



Exploring Theory of Mind for Human-Robot Collaboration

Document Version

Accepted author manuscript

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Citation for published version (APA):

Romeo, M., Mckenna, P. E., Robb, D., Rajendran, G., Nettet, B., Cangelosi, A., & Hastie, H. (Accepted/In press). Exploring Theory of Mind for Human-Robot Collaboration. In *31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN 2022)*

Published in:

31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN 2022)

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Exploring Theory of Mind for Human-Robot Collaboration

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Abstract—The ability to impute mental states to oneself or others, or Theory of Mind (ToM), has been intrinsically linked to trust between humans. However, less is known about how a robot mimicking ToM affects users’ trust and behaviour. We explore this through an online study, where we compare three robot personas in a cooperative maze navigation task: one neutral, one that explains its reasoning in technical terms, and one that mimics ToM. We show that ToM influences human decision-making behaviour and trust in a way that makes it more appropriate with respect to the competencies of the robot. This is key for human-robot collaboration and adoption of robotics moving forward.

Index Terms—trust, theory of mind, online experiment

I. INTRODUCTION

Human-robot collaboration will be key to successful deployment of robots and autonomous systems in our home and workplace. To this end, users will expect information and suggestions provided by robots to reduce decision uncertainty and make collaboration more efficient and effective. But what if this information is not 100% accurate or if the information provided is ambiguous or the task just too complicated? In these cases, is it better to trust the autonomous system or override it?

To develop and maintain trust between users and robots, research has examined how psychological concepts underlying human-human trust affect decision-making and trust in human-robot interactions. One such concept is Theory of Mind (ToM; [1]) defined as the ability *to infer thoughts, feelings, and beliefs of others*. Recent work has shown that robot ToM can increase the perception of anthropomorphism and human-likeness of the robot [2]. Anthropomorphism can then, in turn, influence how trustworthy a human perceives a machine [3], [4].

Furthermore, trust is important to human-robot interaction (HRI) in collaborative tasks, where people and robots must work together to reach shared goals [5]. This is because trust allows one to suspend the meticulous analysis of benefits and risks when cooperating with another [6]. However, challenging and ambiguous scenarios can lead to over-trust in robots [7].

In this paper, we investigate how mimicking ToM in a social robot – in our case SoftBank’s Pepper – affects users’ decision-making and human-robot trust in a cooperative task. We tested

the importance of ToM as a psychological anthropomorphic feature using an online video-based between-subjects study, in which three groups of participants had to escape a large maze by correctly solving 10 mini-mazes with Pepper’s help. For each mini-maze, the robot gave advice on which exit path to head towards and participants decided whether or not to follow the robot’s suggestion. The priming videos and the utterances the robot offered varied per group: the *Baseline group* experienced a robot that simply stated which mini-maze path to follow; the *Sensor group* experienced a robot that gave direction advice referring to its hardware readings; the *ToM group* experienced a robot that expressed the ability to take participant’s thoughts into account while they decided what route to take.

We carefully designed the task to ensure it probed some of the core fundamentals of trust. For example, some mini-mazes were complex enough to warrant assistance from the robot, making participants vulnerable to the accuracy of the robots’ suggestions [8]. Crucially, Pepper’s suggestion accuracy was fixed across trials and across conditions. This ensured that the human’s interpretation of the robot’s mental reasoning abilities was the only variable factor. Thus, our contribution to this domain is the examination of how “robot ToM” affected participants’ decision-making in a challenging collaborative navigational task, where the accuracy of the robot’s advice was manipulated. The results indicate that ToM encouraged a more cautious approach, which was mindful of veracity of the robot’s suggestions, thus instilling a more “appropriate” trust level.

II. RELATED WORK

Trust is a fundamental construct in HRI. The definition of trust commonly cited by the community is a combination of the definitions given by [9] and [10] and can be defined as, “...an attitude that an agent (automation or another person) will help achieve an individual’s goals in a situation characterised by uncertainty and vulnerability” [11], [12]. A significant research effort has been put into identifying the characteristics that influence the trustworthiness of robots [4],

[13], [14]. In particular, Ullman et al. [13] created a scale by analysing trust definitions and conceptualisations (e.g., performance-based trust and relation-based trust of [15]). The resulting Multi-Dimensional Measure of Trust (MDMT) scale generates scores for two trust constructs, Capacity Trust and Moral Trust.

Among the different characteristics that a robot may possess to elicit a stronger (or weaker) idea of trustworthiness is anthropomorphism [3], [4]. There is a distinction to be drawn here between *physical anthropomorphism* and *psychological anthropomorphism*, where the former can refer to robot movements and aesthetics, and the latter, to the simulation of social behaviours in robots [16]. This distinction is relevant as recent work has shown that modifying a robot’s utterances, and not its appearance, affects humans’ trust and compliance [11]. However, anthropomorphism¹ does not consistently improve human trust. For example, participants in [17] preferred a robot that did not understand sarcasm, thereby not showing human-like abilities. Relevantly, Seeger et al. [18], identify two opposing theoretical viewpoints on the relationship between anthropomorphic design and human trust in conversational agents. According to the “human-human trust perspective”, greater agent anthropomorphism will increase trust. Conversely, in the “human-machine trust perspective” humans trust automated agents more than they do other humans. From this viewpoint, increasing anthropomorphism will decrease human trust in an agent as it takes on human like features, including our proneness to error. As ToM is a psychological concept that is intuitively human, there is a significant degree of overlap between this concept and anthropomorphism [19]. So, whether or not humans prefer a robot possessing a ToM may depend on their conceptualisation of human-robot trust.

For this reason, Mou et al. [20] investigated whether showing participants that a robot passes the Sally Anne False Belief Test (see [21]) would result in it being deemed more trustworthy. In a Price Game experiment, they demonstrated that robot ToM positively impacted participants’ trust. However, in an earlier video-based study on robot ToM, results were mixed [22]: The ToM robot was deemed to be more sympathetic to the other robots presentations but less suitable for the task.

So, the evidence that mimicking ToM in robots produces better human trust and decision-making is equivocal. Clearly, further work is needed to clarify the contribution of robot ToM to human-robot trust. As such, this work investigates how mimicking ToM in a robot affects participants decision-making in a trust-based collaborative setting.

III. METHOD

In this section we describe our experiment task (the Maze Task), and how ToM is manipulated. We outline the experimental procedure and summarise the experimental measures.

¹As psychological anthropomorphism is the focus of the current study, we refer to it as anthropomorphism henceforth.

A. The Maze Task

In the Maze Task, participants had to successfully navigate their way out of 10 mini-mazes, representing our experiment trials. Together, the mini-mazes represented a single large maze. Each mini-maze had two different possible exit paths (P1 or P2). In some of them, both exit paths were reachable from the starting position indicated on the map, while in others only one was reachable (as exemplified in Fig. 1). Participants completed the task with the help of Pepper, who suggested an exit path to take on each mini-maze.

1) Maze Task Sequence:

- *Practice*: A pre-trial familiarisation phase where participants first solved 3 simple mini-mazes with smaller grid dimensions: 20×20 .
- *Participants’ ToM Priming*: Participants were shown a video of Pepper either passing (ToM condition) or failing (Baseline and Sensor conditions) the Sally-Anne false belief task [21]. These videos were firstly used in [20] to prime participants to believe that the robot either possessed a ToM or not, and were found to produce the intended priming effect.
- *Trust Building; trials 1 to 4*: Participants solved 4 mini-mazes, with grid dimensions 30×30 , where only one of the two exit paths was reachable from the starting point (see Fig. 1). Pepper’s advice on these trials was always correct.
- *Breaking of Trust; trial 5*: Both available exit paths were reachable and it was up to participants to determine which of the two exits path was shortest. Importantly, Pepper’s path advice on this trial was incorrect, and it subsequently apologised for its error (details provided below).
- *Trust Rebuilding; trials 6 to 9*: Only one exit path was reachable and Pepper’s advice was always correct. This phase could be considered Pepper’s attempt to rebuild trust following its error in trial 5.
- *Assessment of Trust; trial 10*: Same format as trial 5, the *Breaking of Trust* (both available exit paths reachable). However, this time, Pepper’s advice was correct. Thus, here we aim to assess whether trust was rebuilt during the *Trust Rebuilding* trials.

2) *The Maze Task Procedure*: Each of the 10 experiment trials (omitting the *Practice*) had the same design: first, participants saw the mini-maze they had to solve (Fig. 1); then, participants watched and listened to a video of Pepper giving them its advice on which of the two paths (P1 or P2) to follow; finally, participants were asked what was their exit path of choice and to indicate their decision confidence using a 0-100 sliding scale [23]. A maximum of 20 moves to completion was set, but no time limit imposed. Selecting the correct path cost one move, and selecting the incorrect path cost two moves (i.e., choosing a path leading to a dead end, or selecting the longer of the two paths). Participants were not aware of how many mini-mazes they were going to solve. This way, we tried to instil a sense of vulnerability by making it impossible for them to calculate how many mistakes they could afford before the

TABLE I: Examples of utterances used by Pepper during the experiment for the Baseline, Sensor and ToM conditions.

Baseline	Sensor	ToM
Go towards P2.	Using my robot vision I can see P2 is the only reachable exit. Aim for P2.	I suspect you think P2 is correct. I agree, we should follow your instinct and go left to reach it.
Go left, towards P1.	My right sensor is telling me there is no path to P2. Go left for P1.	I understand that you might think P2 is the correct exit. However, I believe we should go towards P1 to get closer to the end of the maze (used in the <i>Breaking of Trust</i> , trial 5).
Go towards P2.	My navigation capabilities are telling me P2 is closer. Go towards P2. (used both in the <i>Breaking of Trust</i> and in the <i>Assessment of Trust</i> , trial 5 and 10)	I know you may think I will get it wrong this time. But I do believe going towards P1 will be faster to reach our goal (used in the <i>Assessment of Trust</i> , trial 10).

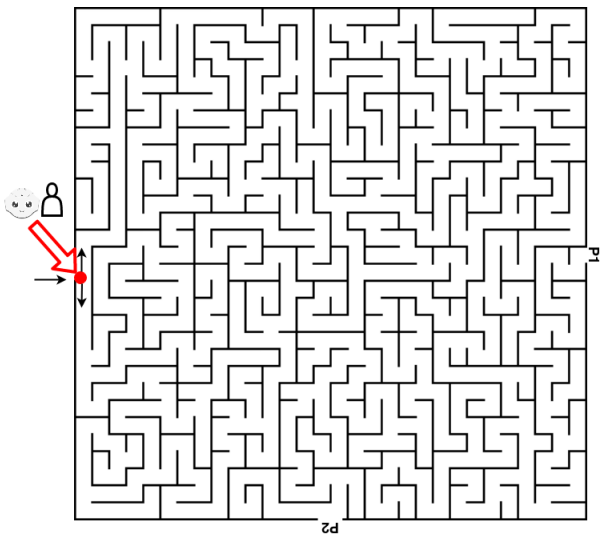


Fig. 1: Example of a mini-maze with grid 30×30 used in one of the trials (trial 3) of the Maze Task.

end of the task. To conclude each trial, participants received text feedback informing them whether their path decision was correct or incorrect, and how many moves it cost them.

3) *Maze Task Apology*: After choosing an exit path on trial 5 (*Breaking of Trust*) all groups were presented the same video of Pepper apologising for its mistake stating, “I am sorry I told you to choose the longer path. I judged the distance incorrectly. It’s my fault, it won’t happen again”. Our decision to implement an *Apology Strategy* derived from the results of [24], where it was shown that a robot apologising for its behaviour was the most successful trust repair strategy.

4) *ToM Manipulation in the Maze Task*: The ToM manipulation was realised in two phases. Firstly, through the *Participants’ ToM Priming*. Participants belonging to the ToM group observed Pepper passing a ToM test, while participants belonging to the Baseline and Sensor group observed Pepper failing the same ToM test (from [20]). Secondly, during the Maze Task trials, the videos of Pepper’s advice aligned to participants’ expectations from the priming videos: in the Baseline group Pepper’s suggestions were simply stating which direction to take; in the Sensor group Pepper’s advice was related to functional aspects of its hardware; in the ToM group Pepper offered advice in a manner that considered the

participant’s perspective (examples of such utterances can be found in Table I).

B. Materials and Instruments

The following list presents the instruments used and the order in which they were administered.

- 1) We collected demographics information on gender, age, and some control items, presented on a 5-point Likert scale, on participant’s familiarity with technology and with robots.
- 2) The Negative Attitude towards Robots (NARS) questionnaire [25]. Participants completed this questionnaire prior to the Maze Task. We used the answers to evaluate the presence of any strong negative bias towards robots that could compromise the experiment results.
- 3) The Disposition to Trust questionnaire (DtoT) [26], one of the most reliable and widely used propensity to trust scales [27]. We used this instrument to verify whether participants’ decision-making may have been affected by individual differences in their propensity to trust humans. Participants completed this questionnaire after the Maze Task, to mitigate potential pre-task trust priming.
- 4) The Propensity to Trust Automation (PtoTA) questionnaire, [28], created to specifically investigate respondents’ propensity to trust automation. For the same reason outlined above, it was presented after the Maze Task.
- 5) The Multi-Dimensional-Measure of Trust (MDMT) [13], one of the most recent scales for measuring different components of trust in an HRI scenario. The MDMT was administered after the Maze Task to assess participants’ Moral and Capacity trust ratings of their Pepper assistant.

Finally, following the final trial of the Maze Task participants were asked whether Pepper took into consideration their thinking while they decided what path to take (on a 7-point Likert scale). This was the ToM condition manipulation check.

C. Experiment Design and Measures

The online experiment followed a between-subjects design. Our three level independent variable was robot ToM: Baseline, Sensor, ToM. Our dependent variables were: a) Decision Time (ms) (i.e., the time participants took to decide which exit

TABLE II: Overview of demographics and dispositional factors by condition. Young Adults are 18 to 35, Middle-Aged are 36 to 55, Old Adults are 56 years or over. Some chose not to disclose their age or gender.

		Baseline	Sensor	ToM
Gender	Female	46%	44%	48%
	Male	51%	56%	51%
	Non-binary	2%	0% (n = 1)	1%
Age	Young Adults	85%	72%	77%
	Middle-aged	12%	10%	6%
	Old Adults	1%	0% (n = 1)	0% (n = 1)
Familiarity with Technology	Low	2%	3%	3%
	Medium	39%	49%	43%
	High	59%	48%	54%
Familiarity with Robots	Low	51%	60%	56%
	Medium	43%	35%	40%
	High	6%	5%	4%
Negative Attitude towards Interaction	Mean (SD)	13.6 (3.64)	14.0 (3.66)	14.2 (4.16)
	Median	13	14	13
Negative Attitude towards Influence	Mean (SD)	15.9 (3.64)	15.5 (3.75)	16.0 (3.55)
	Median	16	16	16
Negative Attitude towards Emotions	Mean (SD)	8.62 (2.33)	8.75 (2.52)	8.74 (2.43)
	Median	8	9	9
Disposition to trust (DtoT)	Mean (SD)	22.9 (6.15)	24.3 (5.39)	23.9 (5.29)
	Median	24	25	25
Propensity to trust Automation (PtoTA)	Mean (SD)	19.1 (3.12)	21.0 (3.52)	21.0 (2.48)
	Median	20	21	21

path to choose following Pepper’s advice); b) Self-reported Decision Confidence for each trial of the Maze Task; c) Robot Suggestion Adherence (e.g., whether participants decided to follow the advice offered by the robot); d) Robot Capacity Trust; e) and Robot Moral Trust. Moreover, we used the instruments in Section III-B to examine the contributions of other related dispositional factors. Hence, the dependent variables fall into two categories: a) *Subjective Measures of Trust*: the answers to the MDMT trust questionnaire and self-reported decision confidence (Conf); and b) *Behavioural Measures of Trust*, collected throughout the Maze Task. Namely, Decision Time (DT) and Robot Suggestion Adherence (SugAd). To clarify, DT is the time participants took to make their decision from the moment the suggestion video ended to the moment participants selected their path of choice: i.e., the length of Pepper videos is not part of DT. Moreover, participants indicated their Conf before knowing if their choice was correct (hence, before knowing whether Pepper’s suggestion was correct).

1) *Experiment Distribution*: We implemented our experiment using Gorilla Experiment Builder², and we carried out our data collection through Prolific³. Before starting the experiment, participants were asked to read a Participant Information Sheet (PIS) and provide consent to take part in the study. Both the PIS and the Consent Form were GDPR compliant. The experiment was approved by our institutions’ ethics boards.

²<https://gorilla.sc/>

³<https://prolific.co/>

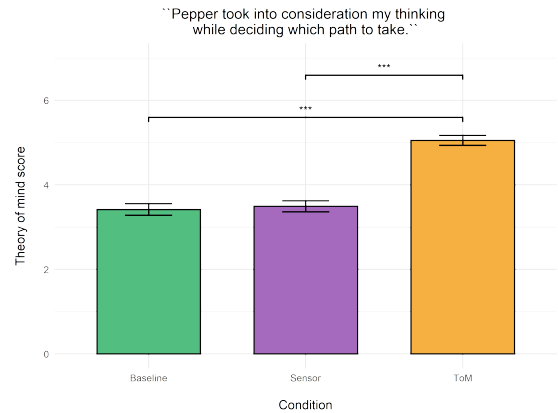


Fig. 2: Mean, Upper CI (confidence intervals) and Lower CI for quantised manipulation check responses. High scores indicate greater agreement with statement. *Signif.code* :*** $p < 0.001$

IV. RESULTS

We recruited 706 participants ($n = 235$ Baseline group; $n = 236$ Sensor group; $n = 235$ ToM group). The demographics of the sample is presented in Table II.

A. Manipulation Check Analysis

This check, posed to participants at the end of the experiment, asked “Pepper took into consideration my thinking while deciding which path to take”, and participants responded on a 7-point Likert scale to indicate their level of agreement (e.g., 1 = Very low; 7 = Very high). Figure 2 shows the results.

A one-way analysis of variance (ANOVA) was conducted to determine whether ToM condition explained a significant amount of the variance in manipulation check agreement responses. This test was significant, $F(2, 734) = 66.17, p < 0.001$. Follow-up simple effect analysis using the Bonferroni correction showed that the ToM group agreement score differed significantly to participants in the Baseline group ($M = 5.05$ vs $M = 3.42, p < 0.001$) and to those in the Sensor group ($M = 5.05$ vs $M = 3.49, p < 0.001$). No other comparisons were significant, indicating that participants in the Baseline and Sensor perceived the robot’s lack of ToM similarly.

B. Dispositional Factors: Negative Attitudes toward Robots and Propensity to Trust (humans and automation)

To ensure differences in performance between our experimental groups were not due to dispositional factors, we analysed participants scores on the NARS subscales (from [25]) and two propensity to trust questionnaires (DtoT [26] and PtoTA [28])⁴. A full breakdown of the participant groups is reported in Table II. The only analysis revealing a significant main effect of condition was that on PtoTA ($p < 0.001$). The follow up post hoc analysis confirmed that the Baseline group

⁴Due to non-normality, Kruskal-Wallis analysis and follow up Dunn’s post hoc tests (where appropriate) were performed on each of these measures.

TABLE III: Subjective and Behavioural Measures of Trust per condition at the Interaction level. Overall Conf is on a scale from 0-100. Capacity and Moral Trust range from 0-7 (computed by averaging the items in each of the scales [13])

		Baseline		Sensor		ToM	
		Mean (SD) or %	Median	Mean (SD) or %	Median	Mean (SD) or %	Median
Subjective Measures of Trust	Capacity Trust	5.38 (0.91)	5.5	5.55 (0.77)	5.62	5.41 (0.88)	5.5
	Moral Trust	5.16 (1.33)	5.38	5.37 (1.08)	5.5	5.26 (1.22)	5.38
	Overall Conf	84.8 (19.1)	92	88.0 (17.9)***	100***	86.4 (18.4)**	98.5**
Behavioural Measures of Trust	Overall DT (ms)	3964 (9538)	1294	5535 (11671)	1682	4795 (11265)***	1724***
	Overall SugAd	82.7%	-	87.6%	-	88.7%	

Signif. codes: *** $p < 0.001$ significance over the other two conditions; ** $p < 0.001$ significance over the Baseline condition.

(Median = 20) scored significantly lower than both the Sensor (Median = 21, $p < 0.001$) and ToM (Median = 21, $p < 0.001$) groups.

C. Behavioural Measures of Trust

Firstly, we report the descriptive statistics from the Maze Task. The results are summarised in Table III, while in Fig. 3 we show how their trend differ per Maze Task trial.

As Decision Time (DT) was positively skewed, we used a robust one-way ANOVA analysis alternative (see [29]).⁵ ToM condition significantly predicted differences in mean DT, $F_t = 48.16$, $p < 0.001$, $\eta^2 = 0.14$. Post hoc tests revealed that the ToM group was significantly slower to respond than the Baseline group $\hat{\psi} = -456.96$ [$CI_{low} = -605.57$, $CI_{high} = -312.02$, $p < 0.001$], but markedly faster than the Sensor group $\hat{\psi} = -602.46$ [$CI_{low} = -776.70$, $CI_{high} = -434.84$, $p < 0.001$].

Analysis of DT at the Breaking of Trust event showed a significant difference between the three conditions, $F_t = 12.23$, $p < 0.05$, $\eta^2 = 0.25$. Post hoc tests found that the mean DTs were significantly longer for the ToM group compared to the Baseline group $\hat{\psi} = -822.19$ [$CI_{low} = -1388.82$, $CI_{high} = -443.69$, $p < 0.001$] and the Sensor group $\hat{\psi} = -612.08$ [$CI_{low} = -1360.49$, $CI_{high} = -200.74$, $p < 0.001$].

Analysis of DT at the Assessment of Trust (i.e. the final trial) found that ToM condition predicted a significant amount of the variance in DT, $F_t = 26.56$, $p < 0.001$, $\eta^2 = 0.29$. Post hoc analysis of the means showed again that participants in the ToM tended to take longer to make a decision relative to the Baseline group $\hat{\psi} = -3599.39$ [$CI_{low} = -5193.78$, $CI_{high} = -2286.32$, $p < 0.001$] and the Sensor group $\hat{\psi} = -2384.53$ [$CI_{low} = -3672.04$, $CI_{high} = -1130.56$, $p < 0.001$].

All Baseline and Sensor group mean DT comparisons were non-significant.

We then assessed the degree of Suggestion Adherence (SugAd) between each of the three groups. A Chi-square analysis on the proportion of *follow* (i.e., observations where the decision of the participant matched the robot's advice) and *not follow* (i.e., observations where participants path decision did not match the robot) for the whole task was not significant, $\chi^2(2) = 2.62$, $p = 0.27$. For the Breaking of Trust trial

there was a near significant effect of group on follow/not follow decisions, $\chi^2(2) = 5.37$, $p = 0.07$. Finally, for the Assessment of Trust there was a non-significant effect of group on follow/not follow proportions, $\chi^2(2) = 1.47$, $p = 0.48$. Follow up poisson regression found that participants adhered to the robot's suggestion significantly more at the Breaking of Trust than at the Assessment of Trust trial ($p < 0.001$), but this did not vary statistically by ToM condition.

D. Subjective Measures of Trust

As the data for Confidence scores (Conf) were not normally distributed (confirmed by Shapiro Wilks tests), they were analysed using Kruskal-Wallis and the medians reported (Table III). Conf trend per trial is shown in Fig. 3. Overall analysis between the groups revealed a significant effect of ToM condition, $\chi^2(2) = 53.5$, $p < 0.001$, $n = 7092$. Dunns post hoc comparisons revealed that the ToM group expressed significantly higher confidence than the Baseline group, (Median = 98.5 vs Median = 92, $p < 0.001$). The Sensor group however were the most confident, showing significantly higher confidence than the ToM (Median = 100 vs Median = 98.5, $p < 0.001$) and Baseline group (Median = 100 vs Median = 92, $p < 0.001$).

Furthermore, during the Breaking of Trust, there was a significant effect of ToM condition on confidence rating, $\chi^2(2) = 7.75$, $p < 0.05$, $n = 706$. Post hoc analysis showed that participants in the ToM group were less confident in their decision compared to the Baseline group (Median = 90 vs Median = 93, $p < 0.05$) and the Sensor group (Median = 90 vs Median = 99.5, $p < 0.05$). Confidence ratings on this trial did not differ statistically between the Baseline and Sensor group ($p = 0.82$).

Conf at the Assessment of Trust also varied significantly by ToM condition, $\chi^2(2) = 31.2$, $p < 0.001$, $n = 706$. Post hoc analysis showed that, both the ToM and Sensor groups were equally confident in their decision on the final trial (Medians = 80, $p = n.s$). Accordingly, both groups were significantly less confident in the final mini-maze decision relative to the Baseline group (Medians = 80 vs Median = 95, $p < 0.001$).

Finally, we assessed whether participants' Moral and Capacity Trust (measured by the [13] scale) differed between our experimental groups post Maze Task. As both of these sets of scores were not normally distributed (confirmed by Shapiro Wilks tests), we report the results of Kruskal-Wallis analyses.

⁵We report bootstrapped trimmed mean differences (denoted by $\hat{\psi}$) between ToM conditions and an analogue of effect size similar to a Pearson's correlation. Hereafter, every time we discuss "mean" we refer to trimmed mean.

We found no effect of ToM condition on Moral Trust scores ($p = 0.40$) or Capacity trust Scores ($p = 0.11$). Full scores are reported in Table III.

V. DISCUSSION

In this experiment, we explored how varying the anthropomorphic feature of ToM affected participants decision-making and trust development in a collaborative navigation task. Our motivation was to build on existing work examining robot ToM and participants performance, as current literature on this topic is somewhat equivocal.

While, through the results of the MDMT questionnaire, we find that the robot exhibiting a ToM was not considered more trustworthy, we can see that ToM affected participants decision-making and induced them to create a more balanced trust relationship with the robot.

Specifically, our results indicate that participants who experienced a robot mimicking a ToM - through the use of perspective sharing utterances - took more time to decide which path to take in the mini-mazes when confronted with a more challenging mini-maze format. Furthermore, at the Breaking of Trust trial, participants in the ToM group expressed the lowest levels of confidence among the three groups. Recall that at the Breaking of Trust, the robot makes its first (and only) error and apologises for doing so. Also, this trial differed for the first time in format, with successful navigation requiring selection of the *shortest* path, whereas only a single path was reachable until that point. Combining these factors served to increase decision ambiguity and participants reliance on the robots suggestion.

It is noteworthy that participants reported their decision confidence *before* learning whether the robot suggestion was correct. Thus, the increased Decision Time at the trust events and general scepticism indicated by the early reduction in Self-reported Confidence from the ToM group shows that, when Pepper mimicked a ToM, participants were more wary of its legitimacy and less prone to over-trust when it mattered [30]. This is positive in that the ToM group demonstrated greater sensitivity to the robot’s performance relative to the other groups. This is also seen at the Assessment of Trust (presenting the same format as the Breaking of Trust trial), where the Self-reported Confidence ratings of both the ToM group and the Sensor group were even lower than those reported in the Breaking of Trust. This hints towards an increased caution to the robots advice by participants. Thus, during the last trial, both ToM and Sensor-based explanations served to mitigate the risk of decision over-confidence, as experienced by the Baseline group in spite of their lower Propensity to Trust Automation (Table II).

On the other hand we see that, in an online collaborative navigational task, participants are more confident and quicker to decide which route to take when the robot interacts as if it were a machine (i.e. the Baseline and Sensor). While this can be regarded as an implicit sign of greater trust towards a more machine-like robot (as with automation bias [31]), we argue that participants in the Baseline group - and, in

reduced form also in the Sensor group - over-trusted the robot’s suggestions until the final trial, when the mini-maze characteristics reminded them of the error the robot made in the Breaking of Trust trial. Automation bias may be reflected in participants lack of familiarity with robots compared to other day-to-day technologies (see Table II). Lack of robot familiarity may have led some to over-estimate the accuracy of Pepper’s suggestions, causing them to blindly follow its advice.

Interestingly, all three conditions followed a similar pattern when it came to Robot Suggestion Adherence. Most participants followed the robot’s suggestion, independently of the group they were in, until the Assessment of Trust trial. Therefore, the main differences across groups are to be found in terms of decision-making process. Looking at Decision Time and Self-reported Confidence, especially during and after the Breaking of Trust trial, we can see that the ToM group was being more ponderous and doubtful. Hence, ToM was successful in instilling an appropriate level of trust.

A possible counter argument to this synopsis is that differences in the robot utterance wording (e.g., utterance length and lexical choice) underpinned performance differences. However, the utterances were designed to uphold our manipulation, reflecting what participants had previously seen in the priming videos: Pepper either passing or failing the Sally-Anne task. Our Manipulation Check results (Section IV-A) support this conclusion by demonstrating that participants in the ToM group thought the robot took their thoughts into consideration more than the Baseline and Sensor groups. Moreover, even if the utterances changed in their characteristics, the behaviour of the robot and its reliability were the same throughout the task across conditions. The different personas participants built of the robot were merely the product of their own perception of how anthropomorphic the robot was, in terms of ToM. This underlines the success of our utterances.

In fact, it could be that the extra caution expressed by the ToM group was due to their anthropomorphisation of the robot. Participants in the ToM group could have consciously or subconsciously been assigning to the robot human fallibility [18] (even before they had the confirmation of its fallibility). Therefore, if the robot was as fallible as a human, they ought to be cautious. This could reflect in the lower scores of the Capacity Trust of the MDMT for the ToM group (Table III). Anthropomorphising the robot by means of ToM might have got them to believe that, while the robot might be acting in good faith (worthy of Moral Trust), it was still not up to the job (and not worthy of Capacity Trust), as similarly noticed in [22]. This is interesting when compared to the other conditions, where the robot might be seen to have “super human” capabilities, particularly in the Sensor case.

On the other hand, it is also conceivable than our results could be explained in terms of robot explanation transparency. Our ToM utterances referred to decision doubt more than the Sensor and Baseline explanations. To exemplify this, here are the utterances for each condition at the Breaking of Trust trial (from Table I): “I understand that you might think P2 is the

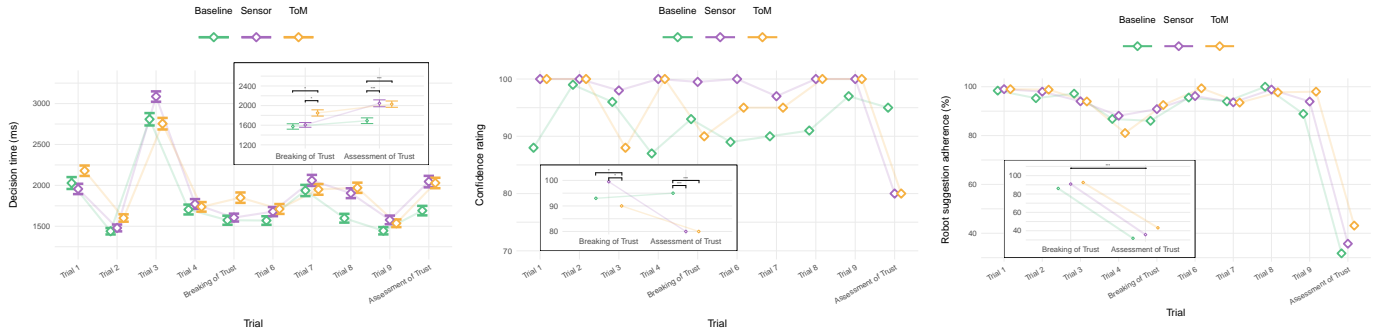


Fig. 3: The overall trend of the three in-task dependent variables. (a) Trimmed means and Upper and Lower CI of Decision time (DT; ms) by trial; (b) Median of Self-reported Confidence (Conf) by trial; (c) Percentage (%) of participants Suggestion Adherence (SugAd) by trial.

correct exit. However, I believe we should go towards P1 to get closer to the end of the maze. (ToM)”, compared to “My navigation capabilities are telling me P2 is closer. Go towards P2. (Sensor)” and “Go left, towards P1” (Baseline). Robot transparency has been shown to vary and predict human-robot trust [32], [33]. So, it is possible that, by revealing that it was taking the participant’s thoughts into account, the robot was not considered as transparent as when it immediately and explicitly stated which exit path to aim for or when it gave hardware based justifications. Including transparency as predictor variable in future studies will help to elucidate the nature of this relationship.

It is possible that an online study - rather than a lab-based HRI experiment - may have influenced our results. An online study does not include factors known to affect human-robot trust (e.g., embodiment, robot presence, power distance [34]). This is because in online studies of interactions, participants are, for the most part, passive observers rather than active protagonists. We tried to mitigate this by giving participants the opportunity to solve the mini-mazes themselves. However limited an online experiment is, these kind of exploratory prototyping are useful in helping researchers refining what (and how) to investigate with an in-person study [35].

In summary, our results show that the importance of ToM varies depending on the setting and the type of advice offered by the robot and, therefore, researchers should think carefully about how appropriate the robot’s anthropomorphic features are to the deployment setting [18], [36]. We show that, relative to two more machine-like presentations, robots mimicking ToM positively impact decision-making processes by making the robot appear fallible, thus encouraging participants to be more critical of its performance. This way, ToM proved to be a factor to take into consideration when developing machines to instil an appropriate level of trust.

VI. CONCLUSION

With this work, we investigated whether a robot exhibiting the anthropomorphic feature of ToM positively impacts hu-

mans’ decision-making process and the development of trust during a cooperative task.

To do so, we devised a novel between-subject online experiment where participants had to successfully escape a large maze, with the aid of the social robot Pepper offering its advice on which path to follow in each trial of the experiment. Participants were either assigned to the Baseline, Sensor or ToM groups, where they experienced either a robot exhibiting or not exhibiting ToM thanks to the use of ad-hoc utterances and priming videos.

Our results show that ToM did not actively positively impact the perception of the robot’s trustworthiness. However, it did have an impact on participants’ decision-making process, whereby participants needed more time to think in order to make a decision and were generally less confident at the Breaking of Trust and Assessment of Trust trials. This informs us and the community on how subtly ToM can affect HRI, leading us to understand that it is a characteristic that encourages people to think more carefully, and thus potentially discouraging over-trust. Of course, the context and scenario in which a robot is deployed play a fundamental role in determining which characteristics the robot should have and what aspect of trust it should trigger.

In the future, we plan to verify these findings with an in-person HRI experiment, to investigate whether the presence of a physical robot would play an important role, in combination with ToM, to improve trustworthiness and decision-making, with a particular focus on the transparency of the interaction. We will also take into deeper consideration which trust repair strategy to follow and how to deliver it. This point was outside the scope of the study we presented, however, the literature suggests that it is not an aspect to underestimate when designing fallible robots if we want to avoid dramatically impacting the HRI [37]. For this reason, we will also direct future endeavours towards better understanding the role of a trust repair strategies in a cooperative task.

ACKNOWLEDGEMENT

This work was funded and supported by the UKRI Node on Trust (EP/V026682/1) <https://trust.tas.ac.uk>.

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