Cooking Up Trust: Eye Gaze and Posture for Trust-Aware Action Selection in Human-Robot Collaboration

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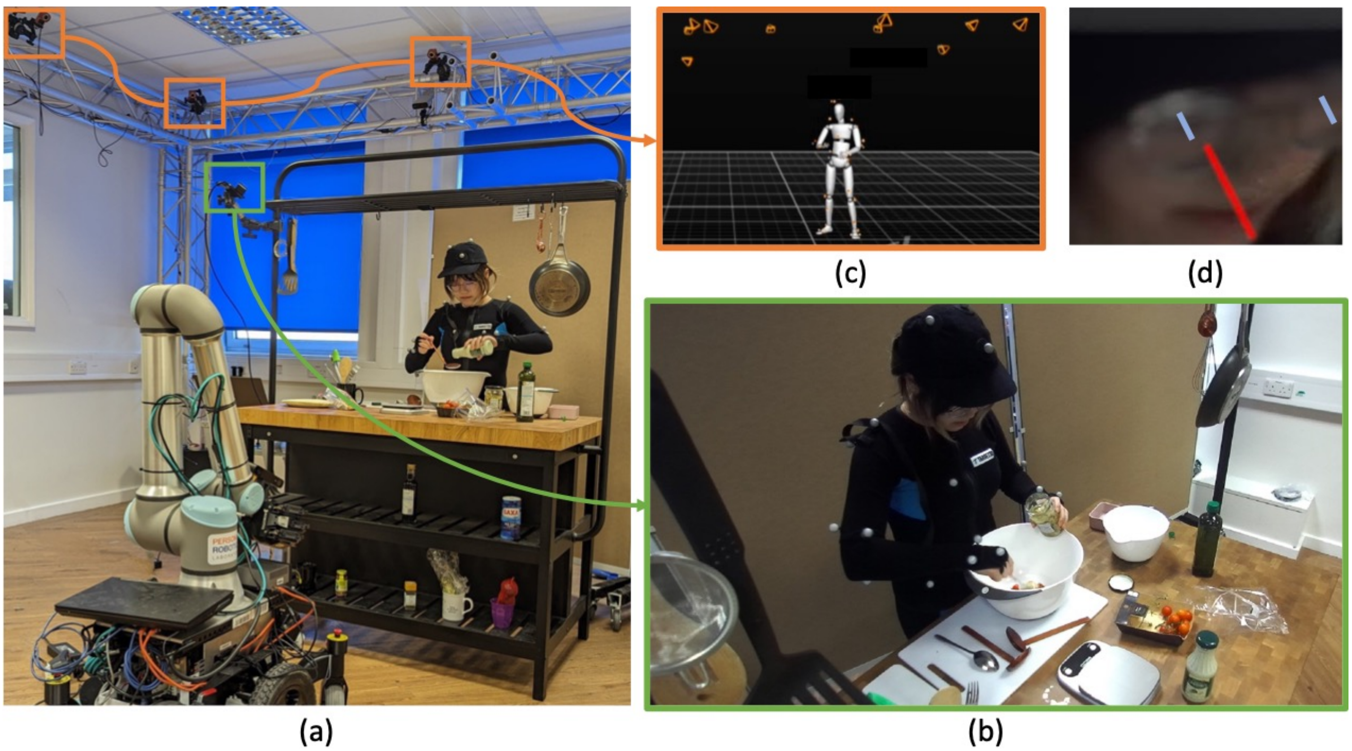

Figure 1: Our assistive cooking setup to study how eye gaze and posture can be used to infer trust-related mental states, which can be included in the robot's action selection method. (a) is an external view of the whole setup, with our custom mobile manipulator. The scene camera gives us the view (b), which is then used to infer eye gaze and head pose shown in (d). The motion capture system also provides us with the full body pose (c).

ABSTRACT

In Human-Robot Collaboration (HRC), trust is an essential factor that can change over time, and robots capable of estimating a human's trust and using that information to select their actions can improve the quality of interaction. In this paper, we present our early-stage research on a trust-aware policy for HRC applied to an assistive cooking scenario. We propose to study how physiological signals, such as eye gaze and posture, can be used to estimate the human's trust level. We describe our experimental platform and the evaluation scenarios used to test the effectiveness of the policy.

CCS CONCEPTS

• **Human-centered computing** → **Collaborative and social computing**; • **Computer systems organization** → **Robotics**.

KEYWORDS

human-robot collaboration, trust, theory of mind, assistive cooking, eye gaze

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1 INTRODUCTION

In real-world scenarios of Human-Robot Collaboration (HRC), both the human and the robot must trust each other's abilities and intentions in order to establish a successful collaboration [23]. Trustworthy autonomous systems are thus essential for ensuring safe, reliable, and effective collaborations between humans and robots. Collaborative cooking is an exciting application scenario for HRC because it involves many opportunities for trust, such as knife handling, sensitive information about dietary restrictions, or the risk of destroying and wasting ingredients. Additionally, cooking requires a variety of skills, from basic chopping to complex recipe following, making it an ideal testbed for evaluating robot performance. While current robots are still incapable of matching the human cooking skills, recent progress in fields such as world perception, learning or dexterous manipulation have led to the development of new highly capable cooking robots; examples include NALA[1] or the Moley kitchen[2].

Despite a significant amount of research in the field, understanding human trust remains a challenge for robots. This difficulty arises from trust's complexity as a subjective, multidimensional, dynamic, and context-dependent concept [1]. While significant work has explored the humans' perception of assistive robots in collaborative settings, relatively few studies successfully implemented trust calibration mechanisms in real-world scenarios; for examples, see [6, 21].

In this paper, we present our early-stage work on a trust-aware policy for HRC applied to the collaborative cooking scenario. Our goal is to study how human physiological signals such as eye gaze and posture can be interpreted by the robot to estimate trust, and included in its policy. We also present our plan for an experiment to evaluate this framework, in the form of a between-group experiment measuring trust levels and delegation ratios.

2 RELATED WORK

Robots' ability to manage human trust is crucial in assistive cooking scenarios. In this section, we review relevant ways researchers have approached trust in HRC scenarios. Then, we focus on assistive cooking specifically, highlighting the wide range of issues to consider.

Trust is a multifaceted concept that has been studied across many fields, including psychology, neuroscience, and economics [11, 19, 28]. It has also been extended to the domains of Human-Computer Interaction and Human-Robot Interaction (HRI) [1, 29]. However, defining and modelling trust is challenging due to its subjective, context-dependent, and multidimensional nature [23]. Researchers have proposed several definitions of trust over the years, but they generally revolve around the interaction between a trustor and a trustee in a given context, which involves a degree of risk or uncertainty [14, 22, 24]. Recent studies suggest that humans extend two main types of trust: performance-based trust and relation-based trust [1]. It is moreover important to note that there is a difference between reported trust, which is measured through questionnaires or scales, and behavioural trust, which directly affects HRI [20].

Theory of Mind (ToM) is a psychological concept that refers to 'the ability to attribute mental states to oneself and others' [25]. In robotics, ToM has been applied to create robots capable of social interactions [8–10]. In recent years, ToM has been used to enable robots to decide whether they should trust the intentions or capabilities of other agents [5, 21, 30], which is crucial for effective HRC. Furthermore, [27] showed that some humans tend to place more trust in a robot exhibiting a ToM. While the studies mentioned so far rely on scenario-specific mechanisms to infer mental states, it is also possible to rely on measures of physiological signals. For instance, [3, 31] showed that eye-gaze patterns could be correlated with mental states such as cognitive overload or confusion about a task. Moreover, [31] demonstrated that these patterns also changed significantly when the human observes a robot failure, which is highly correlated with trust [15].

Finally, some recent studies have identified several crucial factors that need to be considered to enhance the quality and efficiency of HRC cooking tasks. These issues include managing people's expectations, accounting for human preferences, and recognising mistakes and recovery. For instance, [32] found that people's expectations for robot-prepared food were lower than those for human-prepared food, but increasing robot anthropomorphism or capabilities could mitigate this effect. Another study investigated how robots could incorporate explicit human preferences such as healthy eating into their action selection policy [4]. Additionally, researchers have examined how humans perceive different types of robot mistakes [2]. Most of these studies focused on managing initial expectations and post-mistake behaviours in supervised cooking tasks, where humans provide instructions or feedback to the robot. However, fully collaborative cooking tasks pose new challenges.

In this paper, we will focus on the largely unexplored and exciting question of how eye gaze and posture could be used to infer human trust in a real-life, complex collaborative task such as assistive cooking.

3 DESIGN AND ETHICAL CONSIDERATIONS

In this section, we discuss our experimental setup, including the design of the robot and the kitchen setup. Additionally, we highlight the ethical considerations we took into account during the design process. Finally, we detail the main axes of investigation we will pursue.

3.1 System Description

3.1.1 Robot design. For our study, we designed and built AMIGA (Assistive Mobile and Interactive Grasping Agent), which consists of a mobile base, a robotic arm, a gripper, a laptop, a Jetson Orin, and some power and network-related devices. To enable navigation, we mounted a ZED 2i RGBD camera[3] and two RPLidar A1[4] on the mobile base. The ZED 2i camera also provides odometry by combining an embedded IMU and visual data. On top of the base, we mounted a UR10e robotic arm[5] with seven degrees of freedom and its DC controller. To handle the variety of shapes and textures in a

[1]https://nalarobotics.com/nala-chef-one-point-one-product.html
[2]https://www.moley.com/moley-kitchen/
[3]https://www.stereolabs.com/zed-2i/
[4]https://www.slamtec.com/en/Lidar/A1
[5]https://www.universal-robots.com/products/ur10-robot/

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cooking environment, we attached a Robotiq 3f gripper[6] capable of different types of grasps. A ZED 2i RGBD camera was attached to the gripper to facilitate grasping. On the software side, the robot is operated using ROS [26]. The arm's motion is handled by MoveIt [7] with an analytical inverse-kinematics solver adapted from the official Universal Robots one. We implemented a joint planning and control for the arm and the gripper joints, which allows the robot to grasp objects with a single smooth movement. Finally, we trained a custom object detection module for our ingredients, based on a YOLO v5 architecture [17], and ran it on a Jetson Orin using the NVIDIA TensorRT engine.

3.1.2 Memory Module. In light of the significant correlation between a robot's movement behaviour and trust [13, 16], our objective was to optimise the responsiveness and fluidity of its motions. To eliminate the need for repeated object searching upon each grasp trigger, we devised a memory module incorporating class-aware Extended Kalman Filters and a forgetting mechanism. A detection δ_i from the computer vision model is composed of a pose $p_i = (x_i, y_i, z_i)$, an object class $c_i \in [\![1, N]\!]$ where N is the number of classses, and a context vector γ_i of size N where each element is the number of instances of that class detected in the same image. To determine whether a new detection matches an existing filter, the module uses a custom distance metric d inspired by [18] as described in Equation 1 where D is a "critical distance" above which 2 detections of the same class are likely to be different instances. It then feeds the detected position p_i to the proper Kalman Filter, which uses these noisy observations to estimate the actual position. The restricted number of instances from each class enabled us to accurately distinguish them.

$$d(\delta_i, \delta_k) = \frac{\|p_i - p_k\|}{D} + \frac{\gamma_i \cdot \gamma_k}{\|\gamma_i\|\|\gamma_k\|} \tag{1}$$

To prevent the Kalman Filters from infinitely tracking the false positives from the object detection, we also developped a forgetting mechanism. Every time a detection is matched to a tracked object (or to a newly created one), the expiration time of that object in memory is updated based on how many times it has been detected, as described in Equation 2. We note t^{exp} the expiration time, t^{now} the current time, n_{views} the number of times the object has been detected, and a, b, and c are parameters. This mechanism allows the robot to forget about objects that have not been seen in a while, while still keeping track of them if they are detected again.

$$t^{exp} = t^{now} + \min(a + b * n_{views}^2, c) \tag{2}$$

3.1.3 Kitchen setup. Our application scenario is a collaborative task, where both the human and the robot act and cook together. We set up a kitchen table with under-the-counter shelves on one side and a rack to hang utensils above. Various kitchenware items such as scales, bowls, and containers were placed on the table, while ingredients were stored on the shelves. The robot stands on the ingredients' side, and the human stands on the other side. To capture eye-gaze and head pose information from the human, we mounted a ZED 2i RGBD camera on the table, connected to a computer running RT-GENE [12]. We also equipped the room with an OptiTrack motion capture system to capture the human's body pose.

[6]https://robotiq.com/products/3-finger-adaptive-robot-gripper

3.1.4 Assistive Cooking Policy. In order to investigate the relation between ToM, trust, and the various physiological signals we measure, we need the robot to be capable of cooking with a human. We achieved this by combining a set of parametrised skills and primitives with a custom action selection method, which is out of the scope of this paper.

3.2 Responsible Research

In conducting our study, we have taken several steps to ensure responsible research practices. We have obtained ethical approval from our institution's research ethics committee, and all participants will provide informed consent before taking part in the study.

3.2.1 During the Study. We have taken steps to ensure the safety of all participants during the study. We will have a researcher present at all times to monitor the experiment and intervene if necessary. In addition, we have obtained authorisation to bring in participants from diverse backgrounds, not limited to engineering or students, to account for diversity in our study. To protect the privacy and confidentiality of our participants, we will anonymise data as soon as each participant is finished with the experiment. Any personal information collected during the study will be kept secure.

3.2.2 Potential Applications. As with any research that involves technology, we recognise the potential implications and applications of our study beyond its immediate scope. While our focus is on developing assistive technologies for cooking, we acknowledge that our findings could be used in a variety of applications. We will continue to evaluate the potential implications of our research and consider the ethical implications of any potential future applications.

3.3 Policy Design

In order to implement our trust-aware action selection method, we must take into consideration several challenges. Firstly, real-time processing is crucial given the nature of our problem. While our system already currently operates in real-time, the motion capture system may potentially send too much data or create synchronization issues with its 10 cameras. Therefore, we plan to implement fail safes to prevent these issues from disrupting real-time processing, such as reducing the number of cameras, down-sampling the data, or setting up a local time server.

The second challenge we must address is the cold start problem. When we interact with a participant for the first time, we lack any prior knowledge of their mental state and dynamics, making it difficult to estimate the correlation between their physiological signals, mental states and trust. To overcome this challenge, we plan to study different approaches such as bootstrapping or collaborative filtering.

Another challenge we face is the noise present in physiological signals, such as eye gaze, which is linked to multiple mental states and factors other than trust. To minimize the impact of noise, we aim to analyze participant-specific variations in a controlled

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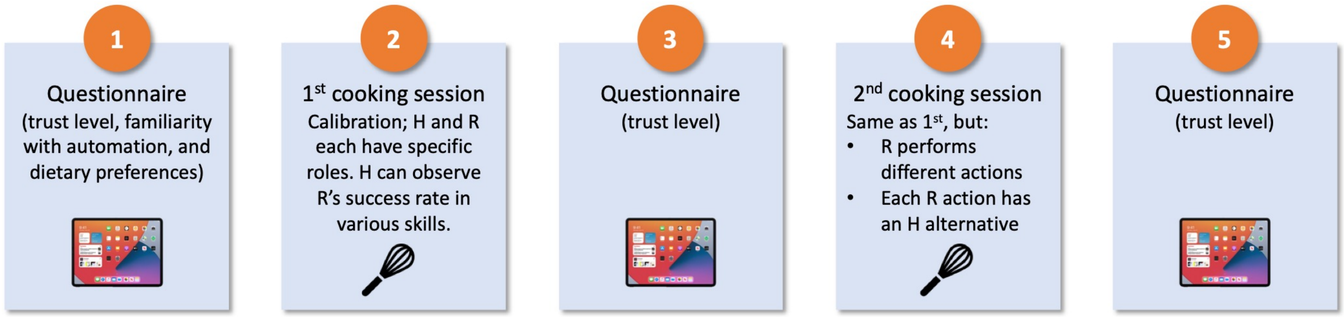

Figure 2: A session for our evaluation scenario. Questionnaires in steps 1, 3 and 5 are used to get a measure of subjective trust. Step 2 allows the human to calibrate his/her trust by observing the robot's proficiency levels. Step 4 is used to get a measure of objective trust using the delegation ratio.

environment, allowing us to better model their mental state. Additionally, we will explore other techniques to improve the accuracy of our trust estimation, such as data filtering or signal processing.

Lastly, we must consider the mental state representation and how to model estimated trust. In the literature, several approaches exist, including latent variable and Markovian function. We plan to explore these options and select the most suitable approach for our system.

3.4 Evaluation Scenarios

To evaluate the effectiveness of our action selection method, an experiment will be conducted in which participants collaborate with a robot to prepare a salad. The robot will either use the basic policy or the enriched policy that includes physiological signals for action selection. Two research hypotheses will be tested.

H1: participants interacting with the robot aware of their physiological signals will report higher levels of trust than those in the control group.

H2: participants interacting with the robot aware of their physiological signals will have a higher delegation ratio than those in the control group.

In designing this experiment, we considered several factors. Trust is a dynamic factor that can be influenced by failures and successes, but initial expectations also play a significant role [15]. Therefore, each participant needs an initial interaction to calibrate their trust. We cannot have one participant perform too many sessions or suffer from fatigue, which might skew the results, especially since we use eye gaze and posture to measure trust. Additionally, objective and subjective measures of trust sometimes diverge; hence, we plan to collect both. Finally, our metric benefits from past interactions with the human, providing another good reason to have two sessions.

To address these considerations, we propose a between-group experiment consisting of five steps for each participant, for an estimated total duration of up to two hours:

(1) Initial set of questionnaires related to trust and personal information
(2) First cooking session
(3) Second set of trust-related questionnaires
(4) Second cooking session, where the participant has a choice to delegate certain actions, enabling us to use delegation ratio as an objective trust measure
(5) Final set of questionnaires

As subjective measures, we rely on previously established questionnaires such as those from [23].

4 PRELIMINARY RESULTS

To evaluate the performance of our policy's modules, we conducted a series of preliminary studies. In these studies, we assessed the robot's ability to assist the human in making a salad, as described in the evaluation scenarios outlined in subsection 3.4. We found that our custom policy can select a relevant action with 82% accuracy, and can successfully perform actions 69% of the time. Additionally, we developed the gaze following module, which can accurately detect when the human is looking at the robot in real-time, provided the human's head configuration allows for accurate eye gaze detection. We are currently in the process of setting up a motion-capture system to collect body pose data and are exploring various methods to integrate these signals into the policy.

5 CONCLUSION AND FUTURE WORK

In this paper, we have presented our early-stage work on a trust-aware policy for HRC applied to the collaborative cooking scenario. Our goal is to study the validity of a policy using physiological signals to estimate the human's trust level and select appropriate actions. We have established an experimental platform with a robot capable of cooking with a human and sensors installed in the environment to collect the necessary data for our ToM-based policy. Furthermore, we have designed evaluation scenarios to validate the effectiveness of our policy. Moving forward, our research will focus on implementing and testing our policy to create a robust and reliable solution that can enhance interaction quality and task performance in various HRC scenarios.

REFERENCES

[1] Gene M. Alarcon et al. 2021. Contributors. In *Trust in Human-Robot Interaction*, Chang S. Nam and Joseph B. Lyons (Eds.). Academic Press, xiii–xvi. https://doi.org/10.1016/B978-0-12-819472-0.09992-5
[2] Pourya Aliasghari, Moojan Ghafurian, Chrystopher L. Nehaniv, and Kerstin Dautenhahn. 2021. Effect of Domestic Trainee Robots' Errors on Human Teachers'

Preprint; final version available at https://doi.org/10.1145/3597512.3597518.

Trust. In *2021 30th IEEE International Conference on Robot & Human Interactive Communication (RO-MAN)*. 81–88. https://doi.org/10.1109/RO-MAN50785.2021.9515510

[3] Pierluigi Vito Amadori, Tobias Fischer, Ruohan Wang, and Yiannis Demiris. 2022. Predicting Secondary Task Performance: A Directly Actionable Metric for Cognitive Overload Detection. *IEEE Transactions on Cognitive and Developmental Systems* 14, 4 (2022), 1474–1485. https://doi.org/10.1109/TCDS.2021.3114162

[4] Jake Brawer, Debasmita Ghose, Kate Candon, Meiying Qin, Alessandro Roncone, Marynel Vázquez, and Brian Scassellati. 2023. Interactive Policy Shaping for Human-Robot Collaboration with Transparent Matrix Overlays. In *Proceedings of the 2023 ACM/IEEE International Conference on Human-Robot Interaction* (Stockholm, Sweden) *(HRI '23)*. Association for Computing Machinery, New York, NY, USA, 525âĂŞ533. https://doi.org/10.1145/3568162.3576983

[5] Moritz C. Buehler, JÃijrgen Adamy, and Thomas H. Weisswange. 2021. Theory of Mind Based Assistive Communication in Complex Human Robot Cooperation. arXiv:2109.01355 [cs.RO]

[6] Min Chen, Stefanos Nikolaidis, Harold Soh, David Hsu, and Siddhartha Srinivasa. 2018. Planning with Trust for Human-Robot Collaboration. In *Proceedings of the 2018 ACM/IEEE International Conference on Human-Robot Interaction* (Chicago, IL, USA) *(HRI '18)*. Association for Computing Machinery, New York, NY, USA, 307âĂŞ315. https://doi.org/10.1145/3171221.3171264

[7] David Coleman, Ioan Sucan, Sachin Chitta, and Nikolaus Correll. 2014. Reducing the barrier to entry of complex robotic software: a moveit! case study. *arXiv preprint arXiv:1404.3785* (2014).

[8] Yiannis Demiris. 2007. Prediction of intent in robotics and multi-agent systems. *Cognitive Processing* 8, 3 (01 Sep 2007), 151–158. https://doi.org/10.1007/s10339-007-0168-9

[9] Yiannis Demiris and Matthew Johnson. 2007. *Simulation theory of understanding others: a robotics perspective.* Cambridge University Press, 89–102. https://doi.org/10.1017/CBO9780511489808.008

[10] Sandra Devin and Rachid Alami. 2016. An implemented theory of mind to improve human-robot shared plans execution. In *2016 11th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. IEEE, 319–326.

[11] Anthony M. Evans and Joachim I. Krueger. 2009. The Psychology (and Economics) of Trust. *Social and Personality Psychology Compass* 3, 6 (2009), 1003–1017. https://doi.org/10.1111/j.1751-9004.2009.00232.x arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1751-9004.2009.00232.x

[12] Tobias Fischer, Hyung Jin Chang, and Yiannis Demiris. 2018. RT-GENE: Real-Time Eye Gaze Estimation in Natural Environments. In *European Conference on Computer Vision*. 339–357.

[13] PA Hancock, Theresa T Kessler, Alexandra D Kaplan, John C Brill, and James L Szalma. 2021. Evolving trust in robots: specification through sequential and comparative meta-analyses. *Human factors* 63, 7 (2021), 1196–1229.

[14] Peter A. Hancock, Deborah R. Billings, Kristin E. Schaefer, Jessie Y. C. Chen, Ewart J. de Visser, and Raja Parasuraman. 2011. A Meta-Analysis of Factors Affecting Trust in Human-Robot Interaction. *Human Factors* 53, 5 (2011), 517–527. https://doi.org/10.1177/0018720811417254 arXiv:https://doi.org/10.1177/0018720811417254 PMID: 22046724.

[15] Kevin Hoff and Masooda Bashir. 2015. Trust in Automation: Integrating Empirical Evidence on Factors That Influence Trust. *Human Factors The Journal of the Human Factors and Ergonomics Society* 57 (05 2015), 407–434. https://doi.org/10.1177/0018720814547570

[16] Ekaterina Ivanova, Gerolamo Carboni, Jonathan Eden, Jorg Kruger, and Etienne Burdet. 2020. For motion assistance humans prefer to rely on a robot rather than on an unpredictable human. *IEEE Open J. Eng. Med. Biol.* 1 (April 2020), 133–139.

[17] Glenn Jocher, Ayush Chaurasia, Alex Stoken, Jirka Borovec, NanoCode012, Yonghye Kwon, Kalen Michael, TaoXie, Jiacong Fang, imyhxy, Lorna, Zeng Yifu, Colin Wong, Abhiram V, Diego Montes, Zhiqiang Wang, Cristi Fati, Jebastin Nadar, Laughing, UnglvKitDe, Victor Sonck, tkianai, yxNONG, Piotr Skalski, Adam Hogan, Dhruv Nair, Max Strobel, and Mrinal Jain. 2022. *ultralytics/yolov5: v7.0 - YOLOv5 SOTA Realtime Instance Segmentation.* https://doi.org/10.5281/zenodo.7347926

[18] Nuri Kim, Obin Kwon, Hwiyeon Yoo, Yunho Choi, Jeongho Park, and Songhwai Oh. 2023. Topological Semantic Graph Memory for Image-Goal Navigation. In *Proceedings of The 6th Conference on Robot Learning (Proceedings of Machine Learning Research, Vol. 205)*, Karen Liu, Dana Kulic, and Jeff Ichnowski (Eds.). PMLR, 393–402. https://proceedings.mlr.press/v205/kim23a.html

[19] Frank Krueger and Andreas Meyer-Lindenberg. 2019. Toward a Model of Interpersonal Trust Drawn from Neuroscience, Psychology, and Economics. *Trends in Neurosciences* 42, 2 (2019), 92–101. https://doi.org/10.1016/j.tins.2018.10.004

[20] Philipp Kulms and Stefan Kopp. 2019. More Human-Likeness, More Trust? The Effect of Anthropomorphism on Self-Reported and Behavioral Trust in Continued and Interdependent Human-Agent Cooperation. In *Proceedings of Mensch Und Computer 2019* (Hamburg, Germany) *(MuC'19)*. Association for Computing Machinery, New York, NY, USA, 31âĂŞ42. https://doi.org/10.1145/3340764.3340793

[21] Joshua Lee, Jeffrey Fong, Bing Cai Kok, and Harold Soh. 2020. Getting to know one another: Calibrating intent, capabilities and trust for human-robot collaboration. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 6296–6303.

[22] John D. Lee and Katrina A. See. 2004. Trust in Automation: Designing for Appropriate Reliance. *Human Factors* 46, 1 (2004), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392 arXiv:https://doi.org/10.1518/hfes.46.1.50_30392 PMID: 15151155.

[23] Bertram F. Malle and Daniel Ullman. 2021. Chapter 1 - A multidimensional conception and measure of human-robot trust. In *Trust in Human-Robot Interaction*, Chang S. Nam and Joseph B. Lyons (Eds.). Academic Press, 3–25. https://doi.org/10.1016/B978-0-12-819472-0.00001-0

[24] Roger C. Mayer, James H. Davis, and F. David Schoorman. 1995. An Integrative Model Of Organizational Trust. *Academy of Management Review* 20, 3 (1995), 709–734. https://doi.org/10.5465/amr.1995.9508080335 arXiv:https://doi.org/10.5465/amr.1995.9508080335

[25] David Premack and Guy Woodruff. 1978. Does the chimpanzee have a theory of mind? *Behavioral and brain sciences* 1, 4 (1978), 515–526.

[26] Morgan Quigley, Ken Conley, Brian Gerkey, Josh Faust, Tully Foote, Jeremy Leibs, Rob Wheeler, Andrew Y Ng, et al. 2009. ROS: an open-source Robot Operating System. In *ICRA workshop on open source software*, Vol. 3. Kobe, Japan, 5.

[27] Alessandra Rossi, Antonio Andriella, Silvia Rossi, Carme Torras, and Guillem AlenyÃă. 2022. Evaluating the Effect of Theory of Mind on PeopleâĂŹs Trust in a Faulty Robot. In *2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*. 477–482. https://doi.org/10.1109/RO-MAN53752.2022.9900695

[28] Ken J Rotenberg. 2019. *The psychology of interpersonal trust: Theory and research.* Routledge.

[29] Harold Soh, Yaqi Xie, Min Chen, and David Hsu. 2020. Multi-task trust transfer for human–robot interaction. *The International Journal of Robotics Research* 39, 2-3 (2020), 233–249. https://doi.org/10.1177/0278364919866905

[30] Samuele Vinanzi, Massimiliano Patacchiola, Antonio Chella, and Angelo Cangelosi. 2019. Would a robot trust you? Developmental robotics model of trust and theory of mind. *Philosophical Transactions of the Royal Society B* 374, 1771 (2019), 20180032.

[31] Lennart Wachowiak, Peter Tisnikar, Gerard Canal, Andrew Coles, Matteo Leonetti, and Oya Celiktutan. 2022. Analysing Eye Gaze Patterns during Confusion and Errors in HumanâĂŞAgent Collaborations. In *2022 31st IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*. 224–229. https://doi.org/10.1109/RO-MAN53752.2022.9900589

[32] Chengli Xiao and Liqian Zhao. 2022. Robotic Chef Versus Human Chef: The Effects of Anthropomorphism, Novel Cues, and Cooking Difficulty Level on Food Quality Prediction. *International Journal of Social Robotics* 14, 7 (01 Sep 2022), 1697–1710. https://doi.org/10.1007/s12369-022-00896-9

Preprint; final version available at https://doi.org/10.1145/3597512.3597518.