The impact of robot gestures on student reasoning about geometrical conjectures

BY

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THESIS

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Dedicated to my sister

I wish you were with me through this incredible adventure

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LIST OF ABBREVIATIONS

STEM	Science, Technology, Engineering and Mathematics
CASA	Computer Are Social Actors
GSA	Gesture as Simulated Action
LCD	Liquid crystal display
WBI	Web-based instruction
GUI	Graphical User Interface

SUMMARY

Robots are becoming an integral component of our society and robot-assisted learning has proved to be effective in promoting students' interest and learning in STEM subjects. An underexplored area of robot-assisted learning is how the physically embodied nature of robots can be utilized to support learning through non-verbal communication, such as gesturing. In this paper, we discuss the design and development of a NAO robot that supports geometry reasoning with gestures. We evaluate two different ways for a robot to interact with college aged students (N = 30) while reasoning about geometric conjectures, and randomly assigned participants in two conditions. In the dynamic condition, the robot uses dynamic gestures that represent and manipulate geometric shapes in the conjectures. In the control conditions the robot uses beat gestures that only serve to match the rhythm of speech. We found that learners in the dynamic condition use more gestures, and more dynamic gestures, themselves and spend more time focusing their attention on the robot. These results support the use of dynamic gestures in robot-assisted learning, and suggest non-verbal communication from robots can have a positive impact on student activity.

CHAPTER 1

INTRODUCTION

Education has become a major concern in people's lives. In particular, guiding students through their courses has become increasingly crucial in order to stimulate student career exploration and enhance their reasoning abilities. Unfortunately, a lack of motivation appears to have a negative impact on student performance in topics or fields related to mathematics, science, technology, and engineering (STEM). By 2019, it is estimated that 92% of traditional STEM occupations are expected to require some sort of post-secondary education, including some level of industry-based certification. [1]. While there is a growing need for STEM talent not just in the United States but across the world, numerous reports have suggested that the US is not doing a great job of aiding students who want to achieve STEM degrees. [2] and the main issues associated with this problematic situation is the lack of student academic preparation at during their studies. One of the reasons for this failure is the use of ineffective traditional learning methods [3]. In traditional education, professors and lecturers frequently utilize didactic lecture-based teaching approaches to deliver and explain material in courses [4]. Students are often sitting quietly, scribbling away as a teacher talks on and on, and even when they are asked to apply the learned information to a problem, they use the information in a systematic way to solve an arbitrary problem. This happens because students' focus is set in taking notes instead of understanding and engrossing new ideas. Moreover, instructors have an entire class to manage, hence a teacher's lecture is generally one-size-fits-all and cannot be dedicated to only one student [5]. Reduced school budgets, an increase in the number of students per classroom, and a demand for more personalized curricula for students are driving research into technology-based support that complements teachers' efforts. [6]. The importance of bridging the gap between the scientific character of STEM-related topics and the use of engaging teaching and learning methodologies was stressed by Rockland, et al. [7]. To meet the need for more engaging and effective learning approaches, our goal is to supplement traditional undergraduate education with robots designed to foster deeper thinking and reasoning in STEM, with a particular focus on geometry notions, describing the interactive process with the robot and the outcomes.

1.1 Educational Robot as Tutoring Agent

While in the past, robots were predominately used in factories for purposes such as manufacturing and transportation, in more recent years robots began to act as partners, assistants or companions of humans [8, 9]. Service robots are starting to cooperate with people, as Figure 1 shows, and assist them in their everyday tasks, including shopping, education, and companionship.

Figure 1: Pepper robot as shopping assistant [103]

Research in human-robot interaction has shown how readily humans ascribe social attributes to robots, and many service robots now interact with humans as social entities, referred to as social robots. The rise of social robots is thought to be due to their participation in social human contact. Social robots [10, 11, 12] are autonomous or semi-autonomous robots that interact with humans in accordance with human social conventions. The responsibilities of social robots are becoming increasingly diverse, according to researchers [13].

An educational robot is a specific application of social robots and may represent a unique alternative or support to traditional educational methods since a robot can be more affordable than a human tutor and can be dedicated to one student at a time. Robots are typically programmed with updated information, and they can be quickly reprogrammed or be given modified curricular approaches, therefore delivering students with the latest methodologies pertaining to any sector [14]. The flexibility of robots allows for a variety of uses in education. Some robots can be used as “learning assistants”, such as University of Hertfordshire’s intelligent assistant, Kaspar [15], while other can be used for “medical training” or “intelligent toys for pre-school children” [16], like Miko [17], shown in Figure 2, an artificial intelligence-based robot that can talk, respond, educate, and entertain kids. Overall, robot supported learning has been found to enhance both cognitive and affective educational outcomes [18].

Figure 2: Miko robot interacting with a child [104]

One of the major challenges in robotics is to recognize which kind of gestures are particularly important in human–human communication and emulate them in such a way that they add communicative value [19]. Because of the robot's presence in the social and physical surroundings, as well as the expectations the robot creates in the user, the employment of a social robot in education adds to this set of problems [18]. A great way to set appropriate expectations for the robot is to clearly define it's role, and using a low pressure peer or tutor role may benefit student engagement [20]. For this reason, in this study the robot was designed as a study companion capable of peer-to-peer interaction.

1.2 Design Criteria of Educational Robot

In this section we discuss the design of educational robots and in Table I we synthetize differences and similarities of educational robots, grouping them by their forms.

Form. Robot appearance can be categorized in three forms: humanoid, semi-humanoid, and pet-like. A humanoid form is conducive to forming gestures, since that type of non-verbal communication from robots may be best understood in familiar human form. For example, Nao [21] looks like a child, and encourage kids to interact. While humanoid robots walks on two robotic legs, semi-humanoid robots, such as Robovie [22], utilize wheels to move around. Pet-like robots may take the form of pets, animals, or fantasy characters. Pet-like robots are usually built with specific goals in mind, such as iCat, which is designed to give the user emotional feedback [33]. Some design elements, such as fur-like materials for pet-like robots and silicon for others, may be required depending on the robot's form. Robots would be covered in metal and plastic if they didn't have any additional "skin".

TABLE I: DIFFERENCES AND SIMILARITIES IN DESIGN OF EDUCATIONAL ROBOT

	Humanoid	Semi-humanoid	Pet-like
DOF	More than 20	More than 20	More than 20
Mobility	Two legs	Wheels	Paws or wheels
Interaction with gestures	Possible	Possible	Not possible
Speech recognition and speech synthesis	Depends on software	Depends on software	Depends on software
Sensors	Navigation and interaction sensors	Navigation and interaction sensors	Navigation and interaction sensors

Mobility. These education robots cover a big range of degrees-of-freedom (DOF). More than 20 degrees of freedom are common in humanoids, semi-humanoids, and legged pet robots. Two legs offer mobility for humanoid robots, while wheels give maneuverability and stability for semi-humanoids. The arms of humanoid and semi-humanoid robots can be utilized for gesturing and delivering feedback to the user, which is an advantage.

Interaction Capability. Robots must be able to engage with users in order to be a learning peer or instructor, hence speech recognition and speech synthesis are the most critical features. The user gives or receives instructions and feedback via voice processing software. While software plays a large role in gesture recognition, generating appropriate gestures to match the robot's audio is primarily a hardware challenge. Humanoids and semi-humanoids have an edge over pet robots in this sense. Only robots with arms can use gestures to communicate and give directions.

Sensors. Without the ability to detect its environment and users, full robot autonomy is hard to reach. Navigation sensors and interaction sensors are the two types of sensors available. In navigation, ultrasonic sensors are used to avoid collisions and help course planning. Collision avoidance can be aided by the installation of pressure and touch sensors on the feet and other body parts. Communication requires the use of a microphone and speakers. In robot vision systems, video cameras are frequently utilized as the physical eyes of robots.

1.3 The Role of Gestures in Education

One strength of a robot tutor is that it can be programmed to provide precise verbal and non-verbal communication, including the types of gestures it uses. Prior work in math education research has demonstrated that some beneficial gestures can aid in mathematical reasoning [97], suggesting that a similar situation can be recreated for geometrical reasoning. The use of body-based reasoning makes the robot especially helpful in supporting student reasoning about geometry, from an embodied cognition perspective [23]. Researchers support the idea that speech combined with body gestures, lead humans to develop higher-order thought [24, 25], supporting that this combination is a powerful and useful tool to inspect and understand how scholastic learning and performance can be improved [97]. A widespread problem in educational settings that do not support combination of speech and gestures, is the increasing difficulty that students demonstrate in constructing proofs, frequently basing their thought only on salient perceptual features or specific concrete examples [26, 27]. Recent embodied learning research has discovered that encouraging students to utilize productive gestures while reasoning about geometric proofs can help them think more clearly. [28]. As a result, learning how geometrical proofs are generated is an essential educational topic, and it may be particularly well suited to learn about the embodied and grounded nature of abstract cognition in general.

In this study we build on this work and aim to understand the benefits and process of reasoning that undergraduate and graduate students can have when the robot interacts with them using dynamic gestures compared with beat gestures. We analyze students' speech and gestures as they construct proofs for the two different conditions, focusing our attention on dynamic gestures, that are particularly relevant for geometrical proof, and on characteristics of student speech during proof production that can possess structural elements of deductive reasoning. This study adds to a growing body of knowledge about the use of speech and gesture as grounding mechanisms in geometric reasoning. Our findings on the impact of a robot using dynamic gestures while performing geometric reasoning activities will help researchers better understand how people construct and express geometrical proofs, as well as contribute to the fields of educational robotics, embodied cognition, and geometrics education.

CHAPTER 2

BACKGROUND

Robots are designed with human-like characteristics including language, personality, emotion, and gender. Individuals socially interact with computers equipped with anthropomorphic cues, behaving "towards computers as they might towards other human beings, although understanding instinctively that computers are not animate," according to the Computers Are Social Actors (CASA) study [29, 30, 31]. Users respond with social behaviors to robots, as robots are in social settings displaying social behaviors [32, 33, 34].

As robots become more popular in our daily lives, it is critical that we comprehend how these technologies can be applied in educational settings. Saerbeck et al. [35] explored whether social engagement with a robot interface might be used effectively in education. Their research involved an interactive cat (iCat, shown in figure 3) whose purpose was to teach a new language to a child. This platform has the appearance of a cat, and it stands at a height of about 40 cm. A socially supportive iCat was compared to a neutral iCat in the study. Students in the socially friendly iCat scenario were more motivated, which is critical for any instructional tool to be effective over time.

Figure 3: iCat shows different emotions

In March 2004, Han et al. of Korea built the world's first e-learning household robot (IROBI) [36]. IROBI, a humanoid robot with a head and torso, showed the potential of robots as a new medium for education. Voice and a touch panel were used to engage with IROBI. While performing this research, Han et al. contrasted common media assisted learning and WBI to Home Robot-assisted learning. When compared to the other instructional media, they found that IROBI was the most successful in fostering and enhancing the kid’s concentration, interest, and achievement.

2.1 Physical Embodiment and Social Presence

Numerous research have indicated that a physical robotic embodiment can boost the effect of being viewed as a social interaction partner [37]. In comparison to identical robots with a digital embodiment, several studies [38, 39] found that robots with a physical embodiment have a beneficial influence on feeling the robot's social presence. When interacting with a robot, users' experiences are knitted together by characteristics including embodiment, social presence, reciprocity, and rapport [40]. Based on the findings of Segura et al. [41], Deng et al. [42] trace the relationships between embodiment, social presence, and rapport: “...for tasks that are relationship-oriented, social engagement is important for maintaining rapport, and physical embodiment is beneficial for increasing social presence, and in turn, engagement and rapport.”

In a learning setting, the physical robotic embodiment is excellent for a student interacting with a robot tutor. As a result, research has been performed on implementing social qualities [43] in educational robots [35, 44] in an effort to assess the RBE strategy. Robots are presently being utilized to teach math [45], history [44], new languages [46], and new tasks [47] in the field of education. Some studies change the robot's feedback (positive, negative, neutral) and behavioral tactics [48], while others change the type of learning adaptation [45]. Students are more involved when it delivers positive feedback [35], [44], are more inclined to learn from it when it provides personalized learning [45], and have better recall capacity when the robot uses particular behavioral strategies to capture them. [48].

2.2 Benefits of Robot as Peer

Peer learning is a bi-directional reciprocal learning activity in which students actively aid and encourage one another to gain knowledge and skills [49]. Learning with peers has the potential to provide learners with unique motivational and cognitive benefits [50]. Peer tutoring has been found to benefit both a peer tutor and a peer tutee, enhancing self-esteem and social adjustment in both [51]. As a result, students who actively participate in both roles in peer learning are more likely to gain from the learning interaction. Mutual peer engagement using social robots is a newer paradigm that has been found to improve student learning [52, 53]. A mixed-initiative peer-like dialog agent was created in a project to help college students acquire Computer Science fundamentals [53]. By shifting task initiative, the agent acted as either a less knowledgeable or a more knowledgeable peer (i.e., who is contributing to achieve a goal). A fixed rule-based model was adopted to identify when to switch initiative within a collaborative problem-solving setting in order to build this reciprocal peer agent model. Based on our previous research, we believe that interactions with a peer robot, which led student to be at the same time a tutor and a tutee of the robot, can foster student learning and social engagement more effectively than interactions with a robot that is either a tutor or a tutee.

2.3 Robot Appearance and Behavior

Because the physical presence of the robot is responsible for the good learning outcomes, the question of what exactly it is about the robot's presence that enhances learning remains unanswered. The appearance of a robot [54, 55], its nonverbal behavior [56], and other behavioral features all influence how a robot is judged (e.g., predictability: [57] etc.). In terms of behavior, the robot's level of interaction skills should have a significant impact on people's opinions for various reasons. Firstly, in contacts with non-human entities, general conduct appears to play a significant role. [58]. Moreover, for a social robot to perform its purpose, interaction skills are required [59], and in Davis's research [60], a perceived usefulness of technology is related to people's attitudes toward and intentions to utilize it, as shown in figure 4. If a robot has poor interaction skills, the interactions with it will be judged in a different way than when the robot has excellent interaction skills. The way in which a social robot interacts with people may be a major factor in people's evaluations of the robot. According to Rickenberg and Reeves [58], the evaluation of a character "depends on what the character does, what it says, and how it presents itself" (p. 55).

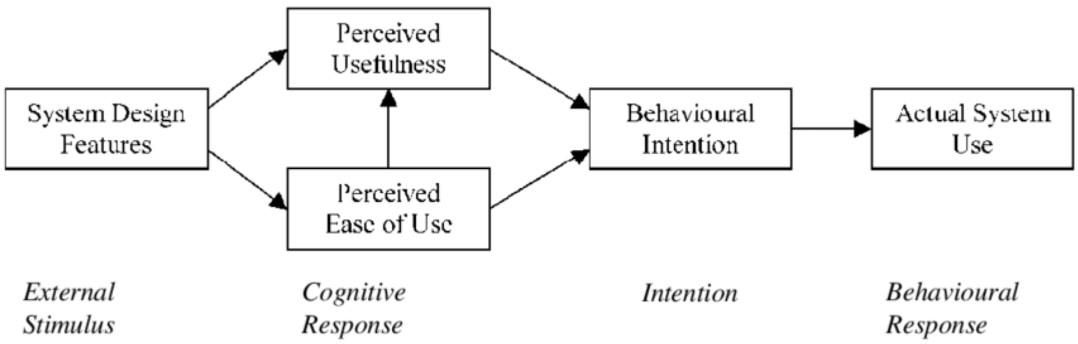


Figure 4: Technology acceptance model

Among possible behavior we considered a gesturing robot. In 1980, Mehrabian [61] demonstrated that gestures generate 55% of the meaning of any message sent by humans. The speech pattern (tone, intonation, loudness, pitch) accounts for another 38%, whereas the words account for only 7%. R. Subramani [62] found that nonverbal communication conveys 65% of the message during any given communication in Tirukkural (India). Kleinsmith et al. [63] also claimed that nonverbal communication is incomplete without gestures. Even though the findings of the above-mentioned experts differ, we can easily conclude that nonverbal communication plays a significant role in our daily interactions.

In prior work a system that integrates a humanoid educational agent into a math-learning scenario was built [64]. Students watched lessons on mathematical equivalency in which an avatar made either a gesture or did not make a motion, with the same eye gaze, head position, and mouth movements in both cases. They claim that when instruction is accompanied by gesture, learners are more likely to benefit from it than when education is not accompanied by gesture. When conveying a valid technique for solving a math problem that complement the strategy provided in the preceding speech, gesture has been demonstrated to be particularly useful in instruction [65].

2.4 Gesture as Simulated Action

Regarding gesture and gesture production, a useful insight is given by the Gesture as Simulated Action (GSA) framework presented by Hostetter and Alibali (2008) [66]. Gestures, according to the GSA framework, depict the instinctive motor activity that occurs when people consider and discuss mental simulations of motor acts. The term "simulation" was used in a variety of settings in cognitive science and neuroscience, but, in this case, it refers to the activation of motor and perceptual systems in the absence of external input. The likelihood of a gesture at a given instant, according to the GSA framework, is determined by three factors:

the producer's mental simulation of an action or perceptual state, motor system activity for speech production, and the height of the speaker's current gesture threshold. The basic architecture of the GSA framework is depicted in Figure 5.

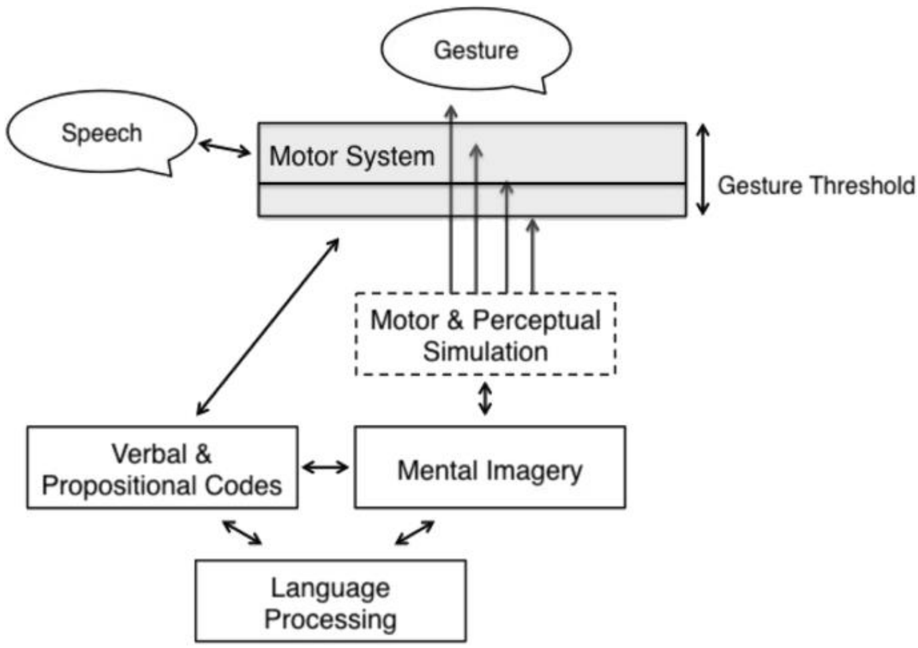


Figure 5: Architecture of the GSA framework

The gesture threshold is the minimal amount of activation required for an action simulation to produce a gesture, and it is the only variable that may be affected by temporary features of the communicative context. Even solid activated action simulations may not be represented as gestures if the threshold is high, whereas even weakly activated simulations can be revealed with gestures if the threshold is low. Based on criteria such as cognitive skills, personality, culture, and experience learning different languages, there may be stable disparities in the set points of people's gesture thresholds. People's gesture thresholds vary depending on transient features of the cognitive or communicative environment, in addition to these more constant differences. When speaking in French, a high-gesture language, bilingual French–English speakers, for example, make more gestures than when speaking in English. [67], revealing that speakers' thresholds may shift depending on the communicative context. Surely, for listeners to benefit from speakers' gestures, they must be able to see the motions. The effect of audience visibility on speakers' gestures has been studied extensively [68], and several of them have found that when speaking to listeners who can see the gestures, speakers gesture at a higher rate than when speaking to listeners who can't see the gestures [69, 70, 71]. According to the GSA research, this consequence arises when speakers' gesture thresholds are lower if their listeners are visible, letting more simulations to overcome the limit. Another interesting conclusion is that when presenters believe the information will be extremely relevant and beneficial to their audience, they will gesture more than when the content will have little clear utility [72]. When communicating to their kids about safety information that is relevant to circumstances that the mothers believe to be especially dangerous, for example, mothers use more gestures [73]. Similarly, while delivering knowledge that is fresh to their pupils, teachers use more gestures than when expressing information that is being reviewed [74, 75]. This suggests that speakers' use of gesture increases when they want to share an important information that they want the listeners understand.

CHAPTER 3

HYPOTHESES

This study is designed to understand how a gesturing robot can promote reasoning about geometry conjectures in a study session with undergraduate students. We also wanted to explore how robot's gestures can enhance a student's engagement and focus on the conversation. Nonverbal communication is effective at expressing speakers' emotions and attitudes [76]. Existing research has indicated that including body gestures and facial expressions into verbal communication can enhance communication efficiency greatly [77]. In human-robot interaction, interest has rising for the interpretation of robots' nonverbal behaviors. In our study we explore the nonverbal behavior by focusing on gestures, referring to dynamic gestures as a moving gesture represented by a sequence of various images conveying information [78], while with beat gestures we identify those which do not carry any speech content but are more in tune with the rhythm of speech [79]. In earlier works, research on robot gesture's influence on humans has been conducted, for example according to Riek et al. [80], the pace of robot gestures can elicit a variety of emotions and attitudes. People are more likely to cooperate with sudden gestures than with smooth ones. Kim et al. [81] discovered that varying the size, pace, and frequency of gestures can reveal distinct personalities. None of those previous studies, however, provide insights on the correlation between different kind of gestures in a learning environment. We base our research knowing that other studies have shown that, in general, the gestures people see from others have the potential to change our thoughts and a clear example in education can be found in the gestures teachers produce, since those gestures have an impact on what learners take from their lessons and may therefore influence learning. [82]. Another key element to remember is that humans adapt to their surroundings, especially to the behavior of other humans when they interact [83]. The mirror system has been identified as a critical component in the process of learning from others' behaviors and the ability to respond appropriately to them [84]. Specifically, mirror neurons fire when subjects observe other individuals perform meaningful actions. Mirroring, according to researchers, is a critical component in the development of social skills such as the ability to recognize intentions, goals of others and the ability to express empathy, as well as in acquiring language and gestures [85, 86]. As a consequence of mirroring, the gestures that learners themselves produce can also have an impact on learning. Several studies [87, 88] have shown that doing gesture can affect how we take in new information and encourage to express ideas that otherwise would not have been expressed. Given all the above premises, mostly made on human-human interaction, we hypothesize that similar results can be achieved on a human-robot interaction, hence we expect that by seeing the gesturing robot, students will tend to gesture more themselves and that those movements will influence cognition and benefit geometrical thinking and learning.

Another interesting mechanism we would like to investigate is gesture's ability to direct visual attention. In a previous work [89] eye tracking was used to measure gesture's ability to direct visual attention. They found out that children who were shown instructional videos that included spoken and gestured instruction look more to the gesture space than children who learned through spoken instruction alone. Based on this finding, we want to further explore and detail this mechanism by making a distinction between types of gestures and supposing that dynamic gestures shape visual attention more than beat gestures, with the consequence of enhancing student's engagement. Our research is guided by the following research question: How does the type gestures used by a robot impact a person's reasoning about geometry and their attention to the robot?

3.1 Hypotheses

Based on our research question, we hypothesize that:

Learners who interact with a robot that uses dynamic gestures to reason about a geometry conjecture when compared to learners who receive the same instruction from a robot using only beat gestures will be more like to:

- H1: produce more dynamic gestures during their own reasoning about a conjecture.
- H2: provide accurate proofs in their own geometric reasoning tasks.
- H3: direct their attention towards the robot.

3.2 Robot

For our research we used a humanoid NAO robot, whose physical features look less mechanical with respect to other robots, to provide a comfortable environment for the student, reducing the gap between humans and robots. The humanoid robot NAO, which first appeared on the market in 2008, was created with the intention of appearing friendly. NAO has the appealing appearance of a human toddler, with a height of 57 centimeters and a weight of roughly 4.5 kilograms, as depicted in Figure 6. The robot has 25 degrees of freedom which enable him to fluently move and adapt to the environment, 7 touch sensors to perceive his surroundings and locate himself in space and is equipped with 4 directional microphones and speakers to interrelate with humans. NAO is the answer for a performant yet affordable humanoid robot.

Figure 6: Nao robot characteristics

Hardware and Sensors: The NAO robot has a unique, proprietary hip kinematics system that utilizes only one motor instead of three and allows NAO to bend forward while spreading its legs. The Maxon TM coreless brush DC motors used by the NAO robot are famous for their precision and dependability. Every 20 [ms] cycle, the sensor data feed is updated. The NAO kit includes a variety of sensors, as well as two gyrometers and three accelerometers for real-time signal gathering. The capacitive sensors on NAO allow it to receive tactile input via touch. These are separated into three segments and are positioned on its forehead.

Motion Control Software: This humanoid robot is programmable with the Choregraphe application, which allows to create animations, behaviors and text to speech, allowing to test them on a simulated robot, or directly on a real one. Choregraphe is a powerful tool that, thanks to its user-friendly interface, allows even complex behavior to be readily implemented. There are useful pre-programmed behaviors that can be enriched with your own Python code and voice shape that can be customized to create a more friendly experience. Its platform agnostic nature enables program control on Windows, MAC OS, and even Linux. In Figure 7 it is possible to see an example of the Choregraphe software.

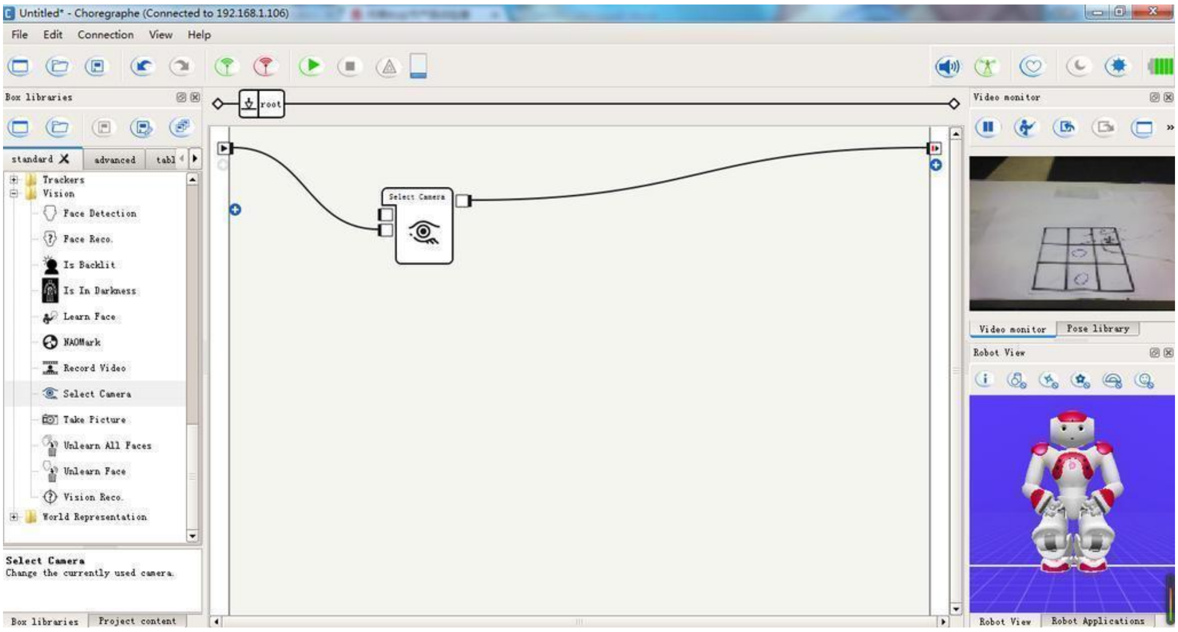


Figure 7: An example of Choregraphe interface

3.3 Gesture Production

Often social robot interactions are designed to be similar to use similar social interactions as a human-human system. However, in the application of HRI, space-separation and time-separation of humans and robots inevitably result in lower quality interaction [90]. To improve this situation and to design more "natural" human-computer interfaces, an attempt to replicate on the robot different gestures used in human-human interactions has been made. Because humanoid robots have similar appearances and control joints that allow them to duplicate a variety of fluid arm gestures, mimicking human gestures appears to be a viable method [91].

Beat gestures by definition are gestures that are used to emphasize parts of the speech do without having any meaning [92]. In particular, beat gestures are commonly generated to communicate highlight and create rhythm during speech acts [93]. In our work, we create beat gestures by implementing a retraction phase, in which one or both arms are brought toward the speaker body (see figure 8.1), followed by an extension phase, in which previously retracted arms reach the point of maximum extension (see figure 8.2). The extension phase coincide with the onset of a stressed syllable, which is a part of a word that people naturally say with greater emphasis than others. The retraction phase quickly follows the extension phase, where the words have less emphasis than in the previous phase. We added in beat gestures to match the pace of the speech and at points in the speech that marks the transition from one "cause" sentence to the "effect" sentence (i.e. if/then).

Figure 8.1: Retraction phase

Figure 8.2: Extension phase

In a *dynamic gesture* the message is contained in the temporal sequence, therefore they require more computational complexity than static gestures, and recognition of dynamic gestures is more challenging than static gestures [94]. In particular, dynamic gestures closely represent the objects themselves, with the hand acting as the object that is being moved or manipulated [92]. We create dynamic gestures as a representation of what is salient in the speaker's mental simulation of the situation while speaking [95], hence there is an observable correspondence between the forms of speakers' gestures and the transformation of the mental simulations they describe [96]. To define sensible dynamic gestures to mimic geometry shapes for a given conjecture, we referred to a previous study of human gesture production in geometry, where specific productive gestures were associated with increased reasoning and proof making about geometric conjectures [97]. We included those productive gestures alongside other gestures to generate a more realistic gesturing experience. An example of this can be seen in figure 9, where the NAO robot was reasoning about whether or not the area of a rectangle is doubled when both its length and width are doubled. The relevant action sequence is in Figure 9 and is composed by the first three gestures in which the robot first represents a rectangle with his arms (Figure 9, left), then doubles the length (Figure 9, middle) and width (Figure 9, right) performing two reflections while keeping its arm bent to a 90-degree angle. After this sequence, to increase the reality and sociality of the robot, another sequence in which the robot rotates its head first to the left and then to the right is added, to simulate a check on its arms position, shown in Figure 10

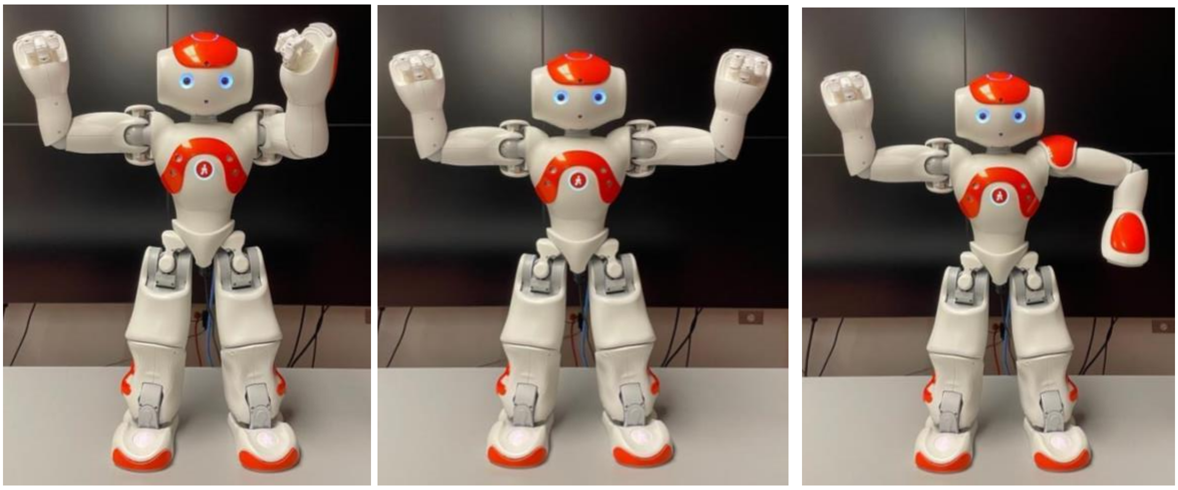


Figure 9: Relevant action in dynamic gesture sequence

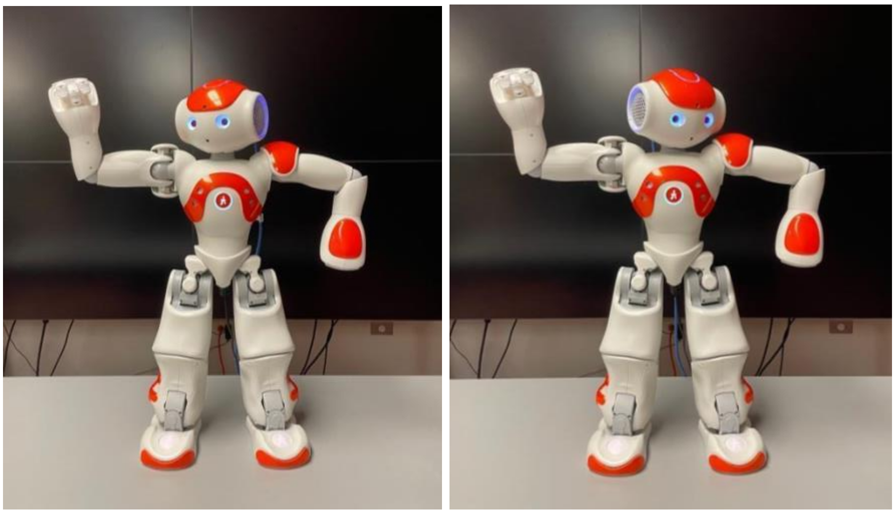


Figure 10: Additional gestures in dynamic gesture sequence

CHAPTER 4

ROBOT DESIGN AND DEVELOPMENT

The development of the NAO robot was done through Choregraphe, a multi-platform desktop application that allowed us to easily create applications containing speech, gestures and others powerful behaviors. A specific behavior is developed in a box and boxes can be connected with other boxes in order to implement the whole interaction experience. In Figure 10 is depicted how the robot was able to simulate reasoning on a geometry conjecture.

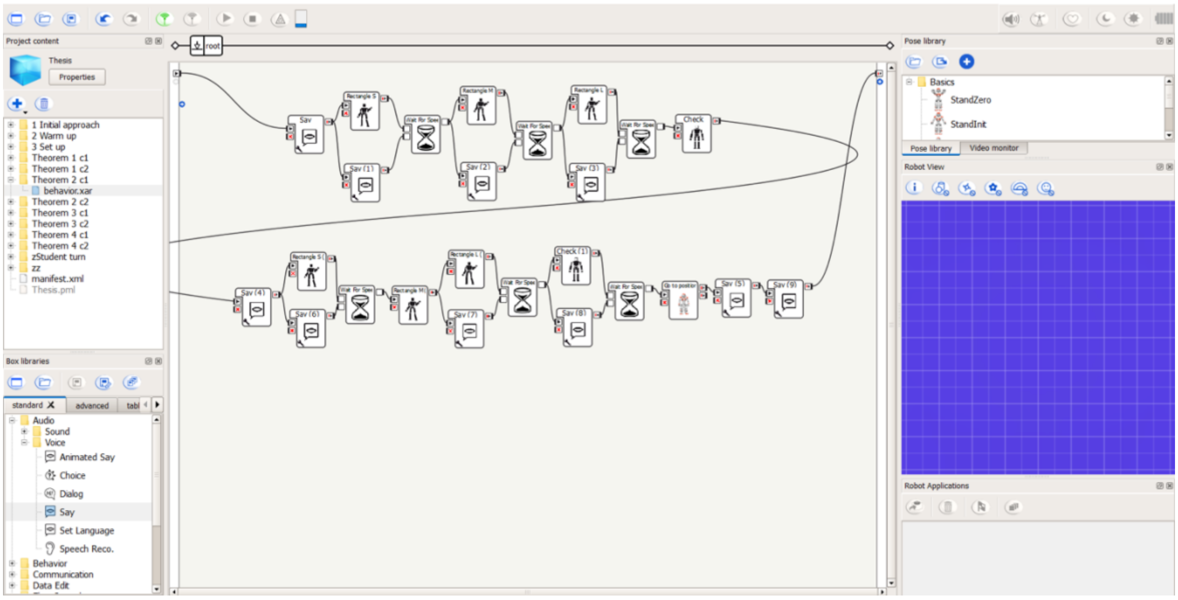


Figure 11: Development of robot reasoning in Choregraphe

4.1 Speech

The first feature we implemented on the robot was the speech. The robot had to be able to speak in order to enunciate geometry conjectures, give and explanation of them and ask the students their opinion on geometry conjectures. In the robot reasoning part, the speech was designed in such a way to recreate a true flow of reasoning, using key expressions like “Let me think about it” or “I think this might be true, let me see”. The speech feature was implemented using the “say” box, shown in Figure 11, an already built behavior present in Choregraphe which allows to easily recreate a speech by typing the sentences we want the robot says and adjusting voice shaping and speed, if needed, as shown in Figure 12.

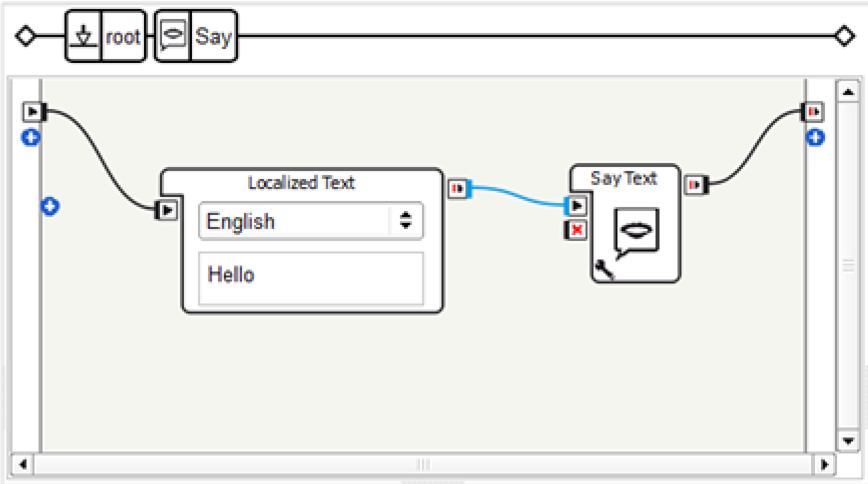


Figure 12: The "Say" behavior in Choregraphe

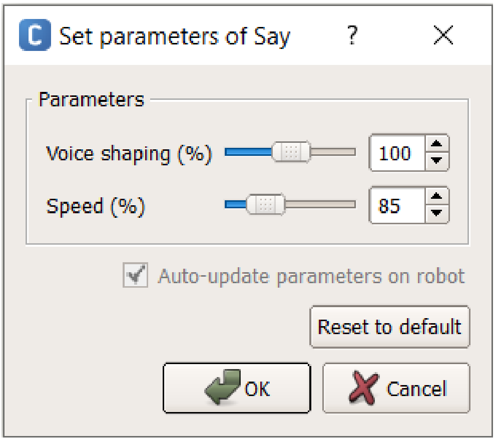


Figure 13: How to set "Say" parameters in Choregraphe

4.2 Gestures

The core part of our study focuses on gestures, hence an important feature to implement was the robot possibility to perform specific types of gestures. We created two new libraries of gestures in Choregraphe, one for the dynamic gestures (in Figure 13) and the other for beat gestures (in Figure 14).

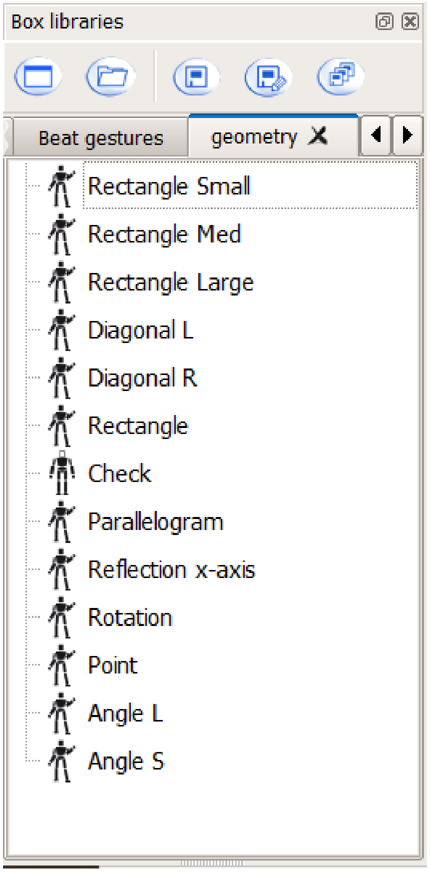


Figure 14: The dynamic gestures library implemented in Choregraphe

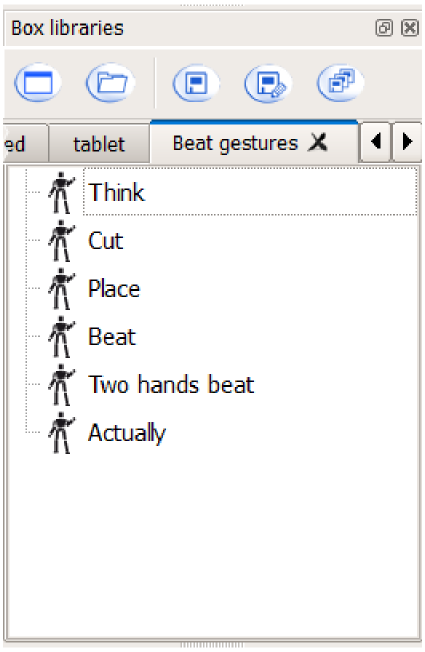


Figure 15: The beat gestures library implemented in Choregraphe

To implement a gesture sequence on Choregraphe, a new Timeline needs to be created. Firstly, the robot has to be set in a starting position and this can be done by clicking on the specific part of the body we want to move in the virtual 3D robot; once clicked, the motion widget (shown in Figure 15) appears and from here the joint values can be easily changed to reach the desired position. Last step is to right-click on the first keyframe and select the store joints in keyframe option. This feature, shown in Figure 16, allows to save the joints values of NAO robot: the joints of the whole body, the head, the arms or the legs.

The whole process can be repeated to implement a sequence, saving in sequence all the needed keyframes.

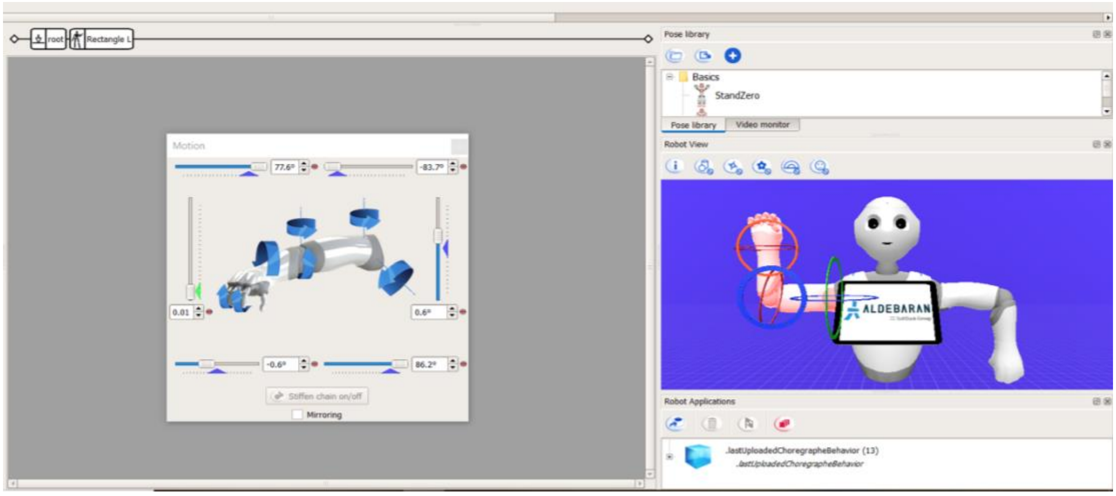


Figure 16: Gesture implementation using the motion widget

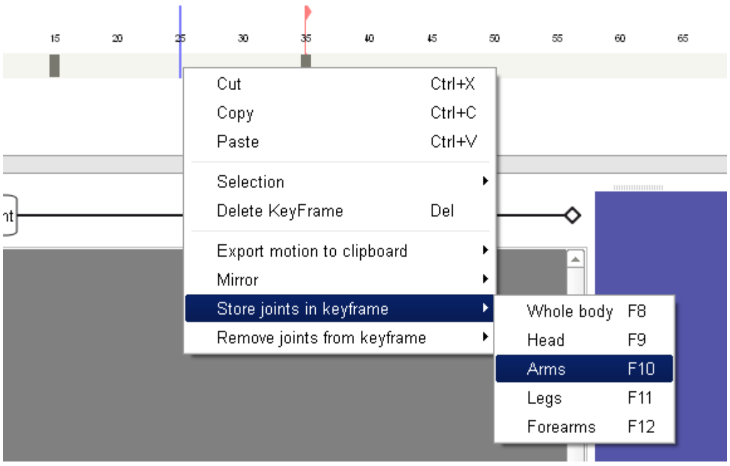


Figure 17: Gesture implementation by storing joints values in keyframe

4.3 Speech and Gesture Coordination

Very often we needed to control the flow of robot behavior and in particular to create a correct harmonization between speech and gestures production to match a particular geometric reasoning with its related geometric gesture. To implement this coordination, the box "WaitForSpeechAndGesture" was used. The box takes as input the output of the two behavior that need to be synchronized and, as soon as it receives a signal from one of the two, set up a signal received. When the box receives both signals, meaning that all the previous behavior are completed, it sends another signal to start the next behavior, connected as output of the box. An example of multiple coordination among speech and gesture can be found in Figure 17.

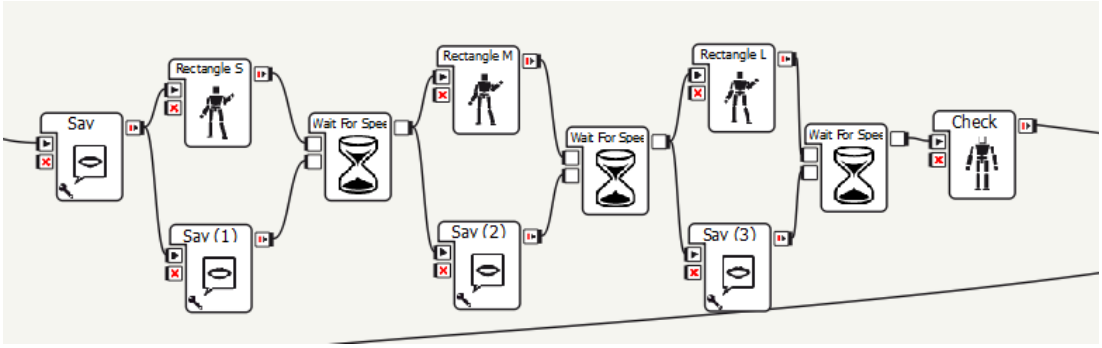


Figure 18: Coordination between speech and gesture

4.4 Speech Recognition

To make the interaction with the robot smooth and semi-autonomous, a basic speech recognition script was needed. When the student is asked to reason about four geometry conjectures, to switch from one to the other, formulas like "This conjecture was difficult to solve, but you were great! Are you ready for the next one?" are used. The robot waits for the student to say "yes" and proceed further only when recognize the word. If the student says "no", the robot allows some extra time before asking it again. In this way, we allow the students to take their time to swipe the tablet pages and show the following conjecture. If the robot hears a word different from "yes" or "no", the "hasn't hear box" is triggered and the robot ask the question again. An example of the implementation of speech recognition is showed in Figure 18.

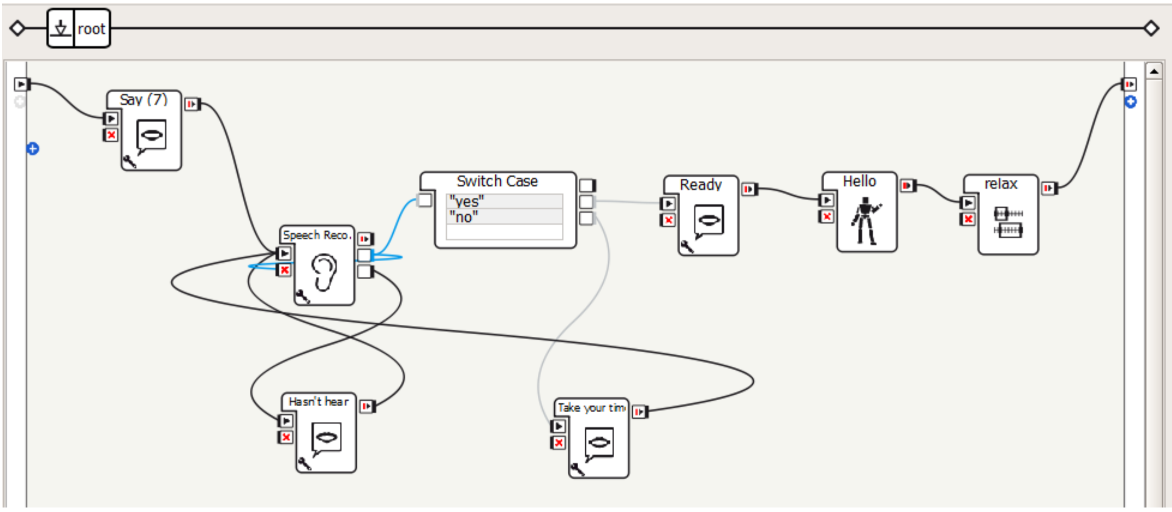


Figure 19: Implementation of speech recognition in Choregraphe

CHAPTER 5

METHOD

The experimental procedure is designed as an investigation of human and humanoid robot interaction in a geometry study session.

5.1 Participants

Thirty undergraduate and graduate students between 19 and 26 years of age (female=37%, age M=20.5 years) from a large, public university in Chicago were recruited to participate in the study and reason about eight geometrical conjectures with a robot.

5.2 Activity Procedures

We chose to create two different conditions with the same NAO robot helping undergraduate and graduate students (N = 30) with geometry conjectures, interacting with them one at a time. To ensure that all recruited participants did not have high levels of math or geometry expertise, they were required to complete a pre-screening survey to determine eligibility prior to scheduling a session. Any participant who scored a 100% on the pre-screening geometry quiz was ineligible for the study while the others were classified as eligible and their background information were collected, including age, sex, major, self-reported English fluency, and the last time they took a geometry or math class. Prior to interacting with the robot we asked the student to sign the consent form and then participants completed standardized spatial reasoning and verbal fluency tests.

Participants were randomly assigned, with half of the students the gestures used by the robot were dynamic hand gestures (dynamic condition), and for the other half, the gestures used were beat gestures (beat condition). It is important to notice that the difference among the two conditions was only in the gestures that the robot used, since the speech and all the others interaction features were the same. In both conditions, participants worked with the robot on their own, and had unlimited time to reason about eight geometry conjecture. After setting up the experiment, an experimenter was remotely available to assist as necessary, but the participants were not typically given any assistance from the experimenter, who provided minimal responses to questions. This setting is intended to mimic a real-world situation such as a student doing his homework at home, with no other presence in the room rather than the robot. The NAO robot was placed on the desk, in front of the student, with a tablet next to it. The sessions were video recorded with a front view and we used the recorded interactions and responses in the analyses. Another camera was placed on the back of the student and connected wirelessly to a computer, to allow the experimenter to have a real time vision of the ongoing session. A diagram representing the environment setting can be found in Figure 20.

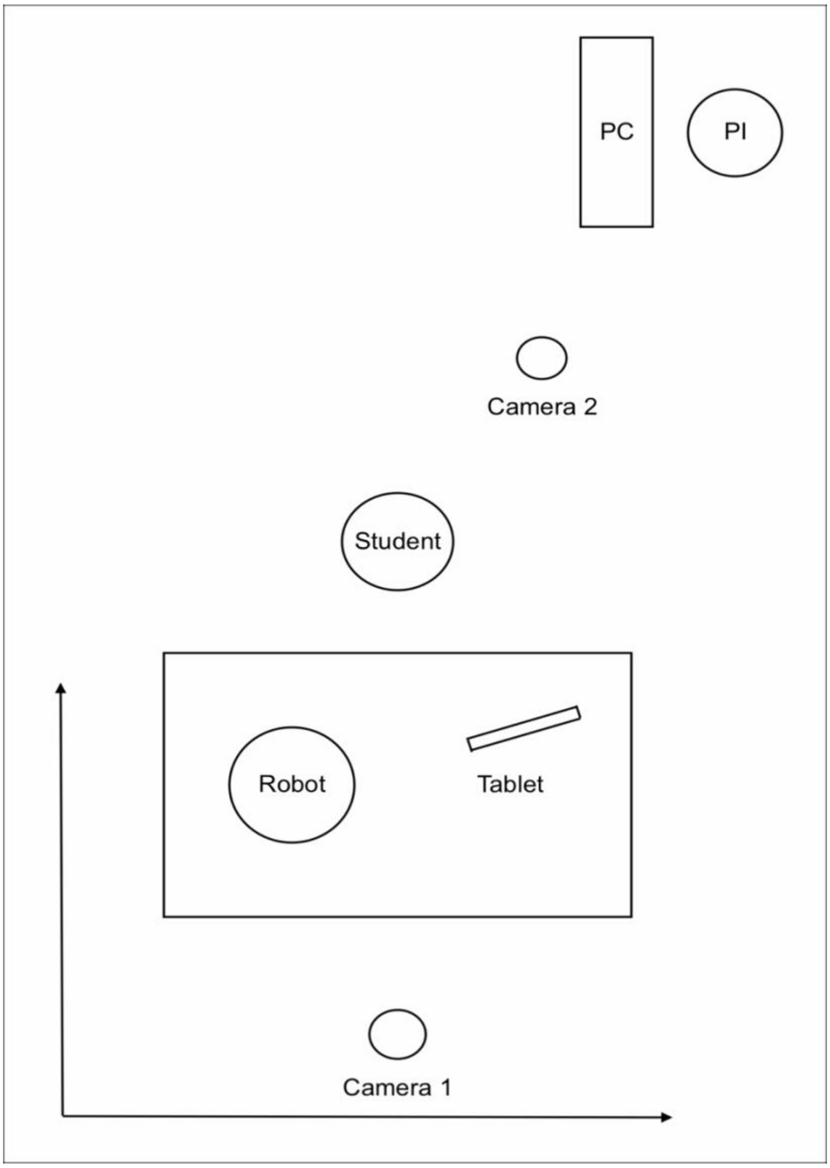


Figure 20: Schema of the environment setting during experiments

The robot began presenting itself and asking the student their name as well as some icebreaker questions, such as their favorite hobbies. Then, an explanation on how to use the system was given by the robot. Then, to help the student familiarize with the robot a brief storytelling activity was used as a warmup task, with the student trying to guess the ending of the story.

The participant then worked with the robot as a study companion to reason about 8 geometric problems of different difficulty and answer whether they believed the conjecture was true or false. The geometry conjecture used during the experiment are based on those used in a previous study by N. Mitchell, shown in Table II.

TABLE II: CONJECTURES USED FOR THE STUDY

N	Conjecture Statement	Answer	Difficulty
1	The area of a parallelogram is the same as the area of a rectangle with the same base and width	True	Easy
2	If you double the length and the width of a rectangle, then the area is exactly doubled	False	Difficult
3	The diagonals of a rectangle always have the same length	True	Easy
4	If one angle of a triangle is larger than the second angle, then the side opposite first angle is longer than the side opposite the second angle	True	Medium
5	The sum of the length of two sides of a triangle is always greater than the length of the third side	True	Easy
6	Given that you know the measure of all three angles of a triangle, there is only one unique triangle that can be formed with these three angle measurements	False	Difficult
7	The opposite angle of two lines that cross are always the same	True	Easy
8	Reflecting any point over the x-axis is the same as rotating the point 90 degrees clockwise about the origin	False	Medium

Each conjecture statement was shown on the tablet screen, one at a time, and the student was told to swipe pages as soon as he was ready to proceed with the next conjecture. The robot reasoned about the first 4 conjectures, explaining why it believed its opinion was true or false, then the participant reasoned about the other 4 conjectures. In both cases the robot read aloud the conjecture statement and during the last 4 conjectures, the robot asked for the student's opinion, suggesting the student orally explain their answer. Figure 21 shows an example of the study session. At the end of the experiment the students completed a post-task survey where they were asked to complete six questions about their perception of the robot.

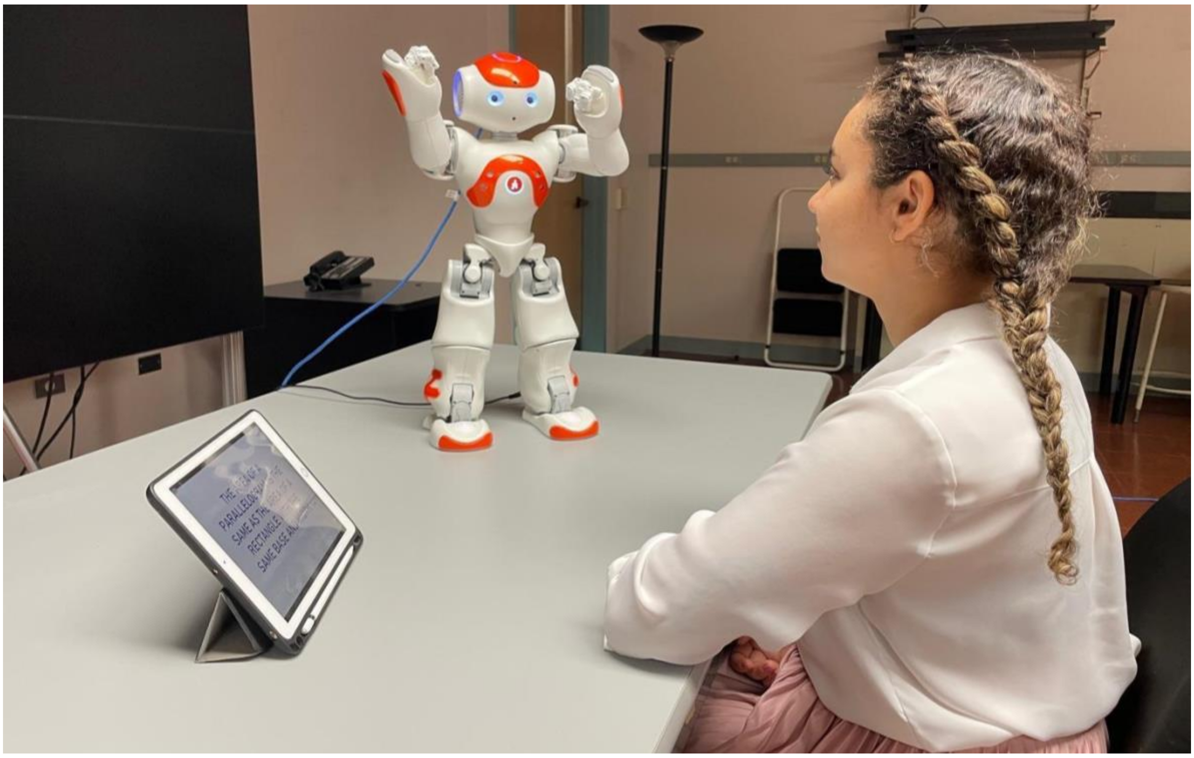


Figure 21: Study session with the robot

5.3 Data Collection

5.3.1 Pre-Screening

An online pre-screening was distributed to all interested students via Qualtrics to determine their eligibility prior to scheduling a session. In particular, all students needed to speak English fluently and be enrolled in a major different from Math or Geometry. The prescreener also included a geometry quiz to test their geometry knowledge and ensure they were not math experts. The quiz consists of 7 true/false questions about geometry conjectures, some easy along with medium difficulty ones. For each correct answer the student earns one point and if the total earned score is equal to 7, they are classified as ineligible. Otherwise, the participant is invited to enroll in the study, and is asked to complete a demographic survey.

5.3.2 Randomization Checks

As a randomization check several measures were included, to estimate whether the randomized groups were relatively equivalent. These measures included the pre-screening geometry test, a verbal fluency test and a spatial reasoning instrument.

The verbal fluency test is a one minute verbal functioning test where students have to say aloud as many unique words as they can starting with a given letter [98]. Each participant's score is the number of correct words.

A spatial reasoning test was used to determine a candidate's ability to manipulate 2D and 3D objects, visualize movements and change between shapes, and spot patterns between those shapes. For this test we chose 6 questions of different difficulty from a previous study conducted by Ramful et al. [99]. Each question has 4 possible answers, but only one of which was correct. The students were given 8 minutes to complete the assessment and later each question was scored with 0 in case of incorrect answer or 1 in case of correct answer, with a maximum possible score of 6.

5.3.3 Post Task Survey

A post task survey was distributed to all participants to collect feedback on their interaction with the robot. The survey consists in 5 Likert-style items and one open-ended question. In the Likert-style items the student was asked how much they agreed with five statements and are given a choice between five answers, from 1 (*strongly agree*) to (*strongly disagree*). These questions were about 1) if they thought the robot is friendly (one item), 2) if they thought the robot made a good study partner (two items), and 3) if they thought the robot's gestures were helpful (two items).

In the open-ended question students were asked what they would change or improve about the experience with the robot. The questions and format used for the post task survey can be found in Figure 22.

We'd like to know more about your experience today

How much do you agree with this statement: the robot was friendly

How much do you agree with this statement: the robot was a good study companion

How much do you agree with this statement: If I had the possibility, I would study with a robot like this

How much do you agree with this statement: the robot's gesture helped me in focusing on the geometry theorem discussed

How much do you agree with this statement: the robot's gesture helped me in better understanding the geometry theorem discussed

What would you change or improve about your experience with the robot?

Figure 22: Questions and format used for the post task survey

CHAPTER 6

MEASURES AND ANALYSES

6.1 Gesture Coding

We based our gesture coding on prior work by Pier, et al. (2019). We started by recognizing gesture sequences, which started when a participant lifted their hands and concluded when they dropped their hands. As a result, a gesture sequence could consist of a single gesture or several motions. We decided to code all general gestures sequences and subsequently to examine the category the gestures belong to. We coded each gesture sequence if it contained at least one *representational gestures*, a category of gestures that represent the ideas and items to which they refer [100]. We focused on a subtype of representational gestures that we believe may enhance reasoning: we define dynamic gestures as motion that depict the gradual changing of a geometrical entity with body movement. When a student forms a triangle shape with their hands, this is a representational gesture that refers to a triangle in the participants mental model of the geometric conjecture. If that student then begins to move their hands to change the length of the sides or angle of the triangle, this is a dynamic gesture that manipulates the representation of the triangle. We coded each gesture sequence as representational or dynamic if it contained any instance of these gesture types within the entire gesture sequence. It is important to note that, any gesture sequence can be composed of multiple gestures, including dynamic gestures and beat gestures mixed up. We did not attempt to count each gesture instance, as often gestures are intermingled and difficult to distinguish between starting and ending points. Fig. 5 provides several examples of dynamic gesture sequences produced by participants. Throughout this paper, when we use the expression “gestures", we are referring to gesture sequences. Each gesture sequence was then coded into one of three categories: (1) representational if the participant produced at least one representational gesture in the sequence; (2) dynamic if the participant produced at least one dynamic gesture in the sequence or (3) non-representational if the participant produced only beat gestures and not any representational gestures. We monitored the number of dynamic, representational and non-representational gesture sequences performed while the participant was reasoning about the last four conjectures.

6.2 Eye Gaze Direction

We used video recordings to code information about the participant’s eye movements during the first four conjectures when the robot explained their reasoning about each conjecture. Video recordings were examined to determine where the participant was looking during these activities and coded for “looking at robot” when the participant’s gaze was directed to any part of the robot and coded “looking at tablet” when the participant’s gaze was directed to the tablet screen, and “looking at other” when their gaze moved away from the robot or tablet. We placed the tablet and the robot with a Euclidean distance of 45 cm between them, which decomposed on the Cartesian axis was 40cm along the x-axis and 20cm along the y-axis, as represented in the schema in Figure. We were able to distinguish between looking at the robot and tablet because to switch from one item to the other participant needed not only to spin their eyes but also to slightly turn their head. ATLAS software was used to distinguish the intervals of time in which the student was looking at the tablet and in which the student was looking at the robot.

6.3 Speech and proof validity

Participants' verbalizations during their reasoning about the last four conjectures were transcribed from the video recordings by the researcher. All records were analyzed and if necessary were edited for correctness. The script were separated into 4 documents (one for every conjecture). Verbalizations were then examined, and it was checked if, for each conjecture, the student gave a correct answer and, in case of correctness, the reasoning or justification for that answer was analyzed to determine whether the participant reasoning related to the context of the conjecture.

The reasoning was classified as non-correct when the premises of the reasoning were unrelated with the conclusion, or the conjecture statement itself was unrelated with the whole reasoning. For example, if the conjecture statement is about opposite angles and they reason on opposite sides length, this was labeled as incorrect reasoning. The reasoning is incorrect also when there is no reasoning at all, and the student just guess an answer or is not able to provide any justification for his response. All others form of reasoning were classified as correct.

Note that while these examples only include verbalizations, we coded for proof validity using both speech and motions, for instance speaking the expression "the triangle" while picturing a growing triangle with hands suggests the speaker was reasoning about general triangles.

6.4 Post-task Survey

Participants were asked to complete a post-task survey after the interaction with the robot. A score from 1 to 5 was assigned to each survey response, according to the legend in Table III. All the surveys responses were analyzed and divided in two groups: two questions (Q2 and Q3) were used to measure the participants feelings about studying with the robot, while other two (Q3 and Q4) were used to measure participants feelings about the effectiveness of the robot's gestures. In the first close question (Q1) we asked the students how friendly the robot was and since we got a 5 score from all the participants excluded this question from the analysis. In this paper, no further measures were conducted for the open question.

TABLE III: RESPONSE AND SCORE ASSOCIATION FOR THE POST-TASK SURVEY

Response	**Score**
Strongly agree	5
Somewhat agree	4
Neither agree nor disagree	3
Somewhat disagree	2
Strongly disagree	1

6.5 Analyses

Analyses were run based on 30 participants, randomly divided in two groups: 15 for dynamic condition and 15 for beat condition.

To ensure random assignment to condition groups, all group characteristics were compared for mean differences, ensuring that no correlation occurred for verbal fluency and spatial reasoning among the two groups.

To test our hypotheses about the relationships between robot gesture type and dynamic gestures, reasoning and attention, we divided the session in four different parts and performed several and different calculations for each of them.

1. The first part was considered as a warmup task, hence no further analysis is required.

2. The second part corresponds to the robot reasoning, in particular it begins when the robot start enunciates the first geometrical conjecture and ends right after the fourth conjecture proof production. For this part the total amount of time the student was looking at the tablet or at the robot was computed while the robot was talking. No computation has been made while the robot was silent between one conjecture and the following.
3. The third part corresponds to the student reasoning and begin with the fifth conjecture enunciation. For this part the total amount of gesture sequences, representational gesture sequences and dynamic gesture sequences the student performed during his reasoning was counted.
4. The fourth and last part starts right after the student reasoning, when the participant is asked to complete the post-task survey. For this part we

We calculated a t-test to compare differences in mean scores between the groups, for (1) dynamic gestures sequences occurrences in control condition and dynamic condition, (2) amount of time the student is looking at the robot in control condition and dynamic condition (3) proof correctness in control condition and dynamic condition, and (4) proof validity in control condition and dynamic condition. An alpha of 0.05 was used as our cutoff for determining statistically significant differences between measures.

CHAPTER 7

RESULTS

Between the dynamic and beat condition groups, all group characteristics were determined to be similar (See Table IV), fulfilling our randomization check. For the dynamic condition, 71.66% of the proof produced was valid, whereas for the beat condition 56.66% of the proof produced was valid. Regarding dynamic gestures across the two conditions, 60% of all participants in both situations made at least one dynamic gesture sequence; this was true for 73.33 percent of the dynamic group and 60 percent of the beat group. In addition, the students who spent most time looking at the robot rather than at the tablet was 86.66% in the dynamic condition and 53.33% in the beat condition.

TABLE IV: COMPARISON OF GROUP CHARACTERISTICS BETWEEN DYNAMIN AND BEAT CONDITIONS.

Measure	Beat Mean (SD)	Dynamic Mean (SD)
Age	20.86 (1.55)	20.26 (1.98)
Spatial Reasoning Ability	5.13 (0.64)	5.13 (0.83)
Verbal Fluency Ability	16.4 (2.06)	16.73 (2.12)

7.1 Hypothesis #1: Dynamic Gestures

The number of produced dynamic gesture in the dynamic condition (34 in total, $M = 2.26$, SD=2.31) is double the number of produced dynamic gesture in the beat condition (17 in total, $M = 1.13$, SD=1.06). The difference in dynamic gestures between the two conditions, was not statistically significant $t(28) = 1.72$, $p = 0.95$). However, analyzing the number of gesture sequences (Beat: 27, Dynamic: 53) and the number of representational gesture sequences (Beat: 25, Dynamic: 53) we noticed that students used gestures mostly for reasoning, with just 2 cases in which they don't make any representation in gesturing. Moreover, what is interesting to highlight is that the total number of gesture sequences measured is statistically different between the two conditions where the beat condition (M = 1.80, SD = 1.58) sequences were lower than the dynamic condition (M = 3.53, SD = 2.7, $t(28)$ = 2.15, p = 0.04) sequences. A similar result was found for the representational gesture sequence measure, where representational sequences for the beat condition (M = 1.66, SD = 1.58) were higher than those in the beat condition (M = 3.53, SD = 2.61, $t(28)$ = 2.37, p = 0.02). All the results can be found in Table V.

TABLE V: DIFFERENCES IN GESTURE MEASURES

Measure	Group	Total Num	M (SD)	t(28)	p
Gesture Sequences	Beat Dynamic	27 53	1.80 (1.56) 3.53 (2.70)	2.15	0.04
Representational Gestures	Beat Dynamic	25 53	1.66 (1.58) 3.53 (2.61)	2.37	0.02
Dynamic Gestures	Beat Dynamic	17 34	1.13 (1.06) 2.26 (2.31)	1.72	0.095

7.2 Hypothesis #2: Reasoning and Proof

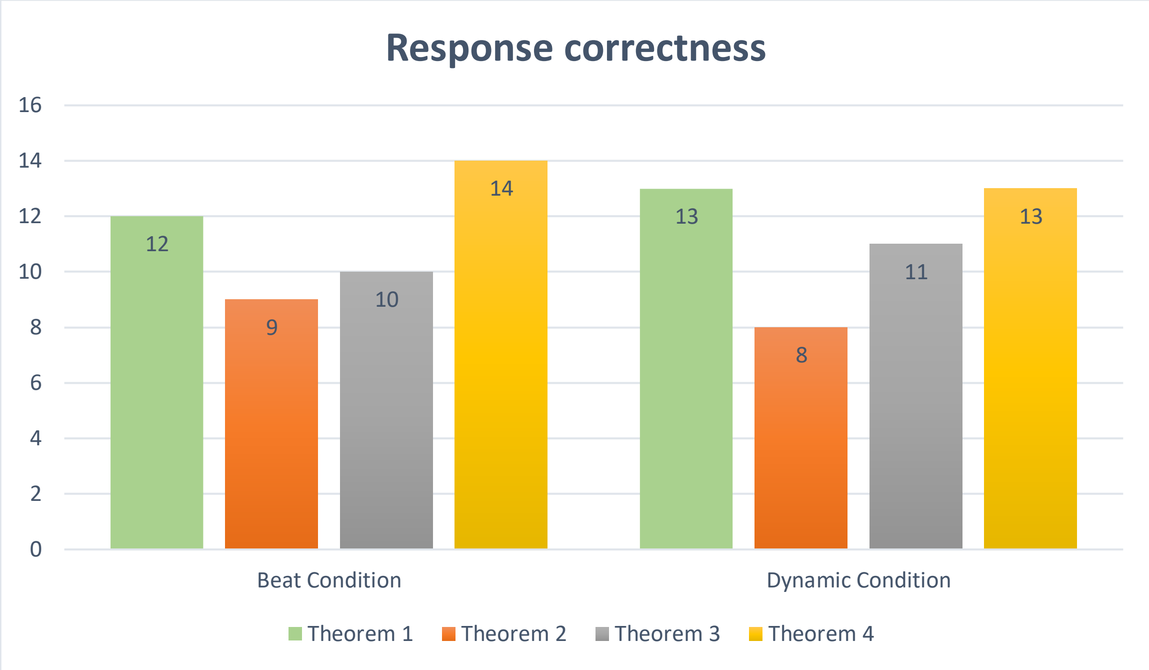
Table VI presents the differences between proof correctness and reasoning correctness in dynamic condition and beat condition. It has been found no difference in the answer correctness among the two groups, since the total number of correct answers is the same (45 over 60 in both cases), and the mean of correct answer per participant is also the same (3 correct answer) with a slightly higher standard deviation in the beat group (*SD* = 0.92) compared to the dynamic group (*SD* = 0.65). A marginal difference has been observed for the construction of a valid proof, analyzing the reasoning flow of participants. Even if measures are not statistically different, we noticed that in the beat condition the correctness of reasoning was lower than in the dynamic condition, with a total of 34 correct proof production in the beat (M = 2.26, *SD*=1.43) compared to 43 correct proof production in the dynamic (*M* = 2.86, *SD*=0.91).

TABLE VI: DIFFERENCES IN REASONING MEASURES

Measure	**Group**	**Total Num**	**M (SD)**	**t(28)**	**p**
Proof Correctness	Beat Dynamic	45 45	3 (0.92) 3 (0.65)	0	1
Reasoning Correctness	Beat Dynamic	34 43	2.26 (1.43) 2.86 (0.91)	1.3	0.18

Further analysis on proof correctness has been carried out to classify proof correctness divided by each theorem. In Table VII is shown the total number of corrected answers for each theorem, divided by condition. Results show that the students had more or less the same difficulty in solving the theorems, since comparing the two conditions, the difference among the same theorem correctness in never more than 1.

TABLE VII: RESPONSE CORRECTNESS FOR EACH THEOREM, DIVIDED BY CONDITION



7.3 Hypothesis #3: Attention

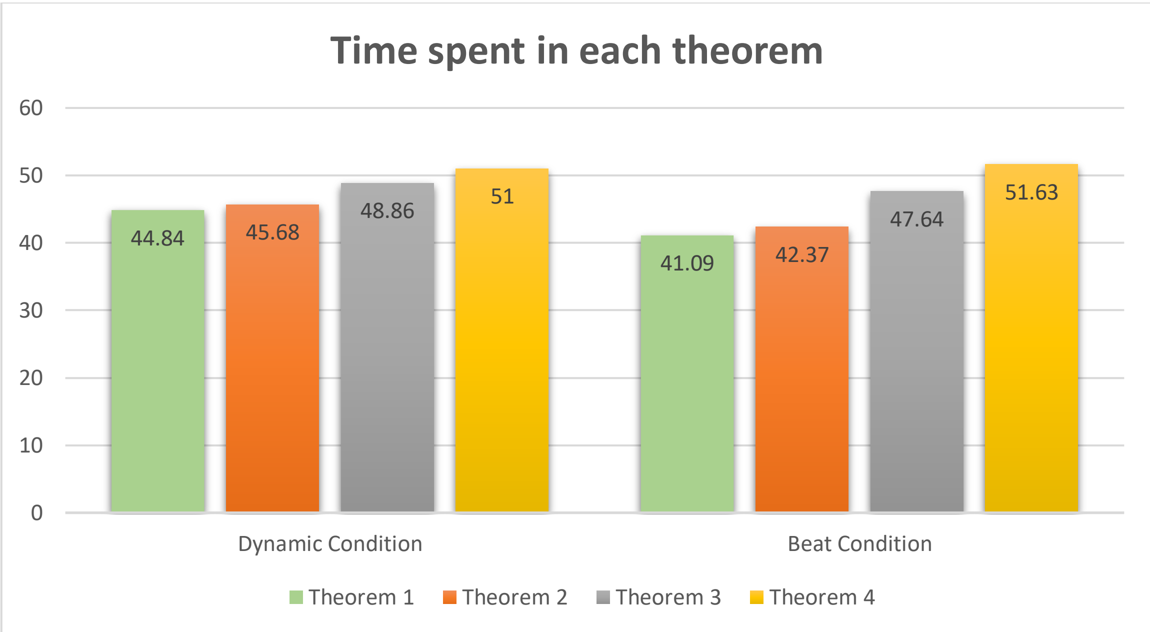
In order to measure whether robot's dynamic gestures direct student attention on the gesture area, hence on the robot itself, we examined where the student was looking at during the robot reasoning, and those results are shown in Table VIII. The total time, measured in seconds, that students looked at the robot gesturing is 899.61 in the beat condition and 1766.37 in the dynamic condition. In average 33.36% of the total time was spent looking at the robot in the beat condition while 61.85% of the total time was spent looking at the robot in the dynamic condition. The difference between the two measures had been found to be statistically significant, with a p value of 0.019.

TABLE VIII: DIFFERENCES IN LOOKING MEASURES

Measure	Group	Total Num	Percentage	M (SD)	t(28)	p
Looking	Beat	899.61 s	33.36%	79.36 s (46.65)	2.49	0.019
Robot	Dynamic	1766.37 s	61.85%	117.76 s (37.26)		

In order to have a more accurate idea of the time spent on each conjecture in both condition and to ensure that no significant difference occurs among the two conditions regarding this time, in Table IX is shown the seconds that, in average, were required to complete each task.

TABLE IX: TIME SPENT (S) IN EACH THEOREM, DIVIDED BY CONDITION



7.4 Post Task Survey Results

From the data analysis conducted on the post task survey we found that when they were asked questions about their feelings about studying with the robot, in both condition students mostly agreed that the robot was a good study companion and if they had the possibility, they would study with a robot like that. In fact, we found out a score mean of 4.25 (*SD* = 0.40, median = 4) for the beat condition and a score mean of 4.73 (*SD* = 0.41, median = 5) for the dynamic condition. An interesting finding is about students' feelings on the effectiveness of robot's gestures. In our result we got that almost all students in the dynamic condition agreed with the extent that the robot's gestures helped them focusing and understanding better the conjecture discussed, with a score mean of 4.86 (*SD* = 0.29, median = 5). In the beat condition we got a quite different result, since we found out a mean of 3.50 (*SD* = 0.38, median = 3.5). The previous results are shown in Table X. Unlike the other results, in this case we chose to use a Mann-Whitney non-parametric test to compare differences, because the survey results are not a continuous variable and the Mann-Whitney non-parametric test can be used when the measured variables are of ordinal type and were recorded with an arbitrary and not a very precise scale [101]. Since there were more than eight observations for each condition, we report on the calculated z statistic and corresponding p value to determine significance of the difference.

TABLE X: POST TASK SURVEY RESULTS

Measure	**Group**	**M (SD)**	**z**	**p**
Feelings about studying with the robot	Beat Dynamic	4.25 (0.40) 4.73 (0.41)	3.08	0.00025
Feelings about effective-ness of robot's gestures	Beat Dynamic	3.50 (0.38) 4.86 (0.29)	4.37	<0.0001

CHAPTER 8

DISCUSSION

In this thesis we presented the quantitative measures of gesture rates, proof and reasoning correctness, eye gaze and self-reported measures of perception of the robot, in order to test the hypotheses that: interacting with a dynamic gesturing robot will result in a greater production of dynamic gestures from the student itself, strengthening their reasoning and directing their attention toward the robot. We found strong statistical support favoring that the dynamic gesturing robot enhanced gesture production in students, not only regarding the number of dynamic gestures produced, but there is also a considerable difference in the number of representational gesture sequence, too. An explanation of this finding can be found considering the GSA framework, explained in section 2.4, where we reported that according to this theory, human gestures production depends also on the height of the speaker current gesture threshold and that this threshold may be lowered when speakers knows that listeners are seeing them and when speakers want to convey an important information. Of course students know that the robot cannot see them while they are gesturing but, an interpretation of this phenomenon can be given considering how the robot interaction skills enhance the social part of the robot, leading the students to act as if the robot is a human. The fact that students are gesturing more in the dynamic condition could mean that a dynamic gesturing robot enhances social presence more than a beat gesturing robot. This result is in line with other research [102] in which the use of different types of gestures positively or negatively predicted participants' perceptions of the naturalness of the robot's behaviors, describing how robots might selectively use different types of gesture to improve specific interaction outcomes.

We also found that the dynamic gesturing robot captures the student attention more than the beat gesturing robot, confirming our hypothesis that dynamic gestures direct student's attention toward the robot, a very similar result found by previous studies on the human educational gestures [89].

However, we did not find differences in proof correctness but just a slightly perceivable difference in the correctness of their reasoning. This suggests that in this case, the use of gestures did not enhance their reasoning, but it is worth further exploration to better understand why this is inconsistent with human-human interaction studies.

What is interesting to me, is the different perception of usefulness and willingness to use the robot between the two conditions, emerged from the post-task survey. What is visible from the results is that the remarkable difference between the two conditions was not about the student's perception of the robot, but the differences in their willingness to use the robot in an educational setting and the perception they had about robot's gestures. In particular, the majority of them found the robot's gestures helpful in the conjectures understanding and believe that the gestures help them in focusing on the conjecture. This result is confirmed from the analysis of student attention we discussed earlier, that showed a stronger focus on the robot in the dynamic condition.

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