JESSIE: Synthesizing Social Robot Behaviors for Personalized Neurorehabilitation and Beyond

Alyssa Kubota[1], Emma I. C. Peterson[2], Vaishali Rajendren[1], Hadas Kress-Gazit[3], Laurel D. Riek[1]
[1]Computer Science and Engineering, University of California San Diego, USA
[2]Computer Science and Engineering, University of Minnesota Twin Cities, USA
[3]Sibley School of Mechanical and Aerospace Engineering, Cornell University, USA

ABSTRACT

JESSIE is a robotic system that enables novice programmers to program social robots by expressing high-level specifications. We employ control synthesis with a tangible front-end to allow users to define complex behavior for which we automatically generate control code. We demonstrate JESSIE in the context of enabling clinicians to create personalized treatments for people with mild cognitive impairment (MCI) on a Kuri robot, in little time and without error. We evaluated JESSIE with neuropsychologists who reported high usability and learnability. They gave suggestions for improvement, including increased support for personalization, multi-party programming, collaborative goal setting, and re-tasking robot role post-deployment, which each raise technical and sociotechnical issues in HRI. We exhibit JESSIE's reproducibility by replicating a clinician-created program on a TurtleBot 2. As an open-source means of accessing control synthesis, JESSIE supports reproducibility, scalability, and accessibility of personalized robots for HRI.

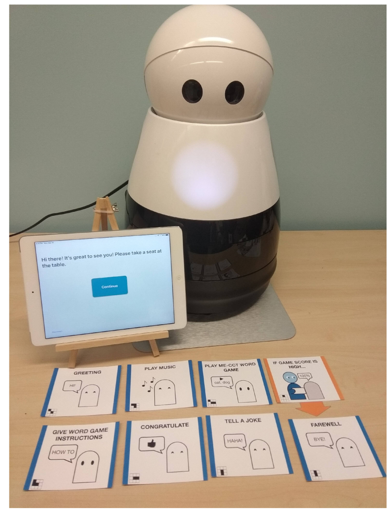

Figure 1: JESSIE employs control synthesis with a tangible front-end to enable people to create customizable programs for social robots within the context of neurorehabilitation.

CCS CONCEPTS

• **Computer systems organization** → *Robotic control*; • **Applied computing** → *Health informatics.*

KEYWORDS

Human robot interaction; Robotics; Control synthesis; Healthcare robotics; Neurorehabilitation; Dementia

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1 INTRODUCTION

Healthcare is an important domain to support key stakeholders by creating customized robot programs [7, 29, 30]. 15-20% of the world's population has a disability [94], and as aging trends increase, this number will also increase [79]. This greatly impacts independence of many people; however, the availability of full time care providers are exceeding existing resources around the world [95]. Thus, human robot interaction (HRI) researchers are exploring robots to fill these care gaps, particularly home-based social robots deployed longitudinally [3, 7, 10, 20, 25, 28, 44, 76, 80–82, 87, 89].

As HRI researchers collaborate with clinicians, community health workers, and family members, many have reported challenges stymieing their progress [5, 12, 43]. First, they lack the tools to enable clinicians to create tailored, personalized interventions and modify robot behavior at a high level. Personalization is critical in any robotics healthcare application, as no care receiver is the same and requires uniquely tailored interventions to support their health. Another challenge is that HRI researchers must manually and painstakingly create customized programs for each stakeholder domain, limiting the scalability and potential impact of their work.

Most stakeholders, particularly clinicians, lack the time to learn how to program robots to exhibit custom behavior, especially if they must consider each individual action the robot should perform (e.g. what to say, how to move). This can cause unusable code or unexpected robot behavior, and must be extensively tested, else risks unintended consequences on potentially vulnerable populations.

While prior work exists to support novice programmers via visual, aural, and tactile languages (i.e., via End User Programming

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(EUP)) [9, 24, 61, 68, 84, 85], these frameworks are almost entirely procedural, require understanding code structure, and do not allow high level specification of desired behavior, including constraints on the robot's actions. For example, a novice user can typically program a sequence of actions (e.g. pick, then move, then place), but implementing multiple conditions and constraints on behavior is more difficult (e.g. pick, place, and play music if the user is bored, and turn on lights if it is dark). For complex behaviors, users would have to compose constructs such as *if* statements and *for* loops, which can be difficult and error prone even in EUP contexts.

To address this gap,we leverage our prior work on control synthesis for robot behavior from high-level specifications [54, 96]. Such techniques and tools take a description of robot behavior, typically in temporal logic, and automatically synthesize a robot controller guaranteed to satisfy the task, if one exists. Control synthesis enables users to reason about the overall behavior, then automatically creates the specific implementation for the robot. It automatically transforms complex behaviors (e.g. sequences of actions, reactions to external events, constraints on robot behavior) into code. It removes the burden of deciding a program structure, which is non-trivial and difficult for non-programmers, and eliminates implementation errors. However, using existing control synthesis tools requires understanding of temporal logic and typically lack an interface to easily to express the desired behavior, prohibiting novice users from taking advantage of control synthesis.

To address these gaps, we present Just Express Specifications, Synthesize, and Interact (JESSIE), an end-to-end system that enables programmers of any level to quickly and easily program social robots to exhibit complex behaviors. JESSIE leverages existing control synthesis methods coupled with an accessible high-level specification interface to enable users to specify and synthesize social robot controllers which afford personalized activities, reactions, and behavioral constraints. Thus, users need not concern themselves with specific implementation details or individual robot actions, and can instead focus on overarching goals (e.g. therapeutic).

To demonstrate our approach, we implemented our system on a Kuri robot in the context of developing cognitive training treatments for people with mild cognitive impairment (MCI). MCI is an intermediate state between typical aging and dementia which can cause challenges in cognitive functioning (see Section 2.1).

We evaluated JESSIE with six neuropsychologists, its envisioned end-users. Overall, participants without prior programming experience successfully created personalized, interactive therapies for people with MCI (PwMCI), and reported positive comments with regard to its usability. Furthermore, they gave suggestions for improvement including increased support for personalization, varying the robot's status, and collaborative goal setting (Section 5).

The contributions of this paper are as follows: First, we present an end-to-end system that allows non-programmers to specify complex robot behavior through a tangible interface, and automatically generates the associated robot control. This will help inform future real-world HRI research by enabling on-the-fly robot customization. Second, we demonstrate JESSIE in the context of cognitive therapy for MCI, an important application area for social robotics. We report our findings from our evaluation with six neuropsychologists, representative end-users who did not have prior programming experience. To our knowledge, this is the first evaluation of a control synthesis framework by end-users. Third, we demonstrate the reproducibility and extensibility of the system by executing a clinician-created behavior on another platform, the TurtleBot 2. Finally, as an artifact to support reproducibility for other HRI and robotics research contexts, all software, documentation, and supplemental materials discussed in this paper are available as open-source at https://github.com/UCSD-RHC-Lab/JESSIE.

2 BACKGROUND

2.1 Neurorehabilitation and MCI

We focus on using a robot to support neurorehabilitation for PwMCI at home. MCI is a stage between typical aging and dementia, and the prodromal stage for several neurodegenerative disorders, including Alzheimer's disease and vascular dementia [62, 69]. PwMCI struggle with instrumental activities of daily living (IADLs), including problem solving and managing medication and finances. Up to 20% of people aged over 65 experience MCI, and annually 10-15% of PwMCI convert to dementia [35, 58, 86]. There are currently no pharmacologic treatments that lower this [36, 53, 70], so many are exploring non-pharmacologic interventions [57, 71].

Behavioral treatments can improve cognitive functioning, slow the onset of disability, and prolong the independence of PwMCI [11]. Cognitive training (CT) is particularly effective [50, 52]. It teaches PwMCI metacognitive strategies to minimize the impact of MCI on their daily lives, such as planning techniques and environmental re-organization. CT personalization is critical to maximize applicability to individuals, thus improving engagement and sustainment. Our work facilitates this by enabling clinicians to specify a variety of games to help PwMCI practice different cognitive strategies with the robot, and change how the robot reacts to the PwMCI.

We teamed with neuropsychologists interested in building robots to be deployed longitudinally in the home to support CT. We developed a tangible specification interface (Section 3.4), that enables them to write high-level specifications for a social robot and incorporate the types of CT they view as clinically relevant.

2.2 Control Synthesis

Control and program synthesis are techniques to automatically transform high-level specifications into control or programs guaranteed to satisfy the specification. In robotics, researchers typically use different temporal logics to express tasks and automatically transform them into robot behaviors [55]. Thus, users can reason about the robot's overall task rather than implementation details.

In this work, we build on reactive synthesis from linear temporal logic (LTL) specifications [34]. Roughly speaking, LTL formulas are composed of atomic propositions (Boolean variables), logical and temporal operators as follows:

$$\varphi ::= \pi \mid \neg\varphi \mid \varphi \vee \varphi \mid \bigcirc \varphi \mid \varphi \,\mathcal{U}\, \varphi$$

where "not" ($\neg$) and "or" ($\vee$) can be used to create "and" ($\wedge$) and "implies" ($\rightarrow$), and the temporal operators "next" ($\bigcirc$) and "until" ($\mathcal{U}$) can be used to create "eventually" ($\Diamond$) and "always" ($\Box$).

The formal semantics of LTL formulas can be found in [34]. Intuitively, a formula $\bigcirc\varphi$ is true if φ is true in the next time step, $\Box\varphi$ is true if φ is always true during the execution, and $\Diamond\varphi$ is true if at some point in the execution, $\Diamond\varphi$ is true.

LTL allows users to encode assumptions about the behavior of the robot's environment (e.g., the state of the PwMCI) and requirements on the robot behavior (e.g., if the PwMCI is not engaged, play music). Furthermore, there exist algorithms that automatically transform an LTL formula into a finite state controller [55] that is then used for robot control. For computational reasons, we use the GR(1) fragment of LTL [14] as the underlying formalism.

We leverage free and open-source tools for LTL synthesis and execute the resulting controller with the Robot Operating System (ROS [77]). For LTL synthesis, we use slugs [33], which computes a symbolic representation of the controller from the specification. At runtime, slugs provides the next state for LTLstack [96] to execute.

LTLstack is a tool for mapping the propositions in the LTL formula to ROS nodes and executing the synthesized controller. At each time step, LTLstack reads information from the sensor nodes, finds the next state in the controller, and activates behavior nodes.

2.3 End-User Programming

End-user programming (EUP) methods enable those with limited or no programming experience to write programs, and provide visual, aural, tangible, and tactile interfaces for programming [8, 9, 24, 48, 61, 68, 84, 85]. A main concept in EUP is empowered computing – allowing users to personalize systems to their needs and preferences [37]. They are used widely in educational contexts [40, 47, 65, 88], and are used in HRI, home automation, and healthcare contexts [16, 17, 19, 26, 29, 39, 41, 49, 64, 67, 73, 83, 84]. However, these methods are typically procedural, so users require a basic understanding of coding constructs. Thus, creating a correct implementation with the desired behavior is highly dependent on the user's coding skills. For simple behaviors (e.g. sequencing actions), users of all levels can produce programs with minimal instruction. However, increasing complexity of implementation (i.e. there are conditionals and possibly conflicting behaviors) can lead to incorrect programs and excessive testing before achieving the desired behavior.

In robotics, visual programming environments (VPEs) are the most commonly employed EUP technique [2, 26, 29, 32, 38, 39, 49, 60, 64, 67, 74]. For instance, Choregraphe [75] is used to program robots such as Nao, and TagTrainer [90] is used to create rehabilitation exercises. VPEs such as these require users to reason about the implementation of the code - *for* and *while* loops, *if* statements, etc. In contrast, JESSIE provides a specification interface to the user and automatically generates the code implementation. Reasoning at the specification level enables users to specify constraints, such as what the robot should not do, reactions to external events (without worrying about the code structure to implement them), sequences, conditionals, etc. While anything specified in JESSIE can be written as code in a VPE, reasoning about the required behavior rather than the implementation of the behavior lowers the barrier of entry for end-users, such as therapists, to create custom robot behavior.

While there is recent work on incorporating formal methods (e.g. model checking for verification, SMT solvers for synthesis) into such languages [73, 74], the use of reactive synthesis as we employ in this work (i.e. generating a controller with multiple possible correct executions rather than a trace) has not been demonstrated.

Due to disparate backgrounds of stakeholders in our application domain, including people with low technology literacy [21, 59], we implement a card-based tangible specification interface inspired by prior work [8, 13, 24, 47, 48, 61, 65, 84, 85]. Tangible EUP systems typically feature icons on blocks that are strung together in sequence, similar to what JESSIE supports, but unlike our work, tend to be procedural. While a few tangible EUP approaches have been demonstrated in therapeutic contexts [15, 31], to our knowledge making control synthesis accessible to this population is unexplored.

3 SYSTEM OVERVIEW

JESSIE enables end-users to specify high-level robot behavior, such as constraints and reactions, and automatically generates and executes a robot controller using LTLStack. It comprises ROS nodes representing sensor information and behaviors for a social robot, made accessible to users through a tangible specification interface. We implemented JESSIE in the context of cognitive training programmed by neuropsychologists and administered via a Kuri robot.

3.1 Proposed Approach

JESSIE is comprised of LTL synthesis with a tangible specification front-end to enable novice programmers to leverage control synthesis to program robots via high-level specifications. These specifications enable programmers to define desired robot behavior without grappling with unfamiliar code or creating the implementation. Additionally, the synthesis approach is correct-by-construction, so the generated controller is guaranteed to satisfy the specification, eliminating "bugs" that may be introduced by novice programmers.

One goal for our specification interface is to clearly convey the possible robot actions and behaviors, as well as how each one fits in the overall program execution. As people may not be familiar with the robot's capabilities or fundamental computer science concepts (e.g. conditionals), we abstracted these ideas in an intuitive form while still communicating the robot's possible behaviors. In neurorehabilitation, the ability to quickly develop unique programs is essential for clinicians to create customized programs for each individual they work with, each with distinct needs and preferences.

3.2 Computational Back End

3.2.1 Specification to Execution Flow. Fig. 2 summarizes our use of LTL synthesis via a specification interface. First, the end-user programmer uses our tangible interface (Section 3.4) to define the robot behavior through activities, or *activity modules* (e.g. play music, play a number game) (Section 3.2.2). They can also specify constraints for behaviors (e.g. congratulate the user only when they achieve a high score on a game). Then, JESSIE automatically transforms these activities and constraints into LTL specifications by reading the identifying QR tags to determine the order in which the cards were placed. LTLstack [96] then calls slugs [33] and synthesizes a controller to execute the specified activity nodes and reactive behaviors based on sensor input at runtime (Section 3.2.3).

3.2.2 ROS Nodes. The specifications are transformed into LTL formulas over a set of atomic propositions. These propositions are grounded to sensor data and robot behaviors, used to execute the controller. We consider three types of propositions and their grounding as ROS nodes: *Activity module* nodes represent behaviors the robot can execute during the session (e.g. give a greeting, practice number game). *Activity completion* nodes signal the completion of

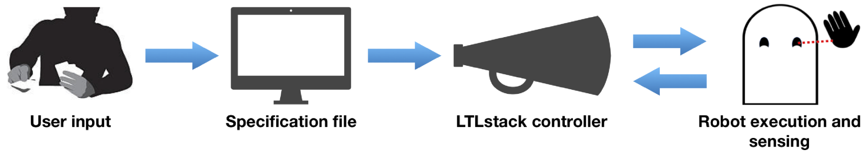


Figure 2: Overview of JESSIE. Users specify the robot's activities and behaviors with our tangible interface. A specification file is then created which includes the desired sensor and actuator nodes, the robot's initial conditions, event ordering, and sensor-reaction maps. LTLstack then synthesizes a controller to execute the associated ROS nodes.

activity modules. *Sensor* nodes are associated with stimuli the robot should respond to (e.g. whether the person touched the robot).

Activity modules represent a particular action which clinicians can have the robot execute. They choose the order of activities for interactive sessions (e.g. they can create a program to first play a number game then congratulate the PwMCI on their performance). These modules consist of dialogue, movement, and other actions. For instance, the *Greeting* module utilizes Kuri's ability to move its head, speak, and play sounds to convey excitement about meeting the person. In the *Mindfulness exercise* module, Kuri asks the PwMCI to close their eyes, then talks them through a script to improve self-awareness. When executed, each activity varies in duration, spanning from between a few seconds to up to ten minutes.

Clinicians can also use activity modules to specify robot reactions to sensor stimuli. For instance, rather than always congratulating the PwMCI after a game, clinicians may choose to do so only if they scored above some threshold. We created 14 activity modules, including cognitive training games and mindfulness exercises developed with input of our clinical collaborators [51], giving greetings, providing instructions, and administering cognitive assessments.

Each activity module node has a corresponding completion node to signal when that activity has completed. While these nodes are necessary for LTLstack to transition between a sequence of activities, we automatically create and link one to each activity. Thus, users need not worry about their implementation or execution.

Sensor nodes enable the robot to perceive its environment. They leverage Kuri's built-in sensors to translate environmental data to a higher-level understanding of the person interacting with it. For instance, the *If tactile interaction...* node uses Kuri's capacitive touch sensor to detect when the person is physically interacting with it.

While we created these nodes specifically for our platform and application domain (Section 3.3), researchers can create other ROS nodes and cards for their desired application and platform by following the guide in our supplementary materials. We demonstrated the reproducibility of our system by implementing ROS nodes for a TurtleBot 2, and synthesizing and executing programs clinicians created for the Kuri. Actions and stimuli are mapped to the new platform (e.g. TurtleBot made a sound whereas Kuri nodded its head). These nodes can be found in our supplemental materials to enable a side-by-side comparison. Note that no other files were modified to execute our approach on a new platform.

3.2.3 Synthesis and Execution. For control synthesis and execution, we used LTLstack, which consists of ROS packages for running with correct-by-construction controllers [96]. It takes a mapping between propositions and ROS nodes and a slugs specification file (LTL formula), and generates and executes an associated controller by listening to sensor and completion nodes and activating activity nodes. The specification file encodes the constraints and requirements that should be satisfied throughout the program's execution, including environment assumptions and system guarantees [14, 33].

To our knowledge, JESSIE is the first end-to-end reactive synthesis framework demonstrated in an HRI context, and the first evaluated by end users. This evaluation informs future control synthesis specification and framework design (Section 5).

3.3 Platform

JESSIE is intended to facilitate reproducibility and systems engineering in HRI, and thus is intended to be used on any platform and within any context. In this work, we demonstrated our system on Kuri, a social robot from Mayfield Robotics (Fig. 1), in the context of neurorehabilitation. It contains a multitude of sensors to perceive its environment, including an RGB-D camera, microphones, and bump and touch sensors. It can communicate through numerous modalities, such as expressive eyes, a multi-color chest light, speech, motion, and sound. To minimize the risk of older adults tripping over Kuri, we deploy it as a tabletop robot, though it is capable of being mobile as well. Kuri runs ROS Indigo on Ubuntu 14.04.

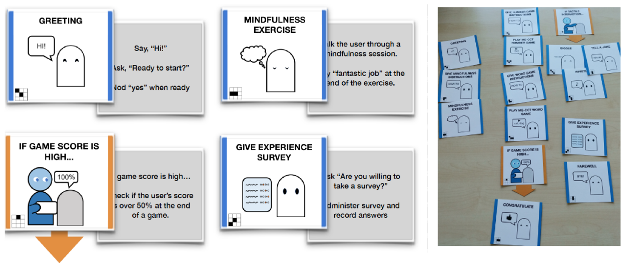
We developed an iPad application (iPad Air, iOS 12.4.1) that connects to Kuri via a websocket as another means of interaction. Clinicians do not interact directly with the Kuri or iPad; they control the behavior and display by selecting which activities to execute.

3.4 Tangible Specification Interface

We created a tangible specification interface as an intuitive way to program social robots via control synthesis. Users simply input actions and reactions, with no need for extensive training or external programmers. Thus, clinicians can create custom treatments for PwMCI via high-level specifications without altering source code.

We designed the interface to be both intuitive and descriptive so it is easy to learn while encompassing the actions of an interaction. Each card depicts a symbol and short descriptor (Fig. 3, left) that represents actions programmers may include, associated with ROS activity module and sensor nodes described in Section 3.2.2. Activity module nodes are blue, and sensor nodes are orange. The arrow on sensor nodes reflects conditionality, analogous to the logical "implies" symbol. Each card has a unique marker to facilitate the automatic translation from cards to specifications to code.

Programmers may place activity cards in any order, from top-to-bottom, left-to-right (Fig. 3, right). Sensor cards can be placed



Order of activity modules

$\neg greetingComplete \implies \neg minfulnessInstructions'$

$\neg minfulnessInstructionsComplete \implies \neg minfulnessExercise'$

$\neg mindfulnessExerciseComplete \implies \neg numberGameInstructions'$

$\neg numberGameInstructionsComplete \implies \neg numberGame'$

$\neg numberGameComplete \implies \neg wordGameInstructions'$

$\neg wordGameInstructionsComplete \implies \neg wordGame'$

Sensor nodes and reactive behaviors

$(scoreHigh' and \neg congratulateComplete') \implies congratulate'$

$(tactileInteraction' and \neg giggleComplete') \implies giggle'$

Figure 3: Left: Example cards and descriptions from our tangible interface. Blue cards are activities the robot can do; orange cards represent stimuli the robot can sense and react to. Right: A program created by a clinician and a partial implementation in LTL. Programmers lay out activity module cards in the order of execution they desire, in addition to reactions to stimuli.

anywhere, as they run in parallel with main activity modules. Users simply place the desired reaction below the sensor card, such that the arrow points to it. Then, the sensor nodes will allow the robot to react to the associated stimuli throughout program execution.

4 EVALUATION

To evaluate the JESSIE system and determine how to improve it, we conducted a study with six neuropsychologists interested in using it. We assessed the system's usability, specifically for clinicians with no programming experience. We taught participants how to use our specification interface to create a program, then allowed them to design their own sessions for PwMCI to complete with Kuri. Our study was approved by the UC San Diego Institutional Review Board, under protocol number 181341.

After giving informed consent, we introduced participants to Kuri and gave an overview of the study. As most participants did not have experience with robots, we showed them a video demonstrating some capabilities they can use in their programs. We then explained how to use our tangible interface, computer science concepts (e.g. conditionals), and actions Kuri can perform.

We then began the programming phase. We asked participants to create an interactive session for a PwMCI they are working with and encouraged them to ask the researcher for help if needed. We recorded the time it took participants to complete their programs. Then, they watched Kuri execute their program[1]. To conclude the session, we conducted an open interview to receive feedback on our system, including ease of use, how often they would recommend people interact with it, and other features they would like implemented in the future, and they completed written questionnaires.

We employed mixed methods approaches in our data collection and analysis. Quantitative measures included the System Usability Scale (SUS) score [18] which measures perceived usability, task completion time, and card usage. Qualitative measures included post-study interviews and researcher observations of challenges participants faced during the study. Questions we asked included *Would you consider using this kind of system to support your work?*, *What other features would you like to see implemented?*, and *Did you feel like you could express the robot behavior you desired with the card-based language?* We recorded and transcribed all interviews.

[1]Automatically generating specifications from the tangible interface was not fully implemented during evaluation, so a researcher conducted a manual translation. Automatic translation is now complete and available in our open-source code.

Two researchers employed a grounded theory [22] approach, and individually coded the audio recordings to find emerging themes through an inductive coding process. They then compared codes and identified three overarching themes among the participants, specifically: increased support for personalization (Section 5.1), means to longitudinally vary the robot's operating mode and interaction style (Section 5.2), and collaborative goal setting (Section 5.3).

5 RESULTS

We recruited six clinical researcher participants through word of mouth, all of whom work with PwMCI. These included four neuropsychologists, a psychiatry professor, and a research coordinator. Five were female and one was male; their ages were 28-49 years old (mean = 34 years, SD. = 7.67 years). They had between 14 months to 23 years of experience working with people with cognitive impairments (mean = 6.53 years, SD = 8.31 years), had little to no general programming experience, and none had ever programmed robots.

All participants were able to successfully program at least one interactive session for a PwMCI, each of which could run to completion on Kuri. Four participants each created one program, and two participants each created two programs, yielding a total of eight programs. These programs can be found in the supplementary materials. On average, participants spent 2:15m (SD = 1:40m) creating a program. They spent an average of 12:35m (SD = 7:45m) viewing their programs. They used an average of 8.25 cards (SD = 4.37) with an average of 7.38 activity cards (SD = 3.78) and 0.88 sensor cards (SD = 0.83) in each program. *Greeting* (8) and *Congratulate* (8) cards were used most often, and *Tell a joke* (1) and *Sneeze* (0) the least.

On SUS, participants scored JESSIE an average of 90.83 (SD = 9.31) which is above average compared to other systems [6]. Participants described using the system as, "easy," "simple," and "straightforward". One participant commented: *"I've never interacted with a robot before, so it's brand new for me, but it's easy to use. I thought it was fairly engaging."* Overall, no participants explicitly expressed frustration or confusion using the system, though they suggested improvements, discussed below. While several of these suggestions can be easily incorporated into the JESSIE system by creating more ROS nodes, other articulate future research directions.

5.1 Increased Support for Personalization

Personalized sessions are critical for PwMCI because their needs and goals can change as their condition progresses [23]. Participants described a range of different PwMCI for whom they imagined using the system, such as people managing comorbidities (e.g. heart disease) interfering with their planning abilities, and people living alone who often forget to bring important objects when they went out. Participants suggested three main ways JESSIE could be extended to enable increased personalization: feedback customization, communication modalities, and adaptation.

5.1.1 Feedback Customization. The frequency and type of feedback the robot provides can greatly impact people's engagement and perception of it [23], so it is imperative that it provides personalized feedback and encouragement. Participants stated that feedback style can significantly impact the PwMCI's recollection of different cognitive strategies and how they apply them outside of treatment. For example, the robot could vary its feedback depending on the activity type and person's performance. One participant explained: *"In the word game... if the robot could give [the PwMCI] feedback... 'When you use this strategy, you really benefited and your recall is better.'... For the number game, ... [therapists] will give more trial-by-trial feedback, [so the robot could give] some indication that [the PwMCI] had gotten one wrong and [needs] to get back on track."*

In contrast, clinicians may not always want the person to receive immediate feedback. For instance, a participant who primarily conducts research assessments for PwMCI stated, *"We don't normally tell [PwMCI] how they perform, ...during the research tests, [we] don't want them to know how they're doing, because it could discourage [or encourage] them on the next test "*

5.1.2 Communication Modalities. Depending on the person's sensory abilities and personal preferences, they may require the robot use and respond to different communication modalities. Participants wanted to be able to specify which modalities the robot use at a given time or for certain populations. One participant expressed, *"For older participants, it might be nice to have some more verbal cues, in case they don't keep up with the robot."* However, they also mentioned that during certain activities, such as mindfulness where Kuri asks the person to close their eyes, visual output on the tablet may be distracting. Thus, more control over each modality, such as speech, the tablet, and movement, would help clinicians tailor each session to individual needs and preferences.

In addition to the tablet, participants discussed other ways PwMCI could communicate with the robot, both explicitly and implicitly. One commonly requested modality was speech, especially as an alternative for people with tremors or difficulty spelling. They also suggested that the robot sense different behaviors about the PwMCI to infer their state, such as sedentary time, social activity, and mood.

5.1.3 Adaptation. It is important for the robot to be able to adapt to the PwMCI, especially as their preferences, cognitive abilities, and moods may change over time, in order to keep them engaged and support consistent interaction with the robot. As one participant suggested, *"Depending on a particular person and what they like, their strengths and weaknesses, the robot might say different things or suggest different strategies."* And another said: *"If the participant seems frustrated, [it could] give them encouragement... if they scored low [it could say], 'Don't worry. Not everyone gets them all right.' "*

Another important aspect of cognitive training is forming habits to routinize tasks [50], so participants wanted the ability to specify the frequency and schedule of activities. Then, either the clinician and PwMCI could work together to define a schedule, or the robot could facilitate scheduling. Participants also wanted to tailor the length and difficulty of activities to help them better integrate with a person's schedule, and thus better support adherence.

5.2 Varying Robot Status

All participants indicated that being able to change the state of the robot at various points would be useful. Since MCI can be progressive, people's needs, goals, and abilities can change over time. Thus, participants identified three categories for which they might want the robot to differ its interaction style, discussed below.

5.2.1 Staged Robot Deployment Support. Depending on the MCI stage, clinicians may have different goals for the robot, such as monitoring, education, or intervention delivery. One participant mentioned, *"The first work we do [with PwMCI] is getting their patterns down. Sometimes they can provide you with what a typical day looks like, but they might be over or underestimating... The first step would be to use Kuri to play more of an observational role in their home environments."* This can also help clinicians identify the ideal intervention strategy. *"Part of us identifying interventions is, how can we help individuals remain independent?"* Thus initially, the robot could observe the PwMCI to help clinicians understand their behavioral patterns and establish a baseline for usual behavior.

Once a baseline is established, the robot could transition to educating the PwMCI on how to navigate their life with MCI, and support independence. For instance, it can help PwMCI form habits and stick to a schedule, which our participants noted is an important step to living with MCI. *"Perhaps they're beginning to form those habits. That's done by pairing it with day-to-day activities that have become habitual, so [these] things don't rely on memory as much."* During this stage, it may also be more explicit when communicating the reason behind each activity. One participant noted that, *"I liked when it gave a break, that it also explained the benefits of taking breaks, because I know that's part of the [cognitive training]."*

As the MCI progresses, the clinician may want to use the robot for further intervention, and allow the PwMCI to rely on it more. For instance, *" If this can help someone retain some level of efficiency and functioning, I think that'd be really important. I'm definitely thinking of those who are on the extreme end of the impairment spectrum."* To help facilitate these stage transitions, clinicians wanted affordances to manage different programs and settings on the robot.

5.2.2 Active vs. Passive Robot Interaction Style. An open problem in HRI is how active or passive a robot should be during interaction [46, 66]. Our participants also raised this concern, particularly when the robot is interacting with the PwMCI. Participants noted that at first, the PwMCI may be more independent, so a passive approach would probably be preferred. They suggested the robot conduct observations, and inform the PwMCI during their normal interactions if any different behaviors were observed.

In other cases, the clinician may want the robot to take on a more active role and give the PwMCI suggestions about how to handle their condition. For instance, a participant suggested having *"moments where we're checking in and saying, 'Well, how stressed are you feeling?' Or, 'How is your mood right now and how much have* *you exercised so far?' Those could be moments where we tell them it's time to go on a walk rather than just monitoring their behavior."*

Participants also discussed initiative - should the robot initiate interaction, or wait for the PwMCI to do so? They imagined being able to leverage Kuri's physical embodiment to have it prompt people when it is time to begin the session. *"But the benefit potentially of having this kind of thing is that... it could remind the patient to do the [activity]."* Another participant mentioned that at set times each day, *"It would present an option of 'Would you like to play the word game now? Yes or no.' Then provide those word game options."*

Other times, it might make sense for the person to initiate engagement with the robot. Participants wondered how this might occur given the varying ability levels of PwMCI. For instance, *"I'm wondering [if] somebody who might be not as mobile would maybe need to wave their hands to get its attention. Or if they're not even able to do that well, are there instructions such as saying, 'Kuri', or a specific codeword that activates the robot."*

5.2.3 Research vs. Intervention Mode Switching. Many of our participants work with PwMCI across both clinical and research contexts, which each have different goals, and the role of the robot in them may change significantly. Thus, clinicians wanted a way to easily create and switch between *"modes"* on the robot.

The first main context for which participants imagined using the system was for clinical intervention. In this context, *"We are interested in what sorts of problems [people with MCI] are having in their daily life. And then the intervention, we use it as sort of like a crutch to help people who already have some impairment. We can't cure their impairment. We can teach them strategies to get by."* In intervention mode, PwMCI would regularly interact with the robot in their home, as prescribed by the clinician.

5.3 Collaborative Goal Setting Support

Participants wanted ways to collaboratively set goals with PwMCI. This is an important aspect of cognitive training, where clinicians and PwMCI work closely to identify goals in training, and set actions to address them [4]. Participants identified three types of relationships where this may occur: the clinician and PwMCI, the robot and PwMCI, and between clinicians. These activities might occur in clinic or at home, and may be clinician-led or PwMCI-led.

5.3.1 Clinician - PwMCI. Participants expressed interest in a way of working with PwMCI to create sessions that support their goals by specifying aspects such as schedules, activities, and reminders. For instance, one participant mentioned that during a session, they *"work with the patient in developing the [session]. 'Based on your routine and the time you get up, what time do you think we should have this thing remind you to take your medications? Or check the mail?"* Similarly, *"A clinician and the patient can collaboratively work to decide, 'We are noticing these are your patterns. We've identified these patterns are certain risk factors or protective factors. Let's work towards helping Kuri to be that point of contact when you're at home. How can we set up these cards to then help nip certain behaviors in the bud before they turn a little bit more worrisome?'"*

Alternatively, the clinicians could also specify higher-level goals for or with PwMCI, then allow them more freedom to choose specific activities. One participant suggested, *"They could pick, 'Today I want to do a [mindfulness exercise].' Or I could pick, 'Today I want them to [practice mindfulness].' Or focus, attention, exercise, [etc.] "* Another participant stated, *"I think there should be several standard things that could be informed by what we know of the patient population that this is being targeted towards. Then certain customizable options that talk about how certain instructions can be changed or activities can be changed but the underlying programming wouldn't change."* Then, the person could choose a specific activity that exercises the broader area each time they interact with the robot.

5.3.2 PwMCI - Robot. Participants discussed how the PwMCI might work with the robot to develop their goals and cater to their preferences. As the clinician will usually not be with the PwMCI when they interact with the robot, PwMCI need ways to work directly with the robot to develop and assess their goals. For instance, one participant mentioned, *"Kuri can [...] recognize those patterns together and intervene in those moments of providing that feedback to that person to be able to help them assess points to improve."*

However, they noted that the card-based specification interface might not be the best means of interaction between the person and the robot directly, particularly those who are not familiar with technology. While participants believed they might be able to create an activity using the cards, they also mentioned that they might have trouble taking a picture of the program for the robot to process and execute. Instead, they suggested allowing the person to interact with the robot primarily directly through the tablet or verbally.

5.3.3 Clinician - Clinician. PwMCI may be working with multiple healthcare providers in addition to a neuropsychologist, such as their primary care physician. Our participants were mindful of this, and suggested that our system allow for multiple providers to program the robot. *"I'm not a primary care physician, so I don't know what that person might need in terms of exercise, or what their physical limitations might be. I'm not allowed to prescribe an hour of exercise a day. So there might be [...] a way for multiple providers to program [the robot]."*

6 DISCUSSION

By making the benefits of control synthesis accessible, JESSIE enabled clinicians, who had no prior experience programming robots, to program cognitive therapy sessions with personalized activities, reactions, and constraints after little time, training, and without errors. Our observations and assessments of participants' experience with JESSIE suggest that our system enables novice programmers to leverage control synthesis techniques to create complex, interactive sessions on a social robot, which would take more time to write and test with procedural programming languages.

Our evaluation using Kuri to execute programs written by clinicians, and the subsequent replication and execution of these programs on a TurtleBot reflects the reproducibility and extensibility of our approach to numerous robot platforms. Researchers can modify our provided ROS nodes to replicate our behaviors on different platforms, or create entirely new behaviors to leverage our approach for many different applications, such as in manufacturing or entertainment. The approach presented in this paper will expand the accessibility of control synthesis for social robots for people of all programming skill levels across many domains.

6.1 Key HRI Considerations

In our discussions, participants raised some crucial HRI concepts that have yet to be thoroughly explored, which we discuss below.

6.1.1 Robot Roles. Since a person's needs and goals may change as the MCI progresses, participants imagined the role of the robot would change accordingly. For instance, they envisioned the robot would take a passive role during the beginning stages of the condition, such as monitoring the person's baseline behavior. As their condition progresses and they need to rely more on the robot, it could take a more active role in educating them about different cognitive strategies, completing interactive sessions, and serving as a virtual assistant. The ability to fulfill different roles is a fundamental aspect of adapting to the individual's needs and preferences. This capability to shift between the foreground and background when interacting with the PwMCI aligns with other HRI research.

Participants also discussed how PwMCI may see the robot as a "companion" as they complete the cognitive training activities. This raises the question of the robot's role in the relationship between the clinician and PwMCI. Whether the robot should be a companion, serve as a point of connection between them, or act as a personal assistant, programming languages and robotic systems need a way for programmers to specify and explore this concept of robot role.

Participants suggested ways the PwMCI might initiate the interaction with the robot as well as how the robot could initiate the interaction. As suggested by other HRI research [1, 66], the initiating party and methodology depends heavily on factors such as the robot's role. This work helps to inform the problem of initiative, particularly in longitudinal HRI where users interact with the robot over long periods of time. Additionally, it is currently unclear how we might design a language to reflect this sort of robot behavior.

6.1.2 Timing. The concept of timing is an important aspect of social interaction and robotics research. Participants identified multiple levels of timing to specify for different people and purposes, such as scheduling trial-by-trial feedback, feedback after numerous sessions, and setting the duration of different activities. Thus, our system may need to integrate complex representations of timing to give programmers more control over the timing of activities. However, the specifics of how these details can be both implemented within LTLStack and reflected in the tangible interface requires further research, the results of which will improve the accessibility and expressivity of end-to-end systems for social robots.

6.1.3 Multi-party programming and longitudinal HRI. In addition to supporting a single novice user programming a robot to perform a task in longitudinal HRI settings, our study illustrated that multiple stakeholders with different goals and backgrounds may need to program the robot at various points throughout its deployment, including neuropsychologsts, PwMCI, family members, and other clinicians. This raises a series of interesting questions about how to support these differing needs within a system like JESSIE, particularly with users (PwMCI) who may be experiencing rapid changes to their brains in ways where it is difficult for others to keep up.

6.1.4 Cultural Considerations. Cultural background plays a key role in determining an individual's preferences, such as the robot's communication style [56, 92]. For instance, in Western culture, the robot may adopt a more direct, proscriptive communication style. Contrastly in Finland, where people tend to have more reserved communication styles [63], people may prefer a more passive robot. Even non-verbal aspects of communication (e.g. eye contact) may impact a person's interaction with a robot. This can significantly impact adherence to treatment plans [45] and robot adoption. More research is needed to explore how to support this variablity.

6.1.5 Ethical Considerations. As we designed this system to support PwMCI, a vulnerable population, there were several ethical considerations that arose in our discussions with participants. Many participants wanted the robot to monitor PwMCI and send reports back to the clinician. They imagined the robot could monitor daily patterns to establish baselines and identify abnormal behavior, as well as to produce compliance reports about treatment adherence. While this may have clinical benefits, it raises privacy concerns, particularly for people whose MCI is more advanced or who may have lower levels of technological literacy, which impacts informed consent [42, 66, 78, 91, 93]. This requires thoughtful consideration and additional research to identify how to best balance these potentially conflicting constraints both with JESSIE and more broadly.

6.2 Limitations and Future Work

There are some limitations of this work that must be considered researchers build on our system. First, we only tested with our expected end-user, neuropsychologists. While their input was invaluable for our particular system and context, other end-users may want other features implemented for their applications, and constraints unique to their domain. Additionally, we pre-programmed activity module and sensor nodes to represent behavior specific to cognitive training. To alter existing behaviors or create additional ones, one needs some familiarity with ROS and Python or C++. Nevertheless, JESSIE is a simple and accessible means for novice programmers to specify high-level robot behavior for PwMCI.

As we continue to research this area, we plan to continue an iterative design process with stakeholders, including usability improvements, longitudinal deployments, and evaluations with PwMCI.

6.3 Conclusion

In this work, we presented JESSIE, an end-to-end system that affords control synthesis techniques to enable novice programmers to generate high-level behaviors for a social robot. Robots have shown great potential to support people with MCI [27, 72], and this system will extend the scalability, accessibility, and personalization of social robots. Additionally, this paper presents the first evaluation by possible end-users of a system whose back-end employs control synthesis layered with a tangible front-end. The evaluation and feedback from participants shows that the system is easy to use and articulates future research challenges the community should address. As an open-source, intuitive way of utilizing control synthesis, and artifact to support reproducibility, this work will enable the robotics community to leverage our approach to customize robot behavior, adapt to end-user preferences, and promote longitudinal HRI within their own application domains. We hope that this work inspires researchers to make robot programming more accessible and collaborative, expanding the potential for robots to support people throughout the HRI community.

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