with Display: Controls room temperature by managing the heating and cooling systems according to user inputs. It features modes for heating, cooling, and fan-only. Wire colors for troubleshooting include RH/RC (Red) for heating controls, G (Green) for the fan relay, Y (Yellow) for the air conditioning compressor, C (Common) for 24-volt power return path, and W (White) for the heater.

3. Blue Bulb (Compressor): Simulates the refrigerant pump, absorbing and releasing heat. Represented by a blue light bulb, indicating compressor activity. Specifications: 110V, 6W, Standard E26 Base Lightbulb, with resistance over 180,000 Ohms.

4. Condenser Fan: Expels indoor heat outdoors, shown as a fan pushing air out. Specifications: 120x25mm, works with 110V and 220V AC power, with resistance over 14,000,000 Ohms.

5. Red Bulb (Heater): Mimics an electric heater, converting electric power to heat, indicated by a red bulb. Specifications: 110V, 6W, Standard E26 Base Lightbulb, with resistance over 7,500,000 Ohms.

6. Blower Fan: Circulates air for cooling and ventilation, located on the board's left side. Specifications: 120x25mm, works with 110V and 220V AC power, resistance over 14,000,000 Ohms.

7. Dual Plug Outlet: A duplex 3-prong receptacle supporting 15A, providing power to the compressor and condenser.

8. Contactor Relay: Switches large loads, passing power to motors (fans), the electric heater (red bulb), and the compressor (blue bulb). Specifications: 1 POLE 30 AMPS 24 COIL VOLTAGE.

9. Single Pole Single Throw (SPST) Fan Relay: Controls the blower fan, turning it on or off. Specifications: 24 VAC Coil Voltage, SPST NO NC Contacts.

10. Electric Heat Sequencer: Sequences heating element and blower fan activation to prevent simultaneous operation. Specifications: 24V input control, 2 switches.

11. Double Pole Double Throw (DPDT) Switching Relay: Controls the blower fan and heater, switching between two circuits. Specifications: DPDT 24 Volt Coil Voltage.

12. Circuit Breaker: Protects control circuits from overcurrent, with a 3 amp rating.

13. Terminal Block: Insulated block connecting electrical wires, organizing connections securely. The Thermostat's connections route through this block.

These components collectively replicate the intricacies of HVAC systems, enabling learners to gain practical insights into system design, operation, and troubleshooting. The mock board's design focuses on facilitating an interactive learning experience, bridging the gap between theoretical knowledge and real-world application, essential for proficient HVAC system maintenance and repair, as shown in Figure A.1.

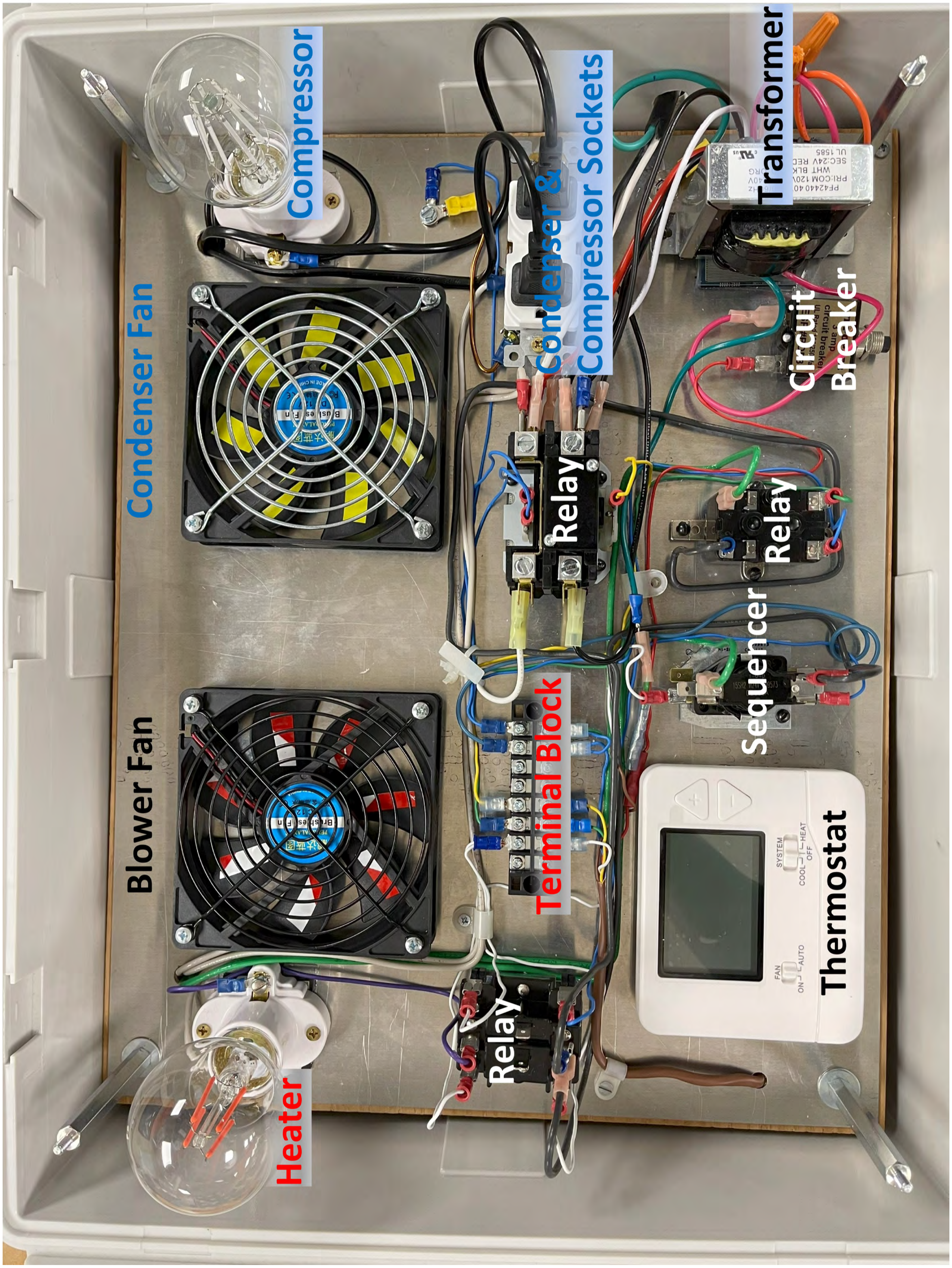

Figure A.1: Close-up of Mock HVAC Board inspired by Tech (2023).

Appendix B

Mock Board Power Circuits

Understanding the 24-volt signal and 120-volt power circuits in HVAC systems is crucial due to their distinct functions and safety implications. Both circuits derive from a single transformer, highlighting the integrated nature of HVAC electrical systems and underscoring the importance of precise engineering and safety measures.

B.1 Common Transformer Specifications

A 40VA Control Transformer with multi-tap capabilities and UL Certification powers both circuits. It accepts primary voltages of 120, 208, 240V and steps down to 24V for the signal circuit, designed for HVAC furnace applications. This setup optimizes system integration and efficiency by supporting both control signals and power needs from a unified source.

The GFCI (Ground Fault Circuit Interrupter) protection on the main power supply line enhances safety by monitoring electrical current flow. If an imbalance is detected, indicating a potential ground fault, the GFCI promptly shuts off power to prevent electric shock. This precaution is crucial in moisture-prone environments or areas accessible to individuals, ensuring overall safety.

Power is safely supplied to the transformer after GFCI verification, where it is adjusted to meet the HVAC system's voltage requirements for control and operation. This dual-circuit supply from a single transformer ensures efficient and safe HVAC operation. The setup not only mitigates electric shock risks but also provides precise control over component operation, ensuring they receive appropriate power for both signaling and mechanical action. Understanding this infrastructure is essential for safe HVAC system installation, troubleshooting, and maintenance, emphasizing the critical role of GFCI protection and the transformer's capability to manage diverse power demands.

B.1.1 Transformer Output for Two Circuits

1. **24-Volt Signal Circuit:** Supplies the control circuit with 24V for communication between the thermostat and HVAC components, enabling the activation of relays and switches.

2. **120-Volt Power Circuit:** The main power supply provides 120V to this circuit, essential for operating the system's high-energy components like blower fans and compressors. Commercial systems may require higher voltages, with specific arrangements to ensure proper power supply.

B.2 120-Volt Power Circuit

This circuit is designed for high-energy tasks within HVAC systems, such as operating the blower fan (left fan) and air conditioning compressors (blue bulb), as well as the condenser fan (right-side fan). It plays a critical role in the mechanical functions necessary for heating, cooling, and air circulation.

1. **Purpose**: Supplies the necessary power for the operation of high-energy HVAC components.

2. **Safety**: Due to its higher voltage, there is an increased risk of electric shock. The incorporation of GFCI protection on the main supply line is a crucial safety measure, automatically disconnecting power in case of ground faults to minimize electric shock risks. This setup requires careful installation and ongoing maintenance, protected by circuit breakers or fuses to avert electrical overloads.

3. **Function**: Directly energizes the system's main components, facilitating essential HVAC processes.

B.3 24-Volt Signal Circuit

This circuit, often referred to as the control circuit, is pivotal for the communication between the thermostat and various HVAC components, managing the operation of the system's high-power elements through relays and switches.

1. **Purpose**: Facilitates communication and control within the HVAC system, linking the thermostat to components such as furnaces, air conditioners, and heat pumps.

2. **Safety**: Its lower voltage significantly reduces the risk of electric shock, making it safer for technician interaction and installation in easily accessible areas.

3. **Function**: Controls the activation of heating or cooling elements without directly powering them, indicating when these elements should be turned on or off.

Appendix C

Notional Socially Collaborative Robots (SCRs)

Human collaboration is enriched by cooperative interactions and communications, requiring the ability to reconcile different perspectives for effective goal coordination. This involves perspective-shifting and discerning the truth of beliefs, essential for meaningful interaction (Fischer, 2019; Görür et al., 2018). Robots working with humans need these skills for true collaboration. In Human-Robot Interaction (HRI), Collaborative Robots (CoBots) assist through physical means, while Socially Assistive Robots (SAR) offer support socially or emotionally (Hayes and Scassellati, 2013; Matarić and Scassellati, 2016). Both types prioritize cooperative dynamics, necessitating skills in managing shared intentions and adapting to human communication styles (O'Madagain and Tomasello, 2022; Tomasello, 2018). Integrating SAR's social skills with CoBots' physical collaboration can significantly improve teamwork (Görür et al., 2018; Baillie et al., 2019). The challenge in HRI is creating robots that navigate the complex social dynamics of human environments, blending SAR and CoBots' strengths. These robots, termed Socially Collaborative Robots (SCR), aim to excel in both social and physical aspects of team interactions.

C.1 Social Collaboration and SCRs: Theory and Challenges

Central to social collaboration is Theory of Mind (ToM), enabling the attribution of mental states like beliefs and intentions to oneself and others, crucial for understanding diverse perspectives (Fischer, 2019; Schmerling et al., 2018). For SCRs, this means inferring human partners' mental states to adjust actions for genuine collaboration (Hoffman and Breazeal, 2004; Tabrez et al., 2020).

Developing SCRs requires them to master social competence, recognizing and anticipating human actions based on mental states. This involves interpreting intentions and emotions and responding with socially competent actions, essential for effective teamwork (Hoffman and Breazeal, 2004; Colombi et al., 2009). SCRs need to deduce beliefs from actions and contexts, synchronizing perspectives with human partners for tailored assistance and seamless cooperation (Tomasello, 2018; Colombi et al., 2009).

However, basic ToM may not suffice. SCRs also need advanced cognitive modeling—specifically, second-order mental modeling—to anticipate both human mental models and those incorporating the SCR itself (Mathieu et al., 2000). This deeper understanding enables SCRs to navigate and enhance human-robot collaboration (Tabrez et al., 2020; Brooks and Szafir, 2019).

Challenges arise from computational methods assuming optimal human behavior, which often misaligns with real-world actions influenced by unpredictability, personal preferences, and cognitive biases (Ziebart et al., 2008; Schmerling et al., 2018). Current models face issues with distributional shift, where training data does not match real-world decision-making, decreasing model robustness (Majumdar et al., 2017; Becker, 1976).

The difficulty in accurately modeling human intentionality adds to these challenges. Assumptions of goal optimization fail to account for the opaque and complex motivations behind human behavior, presenting a "black box" problem. This complexity underscores the formidable task of predicting human behavior with its inherent variability and specificity (Reddy et al., 2018; Schmerling et al., 2018). However, human behavior is not always computationally optimal or near-optimal. Some postulate that the reason for the suboptimality of behavior is due to random noise (Ziebart et al., 2008), preferences, ignorances, or inconsistencies (Evans and Goodman, 2015; Evans et al., 2016; Bergen et al., 2010), or risk appetite (Majumdar et al., 2017). Others propose that such behaviors result from epistemological discrepancies between subjective beliefs and objective reality, implying that humans tailor their actions to achieve their ultimate goals, within the bounds of their understanding and beliefs (Reddy et al., 2018; Becker, 1976). These perspectives underscore the intricate web of factors influencing human decision-making, posing significant challenges for the predictive models used in designing SCRs.

Given the intricate nature of human behavior, marked by its unpredictability and the profound depth of underlying motivations, the task of designing SCRs that can adapt to and anticipate human actions ramifies in complexity. These challenges highlight the inherent limitations of relying exclusively on computational models that aim for an idealized representation of human interactions. Transitioning from the computational difficulties of accurately modeling human intentionality towards exploring viable solutions, the concept of embodiment emerges not as a mere feature but as a cornerstone for enhancing human-robot collaboration.

Embodiment in SCRs grounds the interaction in the physical world and enables a more intuitive and meaningful exchange between humans and robots. This tangible morphological presence, characterized by the capacity to express and interpret non-verbal cues, plays an instrumental role in bridging the perceptual and communicative gap between humans and artificial agents. It underscores the necessity of moving beyond traditional computational models to incorporate the nuanced dynamics of real-world interactions, where embodiment plays a pivotal role.

Embodiment in SCRs serves as a pivotal factor enabling humans to afford robots with "minds", fundamentally altering the dynamics of human-robot interaction. This physical presence, or embodiment, enriches the interaction landscape beyond mere verbal communication, incorporating non-verbal cues like gestures, facial expressions, and spatial behaviors that are intrinsic to human social exchanges. Such embodied cues are instrumental in bridging the perceptual gap between humans and robots, allowing humans to attribute mental states, intentions, and emotions to these artificial agents. This attribution is crucial for developing a ToM within SCRs, which is essential for recognizing and understanding the complex, multifaceted nature of human mental states. By perceiving robots as entities with their "minds", humans can engage in more natural, meaningful, and effective interactions, fostering a sense of social connection and collaboration that is pivotal for the success of SCRs in various domains, including education, healthcare, and personal assistance (Deng et al., 2019).

Moreover, research indicates that the physical embodiment of SCRs significantly enhances their ability to function as social partners and tutors, leading to improved learning outcomes and engagement levels compared to their virtual counterparts or when no robot is present at all. This suggests that embodiment plays a crucial role not only in how humans perceive and interact with robots but also in the effectiveness of these interactions in achieving specific objectives. Embodied SCRs, by virtue of their tangible morphology, can more effectively mimic human social behaviors, making them more relatable and easier for humans to understand and predict. This enhanced relatability and predictability, facilitated by embodiment, are essential for building trust, rapport, and cooperation between humans and robots, ultimately enabling more successful and harmonious human-robot collaborations (Deng et al., 2019; Long et al., 2023).

C.2 Advancing Human-Robot Collaboration through Adaptive Modeling

Our research proposes moving beyond traditional models that predict human behavior through utility optimization. We advocate for a framework that integrates assumptions about human-robot interaction into the development of robots' mental models (Wiltshire et al., 2013). This approach acknowledges the complexity of human decision-making and focuses on the dynamics of human-robot relationships to improve the predictive accuracy and adaptability of robots.

By incorporating predefined objectives, shared knowledge, and roles within human-robot teams, we anticipate the streamlining of interaction strategies. This could enable SCRs to make targeted inquiries, using human feedback to refine their models of human beliefs and intentions. This feedback-driven approach could enhances SCRs' adaptability and accuracy in interpreting human actions.

We the aim to create scenarios reflecting diverse human behavior, SCRs could better understand complex decision-making processes Tabrez et al. (2020). Human responses provide dynamic feedback, enabling SCRs to infer intentions more accurately and adaptively. This iterative learning from direct feedback could foster nuanced and effective collaboration.

This would amount to a methodology that embraces the unpredictable nature of human behavior by including inductive biases specific to human-robot interaction. The result is would flexible, robust framework that adjusts based on human interaction feedback, developing a more responsive model that accurately captures human nuances.

We anticipate that the development of a scalable, resilient model for SCRs, capable of navigating human-robot interaction complexities and adapting to new challenges would be of great benefit to HRI. By incorporating feedback into an SCR's development, we expect a significant refinement of robots for HRI research, enhancing human-robot collaboration towards more adaptive, intuitive, and beneficial interactions.

C.3 Enhancing SCR Capabilities: A Methodology

To transition SCRs from theory to practice, ensuring seamless integration into human settings, a multidimensional methodology focusing on systematizing inductive biases, crafting realistic scenarios, and operationalizing shared mental models, aimed at boosting the robots' predictive accuracy and social adaptability would be required (Mathieu et al., 2000).

C.3.1 Systematizing Inductive Biases

This begins by embedding essential assumptions about human-robot interaction into SCRs' cognitive frameworks. The aim would be to retain robustness against distributional shifts by structurally embedding a subset of the necessary assumptions about the nature of a human-robot team's interactivity into the way a robot comes to form mental models of its human partner. This approach is akin to systematizing the inductive biases to circumscribe the hypothesis space of collaborative interactions. The systematization of inductive biases might be achievable by constructing realistic scenarios aligning the space of the robot's predictions of probable human beliefs, intentions, and actions with its human partners' purposeful decisions (Evans and Goodman, 2015). This involves codifying biases that influence human social behavior into the robots' operational logic, providing them with a foundational understanding of social norms and expectations (Evans et al., 2016). This strategic integration facilitates a proactive approach to social cognition in robotics.

C.3.2 Constructing Realistic Scenarios

To test and refine these biases, SCRs could be immersed in diverse, realistic scenarios that replicate the complexity of human environments, from workplace collaborations to home interactions. This variety tests the robots' ability to interpret intentions, anticipate actions, and adapt in real-time, aligning their operations more closely with human behavior patterns and improving collaboration (Bergen et al., 2010).

C.3.3 Operationalizing Shared Mental Models

A key aspect of this approach is enabling SCRs to accurately model human partners' mental states and understand that humans hold reciprocal models of the robot. This mutual awareness fosters predictability and trust, vital for effective teamwork. By adjusting behaviors based on human perspectives, SCRs achieve a new level of social competence.

This methodology aims to advance SCRs from theoretical constructs to practical collaborators, embedding social understanding, testing it in real-world scenarios, and fostering mutual awareness between robots and humans. By integrating these approaches, we lay the foundation for next-generation robots capable of genuine human collaboration, marking a significant leap in human-robot interaction.