Impact of Multi-Robot Presence and Anthropomorphism on Human Cognition and Emotion

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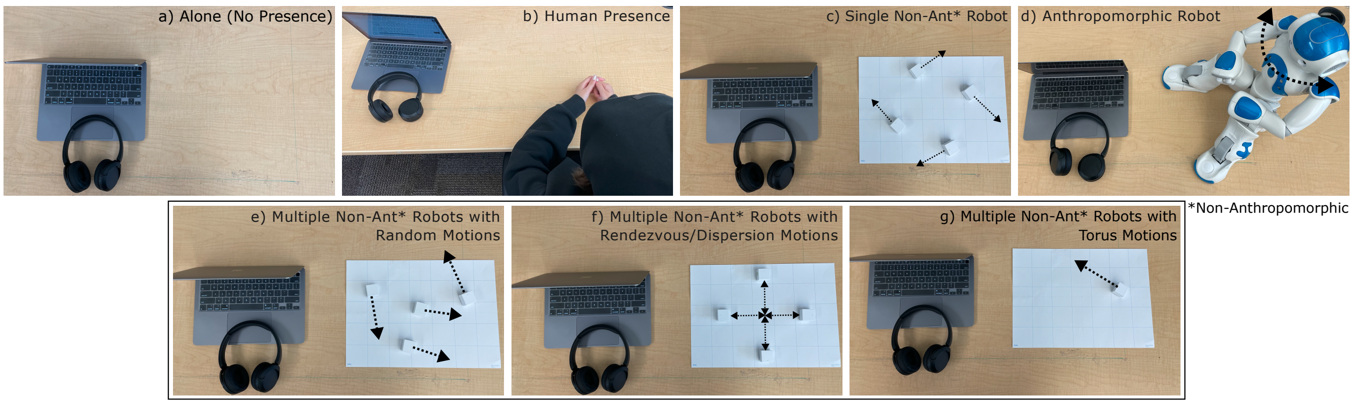


Figure 1: Seven presence conditions were presented to participants to test the impact of multi-robot presence and anthropomorphism on human cognition and emotion. (a) Alone, (b) human presence, (c) single non-anthropomorphic robot, (d) single anthropomorphic robot, (e) four non-anthropomorphic robots with random motions, (f) four non-anthropomorphic robots with rendezvous/dispersion motions, and (g) four non-anthropomorphic robots with torus motion.

ABSTRACT

Exploring how robots impact human cognition and emotions has become increasingly important as robots gradually become ubiquitous in our lives. In this study, we investigate the impact of robotic presence on human cognition and emotion by examining various robot parameters such as anthropomorphism, number of robots, and multi-robot motion patterns. 16 participants completed two cognitive tasks in the presence of anthropomorphic and non-anthropomorphic robots, alone, and with a human nearby. The non-anthropomorphic robot conditions were further varied in the number of robots and their motion patterns. We find that increasing the number of non-anthropomorphic robots generally leads to slower performance, but coordinated patterned motions can lower the completion time compared to random movements. An anthropomorphic robot induces an increased level of feelings of being judged compared to a non-anthropomorphic robot. These findings provide preliminary insights into how designers or users can purposefully integrate robots into our environment by understanding the effects of anthropomorphism, number of robots, and multi-robot motion patterns on human cognition and emotion.

CCS CONCEPTS

• **Human-centered computing** → **Empirical studies in HCI**.

KEYWORDS

Social Facilitation, Multi-Robot Systems, Anthropomorphism, Robot Companions, Social Robotics

ACM Reference Format:
Jiadi Luo, Veronika Domova, and Lawrence H. Kim. 2025. Impact of Multi-Robot Presence and Anthropomorphism on Human Cognition and Emotion. In *Proceedings of ACM Conference (Conference'17).* ACM, New York, NY, USA, 15 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

Conference'17, July 2017, Washington, DC, USA

ACM ISBN 978-x-xxxx-xxxx-x/YY/MM…$15.00
https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

In the era of rapid technological advancements, robots have firmly entrenched themselves in both our professional endeavors and daily lives, aiding in productivity [20], education [21], and labor [9]. This surge in their prevalence has led to extensive research dedicated to designing interactions between non-expert users and robots deployed in public and private spaces [53]. Previously, the primary focus was on how robots could assist humans, particularly in tasks that were hazardous, repetitive, or lacked significance [25]. More recent research endeavors have expanded their scope to explore whether robots can assume a crucial role in enhancing human learning across various dimensions, encompassing cognition, emotions, social interaction, and behavior [44, 50, 54, 71].

In particular, the social facilitation effect, which entails the presence of a human observer enhancing one's performance for easy or familiar tasks while hindering it for difficult or unfamiliar tasks [62], has been successfully replicated using anthropomorphic robots as observers instead of humans [63]. Emotionally, the presence of human-like robots has been shown to make users feel more monitored compared to either human presence or being alone [63]. Building upon this line of inquiry, researchers have undertaken investigations into the impact of different levels of anthropomorphism on the social facilitation effect, systematically examining how robot design with varying anthropomorphism levels influence human task performance, emotion, and motivation [33, 34, 55, 75].

While prior research has begun to investigate the role of the anthropomorphism of robots in the social facilitation effect, most studies have primarily concentrated on static robots with minimal movements (e.g., facial expressions) [55, 63, 75]. This overlooks the pivotal role that is played by motion in increasing animacy [24] and conveying emotions [36, 42]. In an effort to address this, Kim *et al.* [33] conducted an online study that examined the impact of motion along with the anthropomorphism of the robots, providing a more comprehensive understanding of these parameters for a single robot. However, the study was conducted online, employing virtual robots rather than real physical ones. It is essential to recognize that virtual and physical robots may exert different influences on human emotions; in fact, many studies found that physically present robots are more persuasive and positively perceived than those displayed virtually [1, 42, 43, 73]. To address this limitation, our study investigates the effects of both motion and anthropomorphism on human cognition and emotion with physical robots.

Many current and future robot-related applications involve the use of multiple robots, especially those that are non-humanoid due to their simple and cost-effective design for applications including tangible user interfaces, pollination, delivery, autonomous vehicles, search and rescue teams, etc. [10, 15, 31, 35, 37, 40, 52, 61, 70, 80, 82]. However, studying multi-robot interaction with humans has proven challenging [52], leading a significant portion of the research to predominantly focus on single robots, even when examining a robot's group dynamics [38]. While some research has explored the impact of the number and types of robots on human emotions [18, 58], no existing study to our knowledge investigates the influence of the number of non-anthropomorphic robots on human task performance and its role in the social facilitation effect. Given that most multi-robot systems that are increasingly common in our daily lives are non-anthropomorphic (e.g., self-driving cars, delivery robots, and security robots) and not anthropomorphic, we chose to focus specifically on multi-non-anthropomorphic robots rather than multi-anthropomorphic robots.

When examining multiple robots, motion patterns emerge as a critical factor. Existing literature indicates that the multi-robot motion patterns can effectively convey fundamental emotions (such as happiness, surprise, etc.) [67], and people's perceptions can markedly differ depending on the specific motion patterns employed [14, 36]. For instance, rendezvous and dispersion collective behaviors were perceived to be more arousing and dominant than torus movements [36]. Given the strong link between arousal and social facilitation [78], we aim to explore how these multi-robot motion patterns influence human cognition and emotion, particularly in the context of non-anthropomorphic robots. This choice aligns with real-world scenarios given the prevalence of non-anthropomorphic robots, which are more common than anthropomorphic robots.

To understand the impact of multi-robot presence and anthropomorphism on human cognition and emotion, we conducted a within-subject study involving 16 participants who engaged in two cognitive tasks (word recall [5] and modular arithmetic [55]) across 7 distinct conditions. These conditions encompass two anthropomorphism levels (non-anthropomorphic robot vs. anthropomorphic robot) in addition to alone (no presence) and human presence, varying numbers of non-anthropomorphic robots (single vs. multiple), and multi-non-anthropomorphic-robot motion patterns (non-patterned motions vs. patterned motions). Participants also self-evaluated and reported their feelings of being judged and their emotions (arousal, valence, and dominance). Overall, our study objective is to better understand how the mere presence of robots affects human cognition and emotion and how various robot parameters like anthropomorphism levels, number of robots, and multi-robot motion patterns change this dynamic. The study results suggest that both the number of robots and multi-robot motion patterns have an impact on task completion time. We also observed that an anthropomorphic robot induces an increased feeling of being judged compared to a non-anthropomorphic robot. These findings provide preliminary insights into how designers can purposefully integrate robots into our environment by understanding the effects of anthropomorphism, number of robots, and multi-robot motion patterns on human cognition and emotion.

2 RELATED WORK

In this section, we describe the theoretical background of social facilitation and related work on robot attributes of interest, such as anthropomorphism, number of robots, and multi-robot motion patterns.

2.1 Theoretical Background on Social Facilitation

Social facilitation, a psychological phenomenon, explores how the mere presence of others impacts an individual's task performance, often resulting in improved performance [62]. It includes two primary aspects: co-action effects [30], where individuals perform better in the presence of peers; and audience effects [6], where performance improves when tasks are performed before an audience. This phenomenon is further underpinned by three key theories: drive-arousal [81], evaluation apprehension [12], and distraction conflict [2].

Social facilitation has its roots in early research, such as the observation that people tend to perform better in the presence of others, like lifting heavier objects [49]. However, the evolution of social facilitation theory has revealed inconsistencies, as the phenomenon did not consistently occur [69]. Addressing these discrepancies, Zajonc [81] introduced the drive-arousal theory. This theory posits that the mere presence of others increases arousal levels, thereby enhancing performance in tasks that align with a natural dominant response. In contrast, complex tasks lacking such a dominant response may lead to impaired performance.

Cottrell [12] extended this understanding with the evaluation apprehension theory, discovering that people do not necessarily perform better on dominant tasks when accompanied by individuals who are blindfolded. This theory highlights individuals' concern about social judgment by others as a factor influencing their task performance [12]. It can either enhance or impede performance based on the perceived positivity of the evaluation. Thus, the nature of the feeling of being judged matters.

Distraction conflict [2] is concerned with the role of attention and distraction: being observed by others while performing a task can either enhance or distract attention. It explains social facilitation through mechanisms such as attentional conflict [28] and physical distraction [3, 39].

Taken together, these theories collectively indicate that co-presence with another individual significantly influences human task performance and emotion. They also lay the groundwork for exploring the impact of robotic presence on humans within the context of Human-Robot Interaction (HRI), which will be introduced in the next subsection.

2.2 Social Facilitation with Robots

Extending social facilitation to HRI, several studies [55, 63, 75] have shown that social robots can induce social facilitation effects akin to those caused by human presence [63]. They also emphasized the role of arousal levels and the feeling of being judged in social facilitation, exploring how the degree of human likeness in robots influences this effect [75]. Additionally, Park and Catrambone suggested that similar to humans, virtual humans can induce social facilitation [55].

Considering that most prior research has concentrated on static robots with minimal movements (e.g., facial expressions) [41, 60, 66], Kim *et al.* conducted an online study to investigate the impact of motion and anthropomorphism of a single robot on the social facilitation effect [33]. However, this study was conducted online with a single virtual 3D robot at a time, and the distinctions in anthropomorphism levels were relatively subtle, determined only by the presence or absence of eyes.

In the realm of robotics, it is crucial to note that the emotional responses humans have toward physical robots can differ from those toward virtual agents. The key distinction lies in their embodiment: physical robots interact with the environment, while virtual agents are software-driven without a physical presence [13]. Many prior studies have consistently indicated that physically present robots tend to be more persuasive and evoke more positive perceptions than their digital counterparts [1, 42, 43, 73]. Therefore, in our study, we employed physical, active moving robots, with a deliberate emphasis on distinguishing between varying levels of the human likeness of the robots.

2.3 Human Perception of Number of Robots and Group Effect

Our interest in studying how the number of robots impacts human task performance is rooted in social psychology research, which has shown that the social perception of a group can elicit significantly different effects compared to individuals [72]. The literature suggests that people tend to categorize individuals into groups based on their invariant facial features (e.g., gender and race) and the emotional expressions conveyed by these features [26], resulting in the development of positive or negative stereotypes [26, 27, 46]. This susceptibility to using stereotypes tends to increase toward an unfamiliar group [76].

When considering robots, several factors come into play. While some individuals harbor negative views and fears about robotics [45], unfavorable emotions and stereotypes are more likely to be evoked towards robotic groups. Moreover, many people still lack significant exposure or experience with robots despite their growing prevalence, and this unfamiliarity can heighten the likelihood of resorting to stereotypes when encountering multiple robots. However, positive emotions can also emerge: people may self-categorize as humans and focus on the distinctions between themselves and robots, leading to more positive perceptions of robots that resemble them (anthropomorphic robots) [18]. As suggested by Fraune *et al.*, there is an interaction effect between the number and type of robots on human emotions and stereotypes. Specifically, multiple anthropomorphic robots elicited more positive responses (trust and liking), and multiple mechanomorphic (non-anthropomorphic) robots tended to evoke negative responses, such as feelings of threat, fear, and anxiety [18], which were perceived as higher arousal [58, 65].

As mobile robot fleets become more prevalent in the environment and most of them are non-anthropomorphic (e.g., self-driving cars, delivery robots, security robots, rescue robots, pollinator robots, etc.), it is critical to understand how non-anthropomorphic swarm robots affect human emotions. However, most HRI research has centered on single robots, largely attributed to the utilitarian nature of motion in robotics, which is typically designed for functional purposes and collision avoidance [16]. We are not aware of existing studies that employed multiple non-anthropomorphic robots and their relationship with the social facilitation effect. In this study, we investigate this effect by using actively moving non-anthropomorphic robots with two controlled conditions: single and multiple.

2.4 Human Perception of Group Robot Motion Patterns

The human perception of motion has always been an interesting topic, and there have been numerous studies highlighting how the way human perceive motions play a significant role in shaping our understanding [24], and how the way object moves can evoke a sense of vitality and influence our feelings [66] [56] [41]. Heider *et al.*'s experiment emphasized how motion can convey stories via animated shapes [24] while Lee *et al.* [41] suggested that physical movement reveals a positive correlation between emotions of pleasure and arousal with speed.

In light of this, it becomes evident that motion patterns also play a crucial role in influencing our emotions. Drawing on insights from social psychology research that has explored the connection between motion and shape descriptors and fundamental emotions [11, 17, 41, 59, 64], Santos *et al.* [67] demonstrated how swarm robots can convey fundamental emotions (e.g., happiness, surprise, anger, and fear) and can effectively communicate these emotions through their coordinated movements.

Furthermore, Kim *et al.* [36] suggested that people's perceptions vary significantly in response to different bio-inspired collective behaviors such as rendezvous [74], dispersion [74], and torus [8, 32]. For instance, both rendezvous and dispersion behaviors were perceived as highly arousing, dominant, and urgent, while torus was perceived another way around [14, 36]. These findings underscore the notion that distinct motion patterns can engender varying degrees of arousal. In line with the social facilitation drive-arousal theory which posits that increased arousal levels due to the presence of others are crucial, it is reasonable to anticipate that differential arousal levels may exert varying effects on task performance [81]. Therefore, our study aims to investigate whether the discrepancies in arousal levels induced by distinct motion patterns have an effect on the social facilitation effect. Similarly, we focus on non-anthropomorphic multi-robot motion patterns, as they align with real-world scenarios involving groups of non-anthropomorphic robots, which are more common than humanoid robots, as mentioned earlier.

3 METHOD

To investigate the influence of multi-robot presence and anthropomorphism on human cognition and emotion, we conducted a within-subject study involving 16 participants. During this study, participants engaged in two cognitive tasks: word recall [5] and modular arithmetic [55], within various experimental conditions that encompassed interested robot parameters, including anthropomorphism levels, number of robots, and multi-robot motion patterns. These conditions were 1) alone, 2) human observer, 3) single anthropomorphic robot, 4) single non-anthropomorphic robot, 5) four non-anthropomorphic robots with random motions, 6) four non-anthropomorphic robots with rendezvous/dispersion motions, and 7) four non-anthropomorphic robots with torus motion. During the experiment, the robot(s) or human observer was just present, with no bi-directional interaction with the participants. Task performance, self-reported perception, and post-study questionnaire results were collected under these conditions. This study was approved by the University's Institutional Review Board with participants providing informed consent.

3.1 Hypotheses

According to the social facilitation evaluation apprehension theory, the presence of the evaluator and the feeling of being judged increase arousal and decrease performance in challenging tasks [12]. Given that the mere presence of anthropomorphic robots can elicit social facilitation effects [63], and considering the previous study solely explored the effects of anthropomorphism level on social facilitation using active moving robots within an online virtual environment with limited variation in anthropomorphic features [33], it is crucial to investigate the influence of anthropomorphism of active robots, that exhibit more pronounced anthropomorphic distinctions within a physical environment, on social facilitation effect. In particular, we hypothesized:

H1a. The presence of an anthropomorphic robot will lead to lower accuracy and longer completion time than the presence of a non-anthropomorphic robot for hard tasks, and

H1b. The presence of an anthropomorphic robot will lead to a higher level of arousal and feeling of being judged than the presence of a non-anthropomorphic robot.

Based on the drive-arousal theory, which posits that increased arousal levels caused by the presence of others are key for social facilitation effect [81], we anticipate that different arousal levels may exert varying effects on task performance. Based on previous research indicating the positive correlation between the number of robots and perceived arousal levels [58, 65], it is essential to understand how the number of non-anthropomorphic robots affects social facilitation. This becomes particularly significant as we increasingly encounter non-anthropomorphic swarm robots in our daily lives (e.g., self-driving cars, delivery robots, and security robots). Therefore, we hypothesize that the number of physical and actively moving non-anthropomorphic robots will affect user cognition and emotion:

H2a. The presence of multiple robots will lead to higher accuracy and shorter completion time than the presence of a single robot, and

H2b. The presence of multiple robots will lead to higher arousal and feeling of being judged than the presence of a single robot.

While multi-robot motion patterns can convey emotional information [67], and people's perceptions can markedly differ depending on the specific motion patterns employed [14, 36], it becomes essential to explore the effects of multi-robot motion patterns on social facilitation. In particular, we hypothesize that the multi-non-anthropomorphic robot motion patterns will affect user cognition and motion:

H3a. The presence of the multi-robot patterned motions will lead to higher accuracy and shorter completion time than the presence of the multi-robot non-patterned motions, and

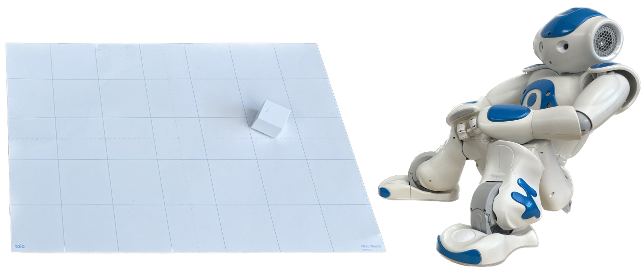
H3b. The presence of the multi-robot patterned motions will lead to higher arousal and feeling of being judged than the presence of the multi-robot non-patterned motions.

3.2 Independent Variables

We manipulated four independent variables: anthropomorphism, the number of robots, multi-robot motion patterns, and task difficulty, in addition to the two baseline conditions (i.e., alone and human presence). This resulted in a total of seven conditions as shown in Fig. 1: 1) alone, 2) human observer, 3) single anthropomorphic robot, 4) single non-anthropomorphic robot, 5) four non-anthropomorphic robots with random motions, 6) four non-anthropomorphic robots with rendezvous/dispersion motions, and 7) four non-anthropomorphic robots with torus motion.

3.2.1 Anthropomorphism. Regarding anthropomorphism, we have incorporated two distinct levels in our study: the non-anthropomorphic robot and the anthropomorphic robot.

For the non-anthropomorphic robot, we used the Sony Toio™ robot as shown in Fig. 2a, which is similar to the one utilized in the previous study [33]. Each Toio robot is a white cube measuring 3.2×3.2×2.5 cm and equipped with an optical sensor, wheels at the bottom for movement, and an RGB LED on the side for additional



(a) Sony Toio Robot (b) NAO Robot

Figure 2: Robots with distinct anthropomorphism levels used in our study: (a) non-anthropomorphic robot (the Toio robot) and (b) anthropomorphic robot (the NAO robot).

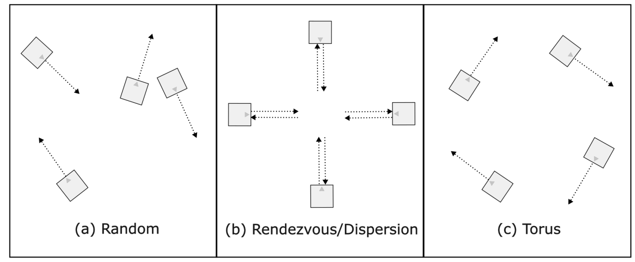


Figure 3: Different multi-robot motion patterns.

functionality [68]. The Toio robot operates on a Toio Tracking Mat, which offers a covered area measuring 55×55 cm, allowing the Toio robots to navigate within this space [68]. We consider the Toio robot as non-anthropomorphic due to its simple geometric and mechanical design, without any human-like features or characteristics. During the study, for all conditions with non-anthropomorphic robots, Toio robot(s) were in an active state, moving randomly within their designated area (except for conditions 5 and 6, which followed specific motion patterns). This was to ensure that the non-anthropomorphic Toio robot(s)'s motion did not elicit strong or extreme emotions, as the random movement is generally considered to be relatively neutral [36].

For the anthropomorphic robot, we used the NAO robot from Aldebaran Robotics as shown in Fig. 2b. This choice differs from the previous study [33], where the distinctions in anthropomorphism levels were relatively subtle, primarily based on the presence or absence of eyes. In our study, we aimed to evaluate a more human-like robot by opting for NAO, a commercial product that has been used in numerous prior research projects [51, 79, 83] and is more widely-used and realistic than the robot used in the prior study [63]. The NAO robot is perceived as highly anthropomorphic, featuring human-like physical characteristics, such as a humanoid shape, limbs, facial expressions, and pelvis kinematics design [19]. These human-like attributes contribute to its anthropomorphic design. It's important to note that, despite its overall anthropomorphic appearance, the NAO robot does not have fine controllable facial expressions, a feature previously examined for its potential influence on social facilitation in prior literature [63]. During the study, the anthropomorphic NAO robot was programmed to sporadically slowly move its head from side to side, while avoiding looking directly at the participants during the experiment. This behavior was implemented to increase its perceived animacy, since prior work showed the importance of having an active moving robot compared to a static robot [33], while minimizing distracting participants' attention by either looking directly at them or making sudden movements.

3.2.2 The Number of Robots. Regarding the number of robots, we have incorporated two distinct levels in our study: the single robot and the multiple robots. As mentioned earlier, our study focused on multiple non-anthropomorphic robots since real-world scenarios frequently involve groups of non-anthropomorphic robots. Consequently, we utilized the non-anthropomorphic Toio robot(s) for this independent variable.

For the multiple robots, we used four Toio robots. This choice was for several reasons: first, the Toio robots require a Toio Tracking Mat (55×55 cm) for programmed motions, and the size of the mat limits the number of robots we can use effectively. Having more than four robots on the mat can become crowded and hinder clear motion patterns that we want to study for the multi-robot motion patterns conditions. While using multiple mats is possible, it doesn't align with the size and setup of our study, where robots were placed on a desk near the participants. Employing multiple mats could potentially overwhelm the participants. The setup of our study will be discussed in detail in the upcoming subsection 3.4.

3.2.3 Multi-Robot Motion Patterns. Regarding the multi-robot motion patterns, we have incorporated two distinct levels in our study: multi-robot non-patterned motions and multi-robot patterned motions. Similarly, we opted for non-anthropomorphic Toio robots for this independent variable because they are a more commonly observed type of robots in daily life similar to delivery robots, vacuum robots, etc.

For the multi-robot non-patterned motions, we opted for random motions as shown in Fig. 3a because they exhibit unpredictable and non-systematic movements, and it is generally considered to be relatively neutral [36]. This choice prevents the motion from triggering any particular emotions and can be better compared to the multi-robot patterned motions.

For the multi-robot patterned motions, it is important to note that people's perceptions can significantly differ depending on the specific motion patterns employed in previous studies [14, 36]. In this context, we purposely selected two distinct motions shown in Fig. 3bc and used their combined mean for comparison with the multi-robot without motion patterns: rendezvous/dispersion and torus, as they have been observed to have a notable impact on arousal levels compared to other motion patterns [36]. To clarify, we combined rendezvous and dispersion motions into a single condition because they both were perceived as highly arousing and dominant [36] and are closely related in terms of their movements enabling smooth continuous repetition. In contrast, the torus motion was perceived differently from rendezvous/dispersion and was rated as less arousing and dominant, justifying their categorization as another level [36]. This approach, involving two distinct motion patterns, ensures that the effects observed in the multi-robot patterned motions are not attributed to a specific motion pattern, but rather to the presence of motion patterns in general. It allows for a comprehensive examination of whether motion patterns affect user cognition and emotion without introducing bias.

3.2.4 Task Difficulty. For the task difficulty, we have incorporated two distinct levels similar to most prior studies investigating social facilitation [33, 55, 63]: easy and hard.

According to the social facilitation effect, task difficulty plays a pivotal role [81]. When a task is easy, the presence of another human may enhance performance, but for hard tasks, it can lead to diminished performance [81]. We incorporated two task difficulty levels similar to prior studies in social facilitation for our cognitive tasks—modular arithmetic [55] and word recall [5]. The specific tasks and task difficulty levels will be discussed in detail in the upcoming section 3.5.

3.3 Dependent Variables

We collected three dependent variables: quantitative task performance, quantitative self-reported perception, and qualitative post-study questionnaire results.

3.3.1 Task Performance. We collected quantitative measures by recording task accuracy (i.e., the number of correctly answered questions) and task completion times across various conditions to analyze their impact on human task performance in our study. These data points were saved locally through our study software as participants completed the tasks (further details on the software will be provided in the subsequent subsection 3.4). While there were no time limits, participants were instructed to work at their typical question-solving pace. Overall, we collected the same task performance-related metrics as prior works [33, 55].

3.3.2 Self-Reported Perception. We collected quantitative feedback from participants as shown in Fig. 4b, focusing on their emotional experiences using the PAD (pleasure, arousal, and dominance) three-dimensional scales [48] using the Self-Assessment Manikin (SAM) [7] on a 7-point Likert Scale. Furthermore, participants' sense of being judged/observed/evaluated was also reported using a 7-point Likert Scale, enhancing our understanding of the social dynamics perceived by participants during the study. Overall, we collected the same perception-related metrics as prior works [33, 55].

3.3.3 Qualitative Responses. We gathered qualitative responses from the participants through the post-study questionnaire. Specifically, they were prompted to share their emotional feelings towards different robot presence conditions. Participants were asked to express perceptions related to the anthropomorphic robot and the non-anthropomorphic robot and if the more human-like one evoke a stronger emotional attachment. The questions also ask their feelings of having a human observer present. Additionally, participants were asked whether the number of robots or specific motion patterns positively or negatively influenced their emotional responses and whether these variables contributed to their task-solving.

3.4 Study Setup

The study was conducted in person, with participants in a separate room from the experimenter except for the human observer baseline condition. This intentional spatial separation was implemented to prevent creating potential confounding variables of the experimenter's presence on the social facilitation effect in all other conditions. Participants were seated at a desk with a laptop running the study software in front of them. The robots were arranged on the right side of the laptop as shown in Fig 1. Additionally, participants were required to wear a headset through which white noise was played to mitigate the effects of noise from the robots on participants' task performance.

The study software, developed in Unity 3D and running as a desktop application on the laptop, guided participants through the study procedure. It provided relevant study information, presented tasks, and recorded participant responses to both tasks and self-reported perceptions. The design of the software, as illustrated in Fig. 4, prioritized a clear and concise user interface, to help participants focus on completing the tasks.

The robots were controlled through their dedicated software running on a separate computer. The Toio robot software, developed in Unity and integrated with a publicly available Toio Sony API [1], enabled precise control over the Toio robots' programmed motions. The NAO robot software, developed using Choregraphe and the NAOqi framework, focused on programming the behaviors of the NAO robot to ensure sporadic random head movements and create the perception of the robot as active as a human.

3.5 Tasks

Participants performed two cognitive tasks that were used in prior work [33]: modular arithmetic [55] and word recall [5]. The modular arithmetic task evaluates calculation and problem-solving skills [4], while word recall assesses memory retrieval [5]. Their selection aims to capture diverse emotional and cognitive aspects influenced by the robotic presence conditions. It is pertinent to scenarios involving physical robots, where effective human-robot interaction requires a nuanced comprehension of cognitive processes influenced by the robots' presence and characteristics [77].

3.5.1 Modular Arithmetic Task. The participants are shown a math expression (Fig. 4c) consisting of three numbers (e.g., '10 ≡ 5 (mod 2)'). Their task is to indicate through a key press whether the difference between the first two numbers is divisible by a third number, i.e., the quotient is a whole number. The choice of modular arithmetic task is grounded in its cognitive nature, with Beilock *et al.* [4] highlighting the advantage of it as a laboratory task due to its unusual characteristics, facilitating controlled learning history [55].

The difficulty of a particular expression was manipulated by controlling the number of digits in the first two numbers: one for an easy case (e.g., '7 ≡ 2'), and two for a difficult case ('51 ≡ 19'). This approach to distinguishing difficulty levels is rooted in the work of Beilock *et al.* [4]. Easy and difficult expressions were presented in fully randomized order. Overall, the task setup is the same as that from Park and Catrambone [55].

[1] https://github.com/morikatron/toio-sdk-for-unity

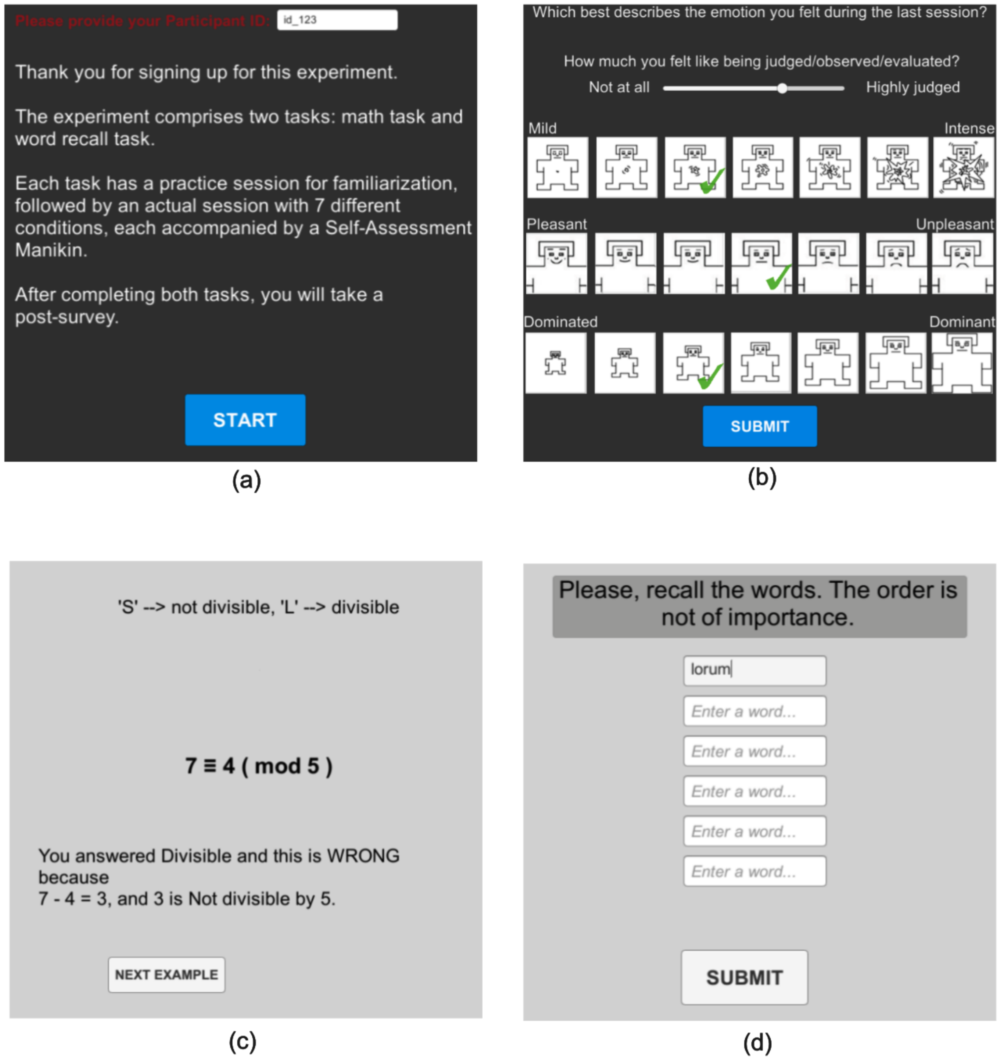


Figure 4: Our study software, developed using Unity 3D, incorporated distinct pages for various study phases: (a) a welcome page, (b) a 7-point Likert Scale for the Self-Assessment Manikin (SAM) used to measure self-reported levels of emotion, (c) the modular arithmetic task, and (d) the word recall task.

3.5.2 Word Recall Task. The participants are shown a set of words one by one (Fig. 4d). Their task is to remember the words and type them after a 10-second pause, similar to the setup by Berger *et al.* [5]. For the answer, only the accurate spelling is important. Relying on the concept of familiar and unfamiliar words [5], we selected 24 familiar words that were used for easy trials (e.g., "baker", "money", "pecan") and 24 unfamiliar words that were used for hard trials (e.g., "bosun", "xilos", "kalab"). The selection of unfamiliar words for the hard trials and familiar words for easy trials aligns with the notion of manipulating task difficulty based on word familiarity [5]. To ensure consistent standards for word familiarity across all participants, we only recruited participants who self-reported to be fluent in English.

3.6 Procedure

The participant was invited to take a seat at the desk in front of the laptop and follow the instructions appearing on the screen. The initial phase involved completing a demographic questionnaire, which gathered demographic information and personal details, followed by a consent form. Subsequently, the study software opened a welcoming screen with an introduction to the study. Participants were then directed to put on the provided headset with white noise being played, answer with maximum accuracy, and rest between the conditions and the tasks if needed.

Upon clicking the start button, the software generates the study flow based on a configuration file specifying tasks, conditions, and parameters. For each task and condition, two task sets are created, each with a defined number of tasks (e.g., 10 tasks for the modular arithmetic and 1 task with 6 words for the word recall task) of easy or hard complexity. Participants receive task descriptions and practice sessions with feedback that informs them about the correctness of their responses before starting the actual experiment. When transitioning to a new robotic presence condition, participants notify the experimenter, who adjusts the robot setting accordingly. After each task set, participants complete a self-reported perception with Self-Assessment Manikin (SAM) measuring emotions and feelings of being judged. The process repeats for all conditions, task types, and sets, with short breaks in between if needed. The experiment concludes when both word recall and modular arithmetic tasks are completed, followed by a post-study questionnaire.

3.7 Participants

For our study, we recruited 16 participants from nearby universities and institutions. We controlled for the order effects among participants by using the Balanced Latin Square design (BLSD) [2]. We designed 14 trials, corresponding to 14 participants, in line with BLSD requirements, which stipulate that odd-sized designs require twice as many rows to achieve balance. Two additional participants signed up and their data was also included.

For the analysis, based on the demographic questionnaire (Table 1), among all participants (n = 16), 4 were women and 12 were men, with an average age of 24 years (SD = 2.048). All participants had completed or were currently pursuing at least a bachelor's degree. On average, participants spent 38 minutes (SD = 4.04) on the actual tasks across all 7 conditions and an additional 13 minutes (SD = 2.31) on the post-study questionnaire. None of the participants had neurological disorders that could affect their performance, and they all had normal or corrected-to-normal vision (for task completion) and hearing (for listening to instructions). Additionally, all participants had the capacity to provide informed consent to participate in the research independently. They were compensated at $18 for their participation.

3.8 Data Analysis

This study involved both qualitative and quantitative responses from the participants.

3.8.1 Quantitative Analysis. We collected quantitative measures, including task performance metrics (task accuracy and task completion times) and self-reported perceptions (PAD scales [48] and sense of being judged [33]).

We conducted repeated measures analysis of variance (ANOVA) to investigate potential differences across various conditions for each task performance measure and self-reported perceptions. The following analyses were conducted to test the 3 hypotheses described earlier:

- Anthropomorphism: 2 (task difficulty: hard, easy) x 4 (presence conditions: alone, Toio robot, NAO robot, human)
- Number of robots: 2 (task difficulty: hard, easy) x 2 (presence conditions: single Toio robot, four Toio robots)
- Multi-robot motion patterns: 2 (task difficulty: hard, easy) x 2 (presence conditions: four Toio robots with random motions, four Toio robots with rendezvous/dispersion and torus motion)

If any of the independent variables or combinations thereof yielded statistically significant effects ($p < 0.05$), Mauchly's test of sphericity was employed to assess the equality of variances of the differences between conditions. In cases where Mauchly's test indicated a violation of sphericity assumptions ($p < 0.05$), Greenhouse-Geisser correction was used indicated by the use of $*$ (e.g., $F*$ and $p*$).

3.8.2 Qualitative Analysis. In our brief thematic analysis, we categorized participants' responses from the post-study questionnaire. We first sorted comments based on different robot presence conditions and then classified them as negative, positive, or neutral. Additionally, we examined whether participants perceived the conditions as helpful or distracting. The results are summarized with quotes from the participants in the following section 4.3.

Table 1: Demographic Information of the Participants.

Measure	Item	Count	Percent (%)
Gender	Male	12	75.00
	Female	4	25.00
Age (years old)	>18 and <= 25	13	81.25
	>25 and <= 30	3	18.75
Education	Undergraduate	15	93.75
	Doctor or above	1	6.25
Occupation	Student	11	68.75
	Healthcare worker	2	12.50
	Self - employed	1	6.25
	Worker	2	12.50
Race	East Asian	11	68.75
	South Asian	2	12.50
	Southeast Asian	1	6.25
	Prefer not to say	2	12.50
Experience with HCI	None*	12	75.00
	Limited**	3	18.75
	Moderate***	1	6.25

*This is their first time.
**They've done a demo or two.
***They've worked with HCI studies.

4 RESULTS

Here, we summarize the study results, including quantitative measures of task performance and self-reported perceptions, as well as qualitative feedback from the post-study questionnaire.

4.1 Task Performance

Here, we report the quantitative measures taken regarding task performance and summarize all findings in Table 2, providing an overview of task performance across all conditions. Furthermore, the results for each task performance related to each hypothesis are included in this section and in Figs 5-7 (*: 0.01 < p ≤ 0.05, **: 0.001 < p ≤ 0.01, ***: p ≤ 0.001).

4.1.1 Word Recall Task. The data analysis for the word recall task is discussed in detail for three specific hypotheses.

H1a: Anthropomorphism

[2] https://cs.uwaterloo.ca/~dmasson/tools/latin_square/

Table 2: Task Performance (M: Mean, SD: Standard Deviation) for word recall and modular arithmetic tasks. The blue and bolded numbers highlight the best score for each difficulty.

Word Recall		Time (s)				Correct Words (%)			
		Easy		Hard		Easy		Hard	
Condition	N	M	SD	M	SD	M	SD	M	SD
Alone	16	26.51	13.68	**20.09**	7.22	58.33	17.21	36.46	18.48
Non-Ant* Robot	16	21.97	9.96	23.92	8.79	**67.71**	25.44	44.79	18.97
Ant* Robot	16	**20.71**	7.51	20.45	8.77	63.54	16.35	32.29	16.63
Human	16	25.13	13.23	22.64	12.61	62.50	17.74	40.63	16.07
Multiple Non-Ant* Robots	16	31.35	12.40	25.60	10.54	61.46	20.83	43.75	18.13
Multiple Non-Ant* Robots R/D**	16	22.23	13.22	23.81	9.64	63.54	22.95	**50.00**	16.10
Multiple Non-Ant* Robots T***	16	26.74	16.83	21.36	9.59	62.50	21.51	44.79	20.83

Modular Arithmetic		Time (s)				Accuracy (%)			
		Easy		Hard		Easy		Hard	
Condition	N	M	SD	M	SD	M	SD	M	SD
Alone	16	**2.30**	0.68	6.54	2.31	93.75	10.88	93.13	11.95
Non-Ant* Robot	16	2.49	1.09	6.62	1.94	95.00	13.66	**95.00**	8.16
Ant* Robot	16	2.65	1.14	7.03	2.67	93.13	12.50	93.13	9.46
Human	16	2.45	0.69	6.35	2.05	**96.25**	6.19	92.50	10.65
Multiple Non-Ant* Robots	16	2.58	0.90	7.61	3.68	93.75	11.47	94.38	8.92
Multiple Non-Ant* Robots R/D**	16	2.53	1.09	6.97	2.75	91.25	9.57	93.75	8.14
Multiple Non-Ant* Robots T***	16	2.44	0.99	**6.20**	1.59	94.38	11.53	92.50	12.58

*Anthropomorphic. **Rendezvous/Dispersion. ***Torus

A 2×4 ANOVA with repeated measures revealed that task difficulty exhibited statistically significant effects on accuracy (i.e., count of correct words within 1 letter) ($F(1, 15) = 57.626, p < .001, \eta^2 = .793$), where the hard difficulty level correlated with lower accuracy. No significant difference between different levels of anthropomorphism was observed. However, the anthropomorphic robot did exhibit the lowest accuracy in hard tasks as shown in Fig. 5a.

H2a: Number of Robots

A 2×2 repeated measures ANOVA revealed that task difficulty exhibited statistically significant effects on accuracy (count of correct words within 1 letter) ($F(1, 15) = 27.455, p < .001, \eta^2 = .647$), where the hard difficulty level correlated with lower accuracy as shown in Fig. 6b.

Furthermore, there was a statistically significant main effect of the number of robots on completion time ($F(1, 15) = 5.721, p = .030, \eta^2 = .276$). Additionally, a close to significant interaction effect ($F(1, 15) = 3.361, p = .087, \eta^2 = .183$) between the number of robots and task difficulty on completion time was observed. Further post hoc tests confirmed a statistically significant result ($F(1, 15) = 6.831, p = .020, \eta^2 = .313$), showing that the presence of multiple robots is correlated with longer completion times. Specifically, the presence of multiple robots is associated with longer completion times for easy tasks but not for hard tasks as shown in Fig. 6a.

H3a: Multiple-robot motion patterns

We calculated the means for our two motion patterns (torus and rendezvous/dispersion) and compared them with the multi-robot non-patterned motions (random). For the analysis, a 2×2 repeated measures ANOVA revealed that task difficulty exhibited statistically significant effects on accuracy (count of correct words within 1 letter) ($F(1, 15) = 16.134, p < .001, \eta^2 = .518$), where the hard difficulty level correlated with lower accuracy as shown in Fig. 7b.

Furthermore, there was a statistically significant main effect of the multi-robot motion patterns on completion time ($F(1, 15) = 7.078, p = .018, \eta^2 = .321$) as shown in Fig. 7a. The presence of multi-robot patterned motions has a reduction in completion time for easy tasks.

4.1.2 Modular Arithmetic Task. The data analysis for the modular arithmetic task is discussed collectively for all three hypotheses, as few significant results were found for each task performance hypothesis.

Task difficulty exhibited statistically significant effects on completion time ($p < .001$) for all conditions, where the hard difficulty level correlated with longer completion time.

No other significant differences were found, but there are noticeable patterns where the increase in the number of robots leads to longer completion times for hard tasks, while multi-robot patterned motions lead to shorter completion times for hard tasks.

4.2 Self-Reported Perception

Here, we report the quantitative measures taken regarding self-reported perception. The data analysis for the overall self-reported perception of emotions and the feeling of being judged for both tasks is discussed in detail for the three specific hypotheses.

H1b: Anthropomorphism

In the data analysis for anthropomorphism, a 2×4 repeated measures ANOVA revealed that anthropomorphism exhibited a statistically significant effect on the feeling of being judged for both tasks ($F(1.830, 27.452) = 9.559, p < .001, \eta^2 = .389$). Further post hoc tests indicated that the presence of the anthropomorphic robot is correlated with a higher feeling of being judged compared to 1) alone ($p = .006$ for modular arithmetic, $p = .076$ for word recall),

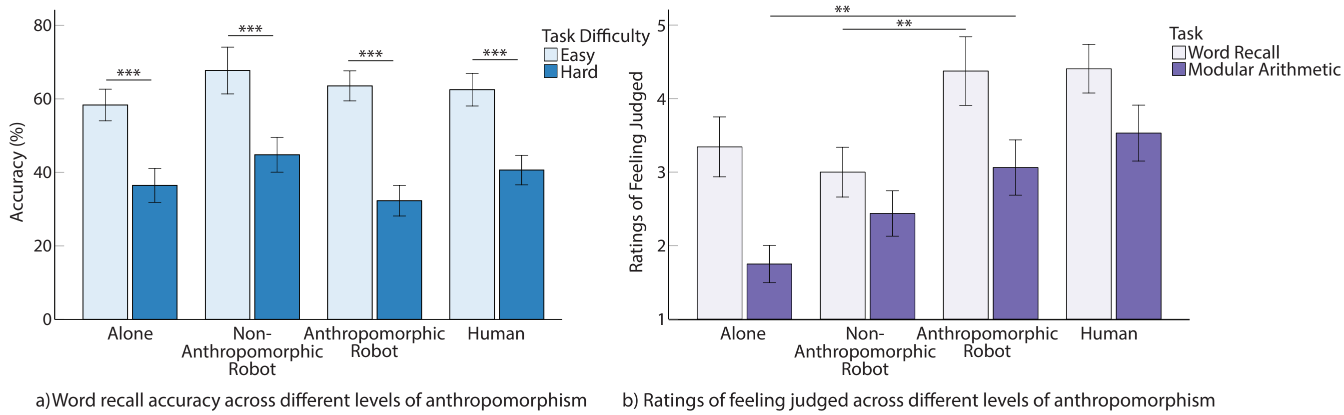


Figure 5: Effects of anthropomorphism on (a) accuracy for word recall task and (b) ratings of feeling judged for both tasks.

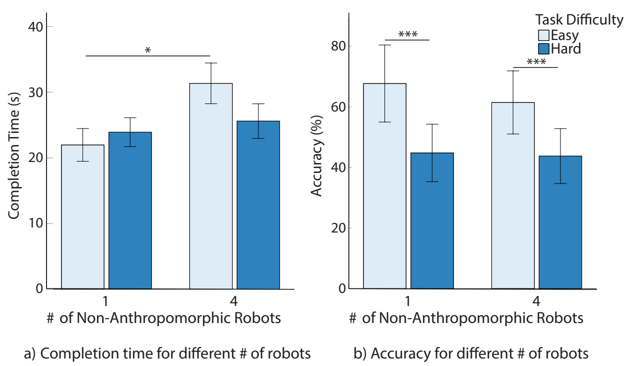


Figure 6: Word recall (a) completion time across different numbers of robots under both task difficulties and (b) accuracy across different task difficulties under the number of robots.

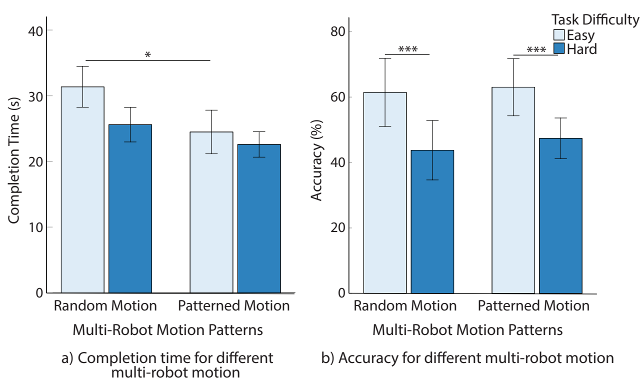


Figure 7: Word recall (a) completion time across different multi-robot motion patterns under both task difficulties and (b) accuracy across different task difficulties under the multi-robot motion patterns.

and 2) the non-anthropomorphic robot (p = .005 for word recall), as shown in Fig. 5b. No statistically significant effects were found for other emotional measures.

H2b: Number of Robots

In the data analysis for the number of robots, a 2×2 repeated measures ANOVA revealed a statistically significant interaction effect between the number of robots and task on the feeling of being judged ($F(1, 15) = 11.571, p = .004, \eta^2 = .435$), where multiple robots correlated with a higher feeling of being judged for the word recall task (p = .050) but not the modular arithmetic task. No statistically significant effects were found for other emotional measures.

H3b: Multiple-robot motion pattern

In the data analysis for multi-robot motion patterns, no statistically significant effects were found.

4.3 Post-Study Questionnaire: Perceived Impact and Noticeability of the Robot

Here, we report the qualitative feedback from the post-study questionnaire.

The post-study questionnaire findings revealed distinct patterns in participants' perceptions of the robots. The anthropomorphic robot came across as mostly negative (10 out of 16 participants), with participants often finding it creepy and weird. For instance, one participant mentioned feeling *"weird and distracted"* [P14], and another expressed, *"it reminds me of movies like AI destroying the world, making me nervous"* [P1]. It is noteworthy that even though we did not have the NAO robot look directly at the participant, people still felt as if the NAO robot was staring: *"it feels like someone is staring at me"* [P8] and *"it negatively affects my emotions and feels like someone is observing me"* [P10]. Perceptions of the non-anthropomorphic robot were largely neutral, with most participants reporting minimal awareness or feelings related to the robot's presence, stating responses such as *"no feelings"* [P5] and *"I hardly ever noticed them because I was so forced into my tests"* [P13].

Only 4 out of 16 participants reported being affected by the presence of anthropomorphic or non-anthropomorphic robots. However, the anthropomorphic robot was perceived to have a more pronounced impact than the non-anthropomorphic robot, albeit primarily negative (distraction, sense of being monitored): *"I could easily see myself getting distracted more by this robot than the other ones"* [P18]. Human presence had a more pronounced impact, affecting 10 of 16 participants, with 6 describing negative effects (feeling of being evaluated, distracted, and nervous) and 4 reporting positive outcomes: *"the experimenter made me want to perform better on the questions"* [P12].

Interestingly, none of the participants reported being affected by changes in the number of robots. However, multi-robot motion patterns did influence perceptions, with 7 participants noting their impact. Six participants had a negative perception, indicating that they noticed both patterns and found them distracting, for instance, *"movement 2 (dispersion/rendezvous) and movement 3 (torus) were definitely more distracting because the patterns were easier to follow and get distracted"* [P13]. One participant had a positive perception, describing the torus motion as calming.

5 DISCUSSION

5.1 Anthropomorphism

Anthropomorphism had a statistically significant effect on the feeling of being judged, where the anthropomorphic robot condition led to higher ratings of being judged compared to the non-anthropomorphic robot condition for word recall tasks. The qualitative feedback from participants echoes the same trend. These results partially support our hypothesis H1b. We did not observe a stronger sense of dominance elicited by the anthropomorphic robot compared to the non-anthropomorphic robot as reported in Kim *et al.*'s online study [33]. These differences in findings may be due to the differences in the level of anthropomorphism for the *anthropomorphic* robot condition (a cylindrical robot with just eyes [33] vs. a fully humanoid NAO robot) and the experimental setup (in-person with physical robots vs. online study with virtual robots). With regards to the level of anthropomorphism, the virtual robot used in the prior study had eyes as the only anthropomorphic feature [33], ranking low (<5) in terms of human-likeness score according to the ABOT database [57]. In contrast, the NAO robot used in our study has an ABOT human-likeness score of 45.92 [57] having a more wholistic anthropomorphic appearance with not only eyes but also a torso and limbs. This difference in the level of anthropomorphism may have resulted in the stronger feeling of being judged that was observed in our study compared to prior work [33]. Another potential source for the varying results is the difference in the experimental setup, where our study was conducted in-person with real physical robots, whereas the prior study was online with virtual robots [33].

Anthropomorphism did not have statistically significant effects on task performance, which led to the rejection of our H1a. However, it is worth noting that the anthropomorphic robot condition did result in the lowest accuracy in the hard difficulty level for the word recall task, which aligns with findings from Wechsung *et al.* [75]. The absence of statistically significant effects on task performance could be due to several factors such as task difficulties and types. According to Yerkes-Dodson law and its derivative Hebb's theory, there is an optimal level of arousal for maximizing performance, and this relationship is non-linear, resembling a U-curve [22, 78]. This implies that up to a certain threshold, an increase in arousal level positively influences task performance. However, once the arousal level surpasses this threshold, task performance begins to decline. Hence, it is evident that various cognitive tasks can have distinct effects on arousal levels, ultimately resulting in variations in task performance. This variability is exemplified in our study by the differences observed between the word recall and modular arithmetic tasks. Modular arithmetic, being relatively easy, exhibited minimal differences in accuracy and completion time compared to the word recall task. Another explanation could be the task type, suggesting that anthropomorphism may have a more pronounced impact on the memory-related word recall task compared to the modular arithmetic task involving mathematical or computational skills.

Our results regarding anthropomorphism underscore important implications for the complex relationship between anthropomorphism and the social facilitation effect. Different levels of anthropomorphism do not consistently produce the desired social facilitation results. Other factors, including physical embodiment, task types, and task difficulties, play significant roles. Given the complexity of human perception of emotions and their effects on task performance, further research into the impact of anthropomorphism on social facilitation is essential, both in experimental design and practical robot development. Designers should avoid a uniform approach to anthropomorphism by incorporating adaptive features in robots that can tailor anthropomorphic characteristics to specific contexts. Moreover, considering the anthropomorphic robot can lead to higher feelings of being judged, designers can consider incorporating more human-like features in scenarios where heightened user engagement or attention is desired. At the same time, while these feelings were observed in word recall tasks but not in modular arithmetic tasks, further study can address different task types and examine if anthropomorphic robots may have a more pronounced impact on memory-related tasks compared to those involving mathematical or computational skills.

5.2 Number of Robots

The number of robots exhibited statistically significant main and interaction effects with task difficulty on task performance for the word recall task. Contrary to our H2a, multiple non-anthropomorphic robots correlated with longer completion times for the easy difficulty level compared to a single non-anthropomorphic robot. Additionally, the number of robots had statistically significant main and interaction effects with the task on self-reported emotional perception for the word recall task. Aligning with our H2b, multiple non-anthropomorphic robots correlated with a higher feeling of being judged compared to a single non-anthropomorphic robot.

One possible explanation for the increase in the feeling of being judged while experiencing a decrease in performance could be attributed to the impact of evaluation apprehension. In this context, the heightened sense of being judged may have inhibited participants' task performance. Notably, despite these effects, none of the 16 participants reported consciously noticing the change in the number of robots, suggesting that the presence of multiple robots had a subconsciously negative impact on participants' experiences for the word recall task.

While the prior study has suggested that people tend to exhibit a more positive psychological state towards observing multiple robots than a single robot [58], one may assume that these positive emotions can help improve task performance. However, our study shows the opposite results and underscores important implications for the design of human-robot interactions and the deployment of robots in the real world. This implies that in certain contexts, designers may want to have multiple robots move visibly within the user's field of view to draw attention and intentionally slow down their performance. One such potentially suitable context is during creative tasks, where the goal is to inspire users to spend more time exploring and engaging with innovative and divergent ideas. More research is needed to investigate whether this conjecture holds in practice and how designers could design robots' behavior in such cases to create an optimal environment for users.

5.3 Multi-Robot Motion Patterns

The multi-robot motion patterns had a statistically significant main effect on task performance for the word recall task, supporting our H3a. Specifically, multiple non-anthropomorphic robots moving in patterns (torus and rendezvous/dispersion) correlated with a shorter completion time for the easy difficulty level compared to multiple non-anthropomorphic robots moving randomly. However, the multi-robot motion patterns did not lead to statistically significant effects on participants' emotions, leading to the rejection of our H3b and contradicting results from prior work [36].

Notably, despite the significant improvement in task performance, only one of our participants mentioned that these patterns actually helped with task-solving by making him feel calm. This suggests that the impact of patterned motions might be implicit or subconscious, affecting human task performance in a subtle way through predictable and systematic motions. One possible explanation could be that individuals are constantly trying to interpret and make sense of their surroundings, especially when movement is involved. This is confirmed by earlier research [47] stating that the human brain has innate sensitivity for the detection of self-produced motion, which provides one of the most powerful cues about whether an object is animate. Similarly, the famous experiment of psychologists Fritz Heider and Marianne Simmel conducted back in the 1940s showed how motion can be interpreted by observers to convey stories and enhance the animacy of even simple geometric shapes [23]. Thus, when observing robots moving randomly, people may be using more of their cognitive resources to try to interpret the unpredictable and random movements, leading to an unconscious diversion of their attention while attempting to complete the tasks. This may have led to slower task completions under the random multi-robot motion condition compared to the patterned multi-robot motion condition.

These implications highlight the potential of multi-robot motion patterns to subconsciously influence user task performance without necessarily eliciting strong emotional responses. Therefore, leveraging different motion patterns during human-robot interactions can lead to different effects for the users. Depending on the goal, designers may want to have the robots move in different multi-robot motion patterns. For example, for scenarios requiring increased concentration and faster productivity, robots moving in a torus or dispersion/rendezvous pattern may be helpful because their predictable nature can provide a focused vibe, facilitating better concentration for users. For cases requiring creativity without time constraints, robots moving randomly without motion patterns may be beneficial because the absence of specific patterns may introduce an element of unpredictability. This unpredictability may stimulate creative divergent thinking by encouraging users to explore in an unconstrained manner.

6 LIMITATIONS AND FUTURE WORK

The specific robots used for the anthropomorphic robot and non-anthropomorphic robot conditions most likely affected the outcome of this study. The NAO and Toio robots used in the study have many inherent differences beyond their human-likeness or anthropomorphism levels that may have led participants to perceive them differently. Firstly, the difference in size could have introduced confounding effects, given that the NAO robot ($standingheight = 57cm$) is considerably larger than the Toio robot ($height = 1.9cm$). Some effects attributed to the NAO robot may be due to its size rather than solely due to the level of anthropomorphism. A prior study showed that the bigger robot was more threatening and contributed to intimidation [29]. Exploring robots with similar sizes, both anthropomorphic and non-anthropomorphic, and investigating how robot size influences social facilitation would be an intriguing avenue for future research. Secondly, their motions differ due to the differences in their physical affordances. Despite coding both robots to move randomly, designing robot motions to be perceived similarly in terms of animacy is challenging, given the difference in affordances. Future research is needed to figure out a way to reduce the effects of confounding factors stemming from using different robotic platforms.

Moreover, our study deliberately chose to investigate the effects of the number of non-anthropomorphic robots and not that of anthropomorphic robots. The focus on non-anthropomorphic robots was primarily motivated by the increasing prevalence of such robots in real-world scenarios, such as self-driving cars [61] and delivery robots [80], as well as the practical advantages that non-anthropomorphic robots offer over anthropomorphic robots (e.g., not needing to have the costly anthropomorphic features like a face or limbs). However, future studies could explore how multiple anthropomorphic robots affect human cognition and emotion and in comparison with non-anthropomorphic robots to further our knowledge.

Additionally, we only used four non-anthropomorphic robots to represent the multi-robot conditions. Given that real-world scenarios often involve a larger number of robots, it would be worthwhile to investigate if having even more robots leads to different or more drastic outcomes and when we start to see a saturation of such effects.

Another notable limitation lies in the relatively small sample size of 16 participants, raising concerns about the generalizability and statistical power of the findings. Additionally, there is a potential gender bias as the participant pool is predominantly male. Previous research has highlighted gender-related differences in how individuals perceive and interact with robots, with females often demonstrating a higher level of motivation and a more desirable affective state in the presence of a non-anthropomorphic robot [34]. Future studies could include a larger and more diverse population to yield more generalizable outcomes with higher statistical power.

As mentioned earlier, the choice of tasks may have introduced a potential limitation, as several participants found the modular arithmetic task to be too easy, even with two different difficulty levels. In terms of Yerkes-Dodson law [22, 78], this scenario aligns with the possibility of encountering a lower peak on the U-curve, where task difficulty may not be sufficiently stimulating to yield significant differences. It is worth noting that the lack of significant differences in the modular arithmetic task was also found and is consistent with the prior study [33], indicating this could have influenced the overall results of task performance, as excessively easy tasks may lead to boredom or apathy, resulting in similar performance across different conditions. Future work could explore a more nuanced selection of task difficulty levels, ensuring a broader spectrum of challenges to better capture the optimal arousal levels.

7 CONCLUSION

As robots continue to proliferate and find increasingly widespread applications, it becomes imperative to gain a comprehensive understanding of robotic presence impact. Given the prevalent presence of non-anthropomorphic robots and the growing demand for multi-robot systems, our study delves into an investigation of the impact of anthropomorphism, number of robots, and multiple-robot motion patterns on human cognition and emotions. The study findings indicate that an increase in the number of robots leads to a decline in task performance at specific tasks and difficulty levels, but patterned motions can enhance it. Anthropomorphic robots also evoke a stronger feeling of being judged. Human perception of robots is a complex and subjective process, and future research should delve further into the intricate interactions among tasks, task difficulty, the number and size of robots, multi-robot motion patterns, and anthropomorphism.

ACKNOWLEDGMENTS

We thank all the participants who dedicated their time and effort to this study. This work is supported by the Canada Foundation for Innovation (CFI) John R. Evans Leaders Fund (JELF) grant no. 44170, and Natural Sciences and Engineering Research Council of Canada (NSERC) Discovery Grant no. RGPIN-2023-04148.

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