What Is Your Other Hand Doing, Robot?
A Model of Behavior for Shopkeeper Robot's Idle Hand

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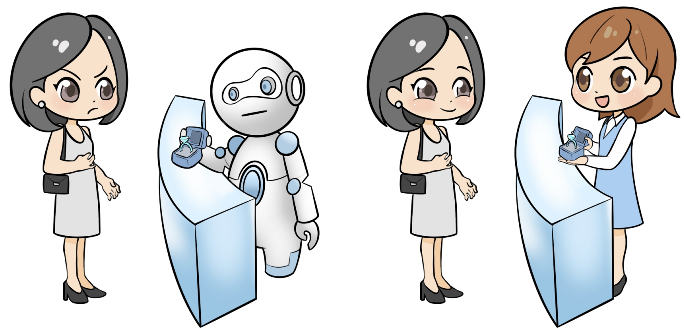
ABSTRACT

In retail settings, a robot's one-handed manipulation of objects can come across as thoughtless and impolite, thus creating a negative customer experience. To solve this problem, we first observed how human shopkeepers interact with customers, specifically focusing on their hand movements during object manipulation. From the observation and analysis of shopkeepers' hand movements, we identified an essential element of their idle hand movements: "support" provided by the idle hand as the primary hand manipulates an object. Based on this observation, we proposed a model that coordinates the movements of a robot's idle hand with its primary task-engaged hand, emphasizing its supportive behaviors. In a within-subjects study, 20 participants interacted with robot shopkeepers under different conditions to assess the impact of incorporating support behavior with the idle hand. The results show that the proposed model significantly outperforms a baseline in terms of politeness and competence, suggesting enhanced object-based interactions between the robot shopkeepers and customers.



(a) Handles the product with only one hand

(b) Handles the product with the other hand supporting it, exemplifing the nuanced social presence and engagement often lacking in robotic counterparts

Figure 1: An example highlighting the importance of hand motion subtleties

CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; • **Computer systems organization** → **Robotics**.

KEYWORDS

Idle hand motion, Support hand behavior, Politeness, Competence

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1 INTRODUCTION

In recent years, the field of robotics has witnessed significant advances in human-robot interaction (HRI), with social robots increasingly being deployed in museums [14, 17], retail stores [10, 31, 35], schools[21, 42], and healthcare [1, 28]. While these technological advancements are undeniably impressive, one cannot help but notice a significant gap in the robots' ability to convey social presence.

The subtleties of hand motion, for instance, play a crucial role in human interactions, but they are often overlooked in robotic design. Imagine walking into a shop where a robot acts as the shopkeeper (Fig. 1 (a)): how would you feel if the robot continually handled a box containing a diamond ring with one hand while its other hand remained idle?

In the human realm, a shopkeeper who interacts with products using only one hand is often perceived as inattentive or even impolite. A competent shopkeeper, in general, actively coordinates both hands in a manner that not only increases efficiency but also adds a layer of social appropriateness and politeness. For instance, in the given scenario where a diamond ring is being shown, a human shopkeeper would typically hold the box with one hand while using the other to provide additional support, as illustrated in Fig. 1 (b). In contrast, a robot shopkeeper that persists in using only one hand could be seen as less lively, lacking the depth of a social entity we would naturally expect.

Recently, there has been a sustained research effort toward improving the acceptance of social robots as social entities. One concept related to this effort is idle motion. It can present a basic level of the "illusion of life," which helps people regard robots as social entities [20]. Idle motions refer to "adaptor movements," i.e. postural or other non-verbal movements often performed during idle moments [2]. Previous studies mainly explored the impact of head motion (e.g., head-scratching), face motion (e.g., eye-blinking,

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mouth movement), arm motion (e.g., arm-folding), and leg motion (e.g., leg-swinging) [9, 22, 24] on enhancing robots' social presence when robots are not engaged in specific tasks.

However, our scenario presents a unique challenge: the robot is not in an idle state, but one of its hands, which is not required for the object manipulation task, remains idle. How this unused hand (hereinafter referred to as the idle hand) should move while the primary hand executes manipulative tasks remains an open question.

To the best of our knowledge, little research has been conducted on the coordination of the idle hand with the primary hand for social purposes. To this end, we introduce the novel concept of "idle hand motion," which here refers to the coordination of the idle hand with the primary hand during ongoing manipulation. Our work makes two main contributions. First, we propose the concept of idle hand motion and its corresponding model. Second, we explore the impact of idle hand motion on enhancing a robot's social acceptance, particularly in the role of a shopkeeper.

2 RELATED WORK

2.1 Gestures in Human Communications

People commonly use gestures during interactions to draw the attention of listeners [15], disambiguate unclear speech, and supplement speech with additional information [23]. All visible hand movements except for self-touching and object-manipulations are regarded as gestures [23, 32]. In general, gestures can be divided into four common types: (1) iconics, which have a close relationship to the semantic content of speech, (2) metaphorics, which present an image of an abstract concept such as knowledge, (3) deictics, which are pointing movements towards concrete entities or abstract space, and (4) beats, which are typically frequent biphasic (e.g., up-and-down, back-and-forth) movements [32]. These gestures greatly support human communication, and they enhance learning and memory. Feyereisen [13] investigated that sentences with representational gestures are easier to recall for listeners than nonrepresentational ones. Cook et al. [8] found that gestures help children learn new mathematical concepts during instruction.

In our study, idle hand motion can be used to draw attention and convey politeness and competence. Therefore, idle hand motion can be considered to be a gesture.

2.2 Idle Motions

Idle motions in animations refer to micro-movements that occur in idle states between animation clips [12]. These subtle motions imbue agents with lifelike qualities. For example, Kocoń [25] proposed a method to synthesize idle motion for virtual persons, enhancing perceptions of friendliness. Egges et al. [12] developed a flexible idle motion engine for virtual agents in idle states.

Research on human-robot interaction has also recognized that micro-movements play an important role in making robots animated and alive in the idle state. Social robots such as Robovie [22] use idle motions like "scratch the head" and "fold its arm" to indicate they are lifelike, but how these idle motions affect the human perception of robots has not been investigated. Song et al. [43] observed clerks via video ethnography, extracted several idle motions (e.g., mouth movement, arm movement), and tested whether these idle motions could be recognized when they were applied to a robot. Cuijpers and Knops [9] conducted an experiment in which participants were exposed to different levels of social verification. They found that robots with low levels of social verification that portrayed idle motions (e.g., breathing, gaze shift motion), were more anthropomorphic and emotionally expressive compared to robots lacking such motions.

To summarize, existing studies focus on the synthesis of idle motions from human behavior observations, primarily in contexts where robots are in an idle state. However, the use of the idle hand during manipulation tasks has not yet been investigated.

2.3 Two-handed Motions

Recent research in human-robot interaction has extensively explored two-handed gestures. Huang and Mutlu [18] analyzed how participants used gestures while describing a paper-making activity, and further investigated the use of gestures for enhancing interaction. They later modeled the coordination of speech, gaze, and gesture in narration using a dynamic Bayesian network [19].

Research on two-handed manipulation has been intensively pursued over the past few decades. Bai et al. [3] presented an approach of dual-arm coordinated control for twisting manipulation, merging optimized motion planning with real-time human-led teleoperation. Vahrenkamp et al. [45] proposed a Grasp-RRT algorithm to generate collision-free dual-arm grasping motions. Bestick et al. [4] developed an approach to estimating personalized human kinematic models, and it could generate safer and more motion for two-handed robot-to-human handovers.

Existing research on two-handed gestures and manipulations has primarily concentrated on coordinating hand motions where both hands are essential for communication or task execution. By contrast, our study is unique in examining how one unused hand can be coordinated with the other hand, which sets our research apart from the existing literature.

2.4 Social Cues of Hand Motions

Legibility, i.e., the intuitive understanding of robots' intentions, is crucial for coordinating joint action and positive perception [30]. Dragan et al. [11] developed a model for generating goal-directed legible arm motions and legible pointing gestures [16]. Bodden et al. [5] introduced a method for synthesizing legible manipulation motions, enhancing the robot's communicative intent.

Polite hand motions are another way to non-verbally signal intent to humans. Politeness can be manifested by etiquette that makes use of verbal, physical, and gestural modes of interaction [33]. A representative example of this is the practice of passing objects with both hands to convey politeness, a gesture deeply rooted in traditions like the Japanese tea ceremony [44]. Central to politeness is Brown and Levinson [6]'s Politeness Theory, emphasizing the importance of maintenance of "face" in social interactions. This theory has been widely applied in the field of HRI. Kumar et al. [27] noted that a robot's polite behavior influenced user perceptions. Ritschel et al. [39] found gender-based preferences for a companion robot: male participants favored polite robotic feedback, while females opted for more direct commands. Rea et al. [37] found that

(a) picking (b) showing (c) giving (d) receiving (e) placing

Figure 2: Situations where the support hand behavior occurs during shopkeeper-customer interaction

(a) support one handbag with right hand (b) grasp another handbag with right hand (c) compare handbags with both hands (d) place another handbag with right hand (e) resupport the handbag with right hand

Figure 3: An example of how a human shopkeeper returns to support an object with the idle hand

although an impolite robot was not preferred during physical exercises, it pushed participants to perform better than a polite one. Lee et al. [29] explored how perceived politeness levels in a robot's speech and gestures can influence a user's intention to comply.

While existing research predominantly focuses on verbal communication, our study aims to address the gap in understanding politeness through non-verbal cues, particularly hand motions.

3 MODEL OF SUPPORT HAND BEHAVIOR

3.1 Observation of Human Shopkeeper Behaviors

3.1.1 ***Scenario and Motivations.*** To understand strategies for idle hand usage during object-based interactions, we initially observed shopkeepers' hand behaviors in ten different retail stores informally, with a particular focus on how the idle hand was used. We noticed that for expensive items like watches and jewelry shopkeepers often used their idle hand to either directly touch or maintain a slight distance from the bottom of them as a support. By contrast, this behavior was less observed with cheap items like snacks and daily necessities.

However, due to limitations in video recording, we could not quantify this hand behavior. Consequently, we conducted an observation of object-based interaction between a shopkeeper and a customer in a simulated handbag store, where two handbags were placed on a table. We selected expensive handbags with the expectation that more interesting interactions would occur during their presentation. We then invited four participants with shopkeeper work experience (2f, 2m) to conduct role-plays where one acted as a shopkeeper and the other as a customer. We focused on how the handbags were presented and handled during the sales process, without specific mention of idle hand usage.

3.1.2 ***Results.*** From observation of the shopkeepers, we found that one behavior, the shopkeeper's "support" hand behavior, consistently reoccurs across multiple interactions as expected. In other words, when the primary hand is tasked with manipulating an object, the other hand, which could actually remain in an idle state, is no longer idle but positions itself to support the object.

We observed that this behavior usually took place in five situations during shopkeeper-customer interactions: picking, showing, giving, receiving, and placing for the primary hand (Fig. 2). In Fig. 2 (a), a female shopkeeper grasped a handbag with her left hand while her right hand provided support from beneath. In Fig. 2 (b), the shopkeeper held the handbag with the left hand while the other hand supported it. In Fig. 2 (c), the shopkeeper used the left hand to pass the handbag to the male customer with the right hand supporting it. In Fig. 2 (d), the shopkeeper retrieved the handbag by grasping it with the left hand while the other hand supported it. In Fig. 2 (e), the shopkeeper placed the handbag on the table while keeping the right hand under it.

One representative example of the support hand behavior is shown in Fig. 3. In Fig. 3 (a), a female shopkeeper held one handbag with the right hand supporting it. When a male customer inquired about the difference between the handbag she was holding and another on the table, she then used her right hand to pick up the second handbag for comparison. Afterwards, she placed the second handbag on the table as shown in Fig. 3 (b)–(d). Interestingly, after this brief task, her right hand returned to its support hand position beneath the first handbag, as shown in Fig. 3 (e). This behavior may be surprising because, even after shifting focus to another task, the shopkeeper returns to the initial support hand position, highlighting the importance of this motion.

3.2 Analysis of Support Hand Behavior

To quantify how the idle hand behaves, we examined the hand behaviors for the idle hand and classified them into four patterns: supporting an object (supporting), other idle hand motions such as putting the arm down and hanging the arm (others), various gestures such as pointing somewhere on the object (gestures), and different manipulation types such as picking and placing another

Table 1: Observed hand behaviors

Primary Hand State	Secondary Hand			
	Idle State		Busy State	
	supporting	others	gestures	manipulations
picking	6	1	0	0
showing	16	3	9	11
giving	4	0	0	0
receiving	5	0	0	0
placing	6	2	0	1
total	37	6	9	12

handbag (manipulations). Table 1 shows the frequency of these patterns in different situations.

From this table, it is clear that the support behavior is by far the most commonly used behavior in all situations compared to other idle hand motions. Therefore, we chose to focus on the support behavior for the idle hand.

3.3 Reasons for Support Hand

After the role-plays, we conducted interviews with the participants to explore the underlying motivations for their frequent use of the support hand behavior while role-playing as shopkeepers. These interviews revealed three primary reasons for this behavior:

- To show politeness to customers, since being polite is an expected attitude and even a requirement for shopkeepers.
- To prevent the products from accidentally falling as it would make customers feel uncomfortable. Furthermore, this behavior would make customers appreciate the value, fragility, and other attributes of the product, which cannot be conveyed by casual handling such as one-handed behaviors.
- To draw customers' attention to the item being showcased.

3.4 Modeling

From the observation of shopkeepers' behaviors and subsequent interviews with the participants, we found that the support hand behavior is the main one performed by the idle hand, hence we developed a model for this behavior consisting of computing a support point and positioning the support hand.

3.4.1 ***Computing Support Point.*** The support point serves as a crucial component in our model. As illustrated in Fig. 4, the primary hand holds the object while the idle hand supports it beneath the "support point." Here, the support point is essential to the model of idle hand motion, and the idle hand basically moves under the support point. While for this study we manually selected a point at the bottom of the held object to be the support point, let us explain how the support point could be computed.

In theory, this point can be computed through physical simulations that take into account geometric shape, weight distribution, and a set of specific criteria defining what makes a "support point" optimal in the given context (e.g., most stable, most visually human-like). The steps for the computation are as follows. First, calculate the center of mass of the object using the available information on the geometric shape and weight distribution of the object. Second, sample candidate points along the edge of the object that are located below the center of mass. Third, assess and rank these candidate points based on the provided criteria. Finally, choose the optimal point that best meets the defined criteria. The point we manually chose satisfies the idea included in these computation steps.

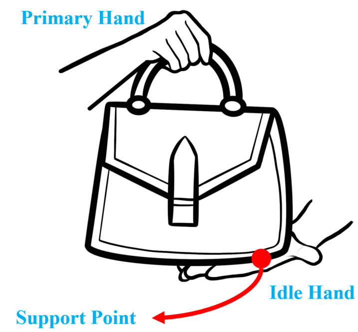


Figure 4: Schematic diagram of support hand behavior

3.4.2 ***Positioning Support Hand.*** Upon determining the optimal support point, the next step is to accurately position the idle hand. This involves not only computing the position but also the orientation of the idle hand. In observations of the human shopkeeper, the idle hand was frequently situated just below and in direct contact with the handbag, with the palm facing upwards and fingers pointing sideways and forward, to naturally support the object being held by the primary hand as illustrated in Fig. 4.

However, the support hand behavior does not always imply direct contact with the object. Physical support is only necessary when the object is too heavy to be effectively handled by one hand. In the case of lighter objects, it is sufficient to place the support hand below, but not touching, the object. Placing the support hand in such a way accomplishes the goal of emphasizing the object and signaling politeness, while also making it possible for the primary hand to showcase the object by rotating it and showing different angles. For instance, human shopkeepers showcasing a handbag might rotate it repeatedly to display its shape and finer details while maintaining a slight gap between the object and the support hand. Thus, the robot should emulate this behavior.

4 IMPLEMENTATION

We implemented an autonomous robot system that reproduces the support hand behavior observed in Section 3.

4.1 Robot Hardware

We used the TIAGo++ robot [36] from PAL Robotics. The robot features a mobile base, a lifting torso, a head, and two arms. Both arms have 7 degrees of freedom (DoF) ending in grippers, and the torso has a stroke of 35 cm so that the height of the robot can be adjusted between 110 and 145 cm. Its eyes are equipped with an RGB-D camera, and there are speakers inside the base.

4.2 Architecture

Fig. 5 illustrates the architecture of the proposed model. The point cloud from the RGB-D camera is passed to the collision avoidance module, which represents the operating environment for the robot. Meanwhile, to address the potential occlusion of parts of the object by the robot's gripper, a 3D model of the object is also fed into this

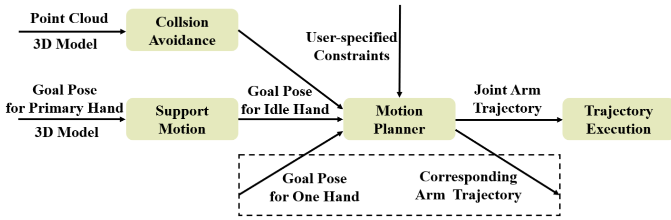


Figure 5: Diagram of implementation of proposed model

module. The support motion module takes the goal pose for the primary hand and the 3D model of the object being held as input, and it outputs the joint goal poses for both hands. To generate an optimal joint arm trajectory for both hands, the motion planner module takes the goal poses of both hands as input, subject to meeting the user-specified constraints and avoiding collisions. When the idle hand is engaged in specific tasks, its goal pose is fed to the motion planner module, which generates an optimal arm trajectory as shown in the dotted box in this figure.

4.3 Collision Avoidance

To generate hand motions without collision, we need to build a 3D representation of the environment around the robot. This is achieved by the collision avoidance module, which uses point cloud data from the RGB-D camera to create a 3D occupancy grid map called Octomap. This Octomap provides information on where obstacles are located in the robot's environment, and it is directly passed to the flexible collision library (FCL) for collision checking.

4.4 Support Motion

The support motion module generates the goal pose for the idle hand. As described in Section 3.4.2, human shopkeepers leave a slight distance between the bottom of the object and the idle hand. Therefore, we decided to keep such a distance. We empirically adjusted the distance between the support hand and the object to 10 centimeters, aiming to reproduce this distance impression as well as the stability and safety of the arm motion (too close a distance sometimes causes planning failure, as the carried object becomes an obstacle for the planner).

Meanwhile, we found that the palm of the idle hand is parallel to the ground from our observations of how human shopkeepers used the support hand behavior. Consequently, the roll angle was set to 90 degrees, which makes a wider surface of the gripper to support the object, the pitch and yaw angles were set to zero and 45 degrees respectively.

4.5 Motion Planner

Given the goal poses of both hands, the motion planner module computes the joint arm trajectories, i.e. time-series of all joints of both arms. Here, we assume that the goal pose is within short straight lines from the current poses. In cases where longer distance travel is needed, a series of sub-goals for both arms need to be pre-computed and provided to this module to ensure synchrony between both arms. Thus, we use the support motion module in conjunction with the motion planner module to plan trajectories from one sub-goal to the next.

We select the RRT-Connect motion planner [26] for our system because of its ability to quickly find a feasible arm trajectory between the start pose and the goal pose, and its suitability for user-specified constraints. The motion planner module takes the goal poses for both hands as input, and outputs a synchronized joint arm trajectory, enabling both arms to reach their corresponding pose at the same time.

However, due to the characteristics of RRT-Connect, the generated arm trajectory is often not optimal, as it is excessively long and visually strange to humans. To counteract this, we sample many candidate arm trajectories, and select the one with the shortest length as optimal, since a good arm trajectory should avoid long detours between the start pose and the goal pose. The length of the trajectory can be summed by the coordinates of both grippers computed by forward kinematics and basic transformation for points in the planned arm trajectories. Moreover, to make the trajectories natural and human-like, we set user-specified constraints on joint angles that conform to human shoulder and elbow positions.

The entire process of deriving the optimal joint arm trajectory for the support hand behavior is encapsulated in Algorithm 1, where $L(t)$ represents the length of the joint arm trajectory for both arms.

Algorithm 1 Generation of optimal joint arm trajectory

Input: Start Pose $P_{\text{start\_p}}$, Start Pose $P_{\text{start\_s}}$, Goal Pose $P_{\text{goal\_p}}$, Object O being held, Number of Candidate Trajectories n, User-specified constraints C_{user}
Output: Optimal joint arm trajectory T^*
1. Compute Goal Pose for Support Hand:
$P_{\text{goal\_s}} \leftarrow \text{SupportHandModel}(P_{\text{goal\_p}}, O)$
2. Generate Candidate Arm trajectories:
for $i = 1$ **to** n
$t_i \leftarrow MotionPlan(P_{\text{goal\_p}}, P_{\text{goal\_s}}, C_{\text{user}})$
end for
List candidate joint arm trajectories $T = \{t_1, t_2, ..., t_n\}$
3. Select Optimal Arm Trajectory:
$T^* = \arg\min_{t \in T} L(t) \quad subject\ to \quad C_{\text{user}}(t)$

4.6 Trajectory Execution

Our robot system is based on the MoveIt framework [1]. The trajectory execution module is responsible for taking a planned trajectory and executing it with the physical robot automatically.

5 EVALUATION

5.1 Hypotheses

Drawing from the insights in Section 2.4, handling an object with two hands is generally considered more polite than using just one. Supporting this, Tagai et al. [44] found in their fMRI study that observing an action involving two hands was associated with higher politeness compared to the use of one hand. Additionally, our observations of polite and competent shopkeepers revealed that they often use the support hand behavior when picking, placing, showing, and passing items to customers or receiving them back, and thus we made the following two hypotheses:

[1]https://moveit.ros.org/

- **H1**: Participants perceive robots with the support hand behavior as **more polite** than those without it.
- **H2**: Participants perceive robots with the support hand behavior as **less rude** than those without it.

Meanwhile, Cuijpers and Knops [9] reported that robots performing meaningful motions are seen as more socially competent and skilled than those engaging in idle or no motions. In our study, we regard the support hand behavior as one such meaningful motion. Considering that demonstrating politeness is a crucial aspect of a shopkeeper's role, we expect robots behaving in a polite manner to be perceived as competent in their role as a shopkeeper. We thus developed the following hypothesis:

- **H3**: Participants perceive robots with the support hand behavior as **more competent** than those without it.

5.2 Participants

We recruited a total of 20 participants from a part-time job recruiting website in the age range of 18 to 60 years (M = 35.75, SD = 14.79). Ten of them self-identified as male, and ten as female, with a similar number for different age groups. All participants who took part in the experiment were compensated with 3000 JPY.

5.3 Conditions

The robot's performance was compared under the following two conditions:

- Proposed: The robot runs in the support hand mode as described in Section 4.
- Baseline: The support motion module is excluded from the architecture of the proposed model. In this case, the goal pose of either hand is directly fed to the motion planner module. It then outputs the arm trajectory for the corresponding hand, as shown in the dotted box in Fig. 5.

We chose a within-subjects design to allow participants to experience different conditions since even in Japan, where many robots are being deployed in public spaces, people remain unfamiliar with robots and lack consensus on the standards for politeness in their behaviors. Meanwhile, the order of conditions was counter-balanced.

5.4 Procedure

When participants arrived at the experiment site, they were first introduced briefly to the study and procedure. They were then asked to sign a consent form. To make participants comfortable around the robot, we showed several demos of speech and hand movements by the robot, and then we asked them to control the robot through the remote controller. Afterwards, each participant was instructed to play the role of a customer who showed interest in one of the handbags. The robot shopkeeper would show the handbag with synchronized speech and pass it to and from the customer. In response, the customer needed to receive the handbag from the customer and then give it back to the shopkeeper after trying it on. After each condition, the participant was asked to complete a questionnaire. Finally, after interacting with the robot in both conditions, a semi-structured interview was conducted. The experiment was approved as ethical by the Institutional Review Board. The experiments and interviews were conducted in Japanese.

5.5 Measurement

Dependent variables of politeness, rudeness, and competence were measured through a questionnaire that is composed of several 1-to-7 point Likert items.

- **Politeness and Rudeness**

We consulted the latest review on politeness, compiled by Ribino [38], but did not find any validated scales or commonly-used questionnaires for measuring politeness and rudeness. Therefore, we decided to adopt the items used in Salem et al. [40, 41], to assess politeness with the item 'polite' and rudeness with the item 'rude.'

- **Competence**

We adopted all six items for measuring competence from the RoSAS, a validated scale frequently used in the HRI community [7]. These items are 'capable,' 'responsive,' 'interactive,' 'reliable,' 'competent,' and 'knowledgeable.'

6 RESULTS

6.1 Observation

Fig. 6 and 7 show typical interactions in the proposed condition and the baseline condition respectively. The robot first greets the customer and then introduces the handbag while interleaving the pointing gesture. It gives the handbag to the customer and receives it back after the customer examines the handbag. Participants generally behaved with the robot as they would behave with human shopkeepers, nodding to the robot's speech. This behavior was consistent between conditions.

Interestingly, we did observe some social behaviors toward the robot. In both conditions, many participants nodded to the robot when it greeted them. Moreover, a large proportion of participants who rated the robot with the proposed model as more polite tended to bow to the robot before or after they passed the handbag to the robot (Fig. 8 (a)). In addition, one participant attempted to talk to the robot even though she knew it could not respond (Fig. 8 (b)).

6.2 Verification of Hypotheses

6.2.1 ***Politeness and Rudeness.*** First, we conducted the Shapiro-Wilk test to assess the normality of the data. For the item "polite," both the baseline condition (W = .810, p = .001) and the proposed condition (W = .708, p < .001) showed significant departures from normality. Similarly, for the item "rude," both the baseline condition (W = .642, p < .001) and the proposed condition (W = .495, p < .001) were also significantly non-normal. Such non-normality breaks the assumption for using the t-test. Therefore, we decided to use Wilcoxon's rank sum test (also known as the Mann-Whitney U test), a non-parametric test with no strict requirement for data distribution and variance.

As shown in the first set of bars in Fig. 9, there is a significant difference between the proposed model (M = 6.450, SD = .759) and the baseline model (M = 5.200, SD = 1.609) for the item "polite" (U = 96, p = .002). This result supports our first hypothesis: A robot using the proposed model is perceived as more polite than the robot using the baseline model.

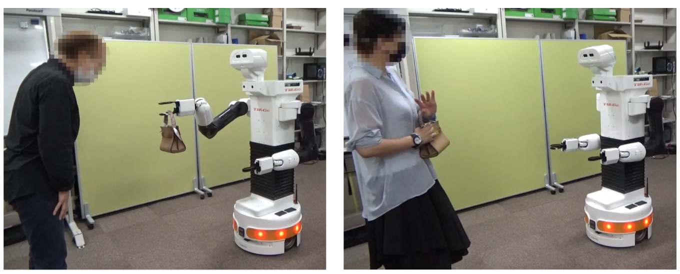
In the second set of bars, the difference between the proposed model (M = 1.200, SD = .410) and the baseline model (M = 1.850, SD = 1.461) for the item "rude" was not statistically significant (U

(a) greeting the customer (b) introducing the handbag (c) pointing to the handbag (d) giving/receiving the handbag

Figure 6: Robot in proposed condition

(a) greeting the customer (b) introducing the handbag (c) pointing to the handbag (d) giving/receiving the handbag

Figure 7: Robot in baseline condition



(a) bowing to the robot (b) talking to the robot

Figure 8: Social behaviors toward the robot

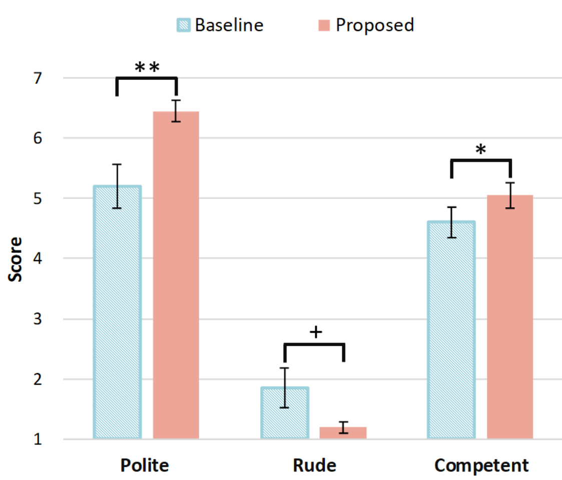


Figure 9: Results. The error bars show the standard error for the mean at ±1 *SE*. (+ : $.05 < p < .1$, $*$: $p < .05$, $**$: $p < .01$)

= 246, p = .063). Although this result does not support our second hypothesis, it suggests its approaching significance.

6.2.2 ***Competence.*** To obtain the data for the item "competence," we averaged the above-mentioned six items for the scale from the RoSAS. As done above, we ran the Shapiro-Wilk test on the data of the item "competence." The test results indicate that the data of both the baseline condition (W = .976, p = .865) and the proposed condition (W = .972, p = .792) followed a normal distribution. Consequently, a paired t-test was used to evaluate the statistical significance of the differences in competence between conditions.

As illustrated in the third set of bars in Fig. 9, the difference between the proposed model (M = 5.050, SD = .949) and the baseline model (M = 4.600, SD = 1.140) was significant (paired t-test t = -2.193, p = .020), and the effect size was small ($Cohen's\ d$ = .204). This result supports our third hypothesis: A robot using the proposed model is regarded as more competent than a robot using the baseline model.

6.3 Interview Results

When asked about the reason for their judgments on politeness, nine participants attributed their positive judgments to the robot's support hand behavior, noting its resemblance to human shopkeepers' respectful service with both hands. Two participants emphasized that the robot's careful handling of products, as indicated by its support hand behavior, suggested a dedication to providing superior service. Another two recognized differences in robot behavior across conditions but perceived equal levels of politeness in both. Six participants reported that they did not find differences between the conditions. Interestingly, one female participant perceived the robot exhibiting the support hand behavior as less polite, interpreting this as the robot exerting sales pressure, which made her uncomfortable.

When it came to the robot's competence, three participants reported that a robot demonstrating great service etiquette implied greater competence. Two participants observed that the support hand behavior mirrored that of human shopkeepers, enhancing perceptions of the robot's competence. Two others linked the robot's meticulous product handling to competence. Additionally, one participant remarked that the robot's enthusiasm in presenting the product was indicative of competence. The remaining participants based their assessments on subjective feelings, without providing specific reasons for their viewpoints.

7 DISCUSSION

7.1 Design Implications

As robots become integral to our daily lives, understanding the sociological aspects of their interactions, especially concerning object manipulation, gains paramount importance. One facet of this is the concept of 'legibility' of robot motions. Recent studies [5, 11] focus on developing robot motions with clear intentions to enhance their legibility. This principle emphasizes designing robot motions that humans can quickly and easily interpret, fostering smoother and more predictable interactions. Drawing parallels to the research on feeding support [34], we see a similar emphasis on the sociological dimensions. Robot feeding behavior, as outlined in their work, must be subtle and not draw undue attention, suggesting that robots should not only perform tasks but also align with the unspoken social codes governing those tasks.

The support hand behavior serves as an illustrative example of this merging between the physical and the sociological, offering insights into designing more socially-aware robots.

7.2 Should Robots Exhibit Support Hand Behavior?

It is arguable whether robot shopkeepers need to exhibit the support hand behavior. While operating both hands consumes more energy than one, potentially requiring more frequent recharging of the battery-operated robots, we believe that stores would prefer to use the support hand behavior simply to give an impression of politeness or competence. If retail stores' target shoppers value a more "human-like" shopping experience, robots with the support hand behavior might be considered justified. Furthermore, given labor shortages, robots will very likely be shopkeepers in the future. Such robots are expected to provide interactions that are not just transactional but also socially-appropriate or socially desirable. Expressing politeness and competence through the support hand behavior can be a vital component of this development, greatly contributing to making the robots more acceptable to users.

7.3 Which Occasions Should Robots Exhibit Support Hand Behavior?

The use of the support hand behavior by robots should align with cultural norms, customer expectations, and specific service contexts. In luxury retail, this behavior not only underscores the item's value but enhances customer engagement. Similarly, in cultural rituals like tea ceremonies, the dual-handed presentation is synonymous with respect, warranting robots to emulate this to uphold the ceremony's essence. In hierarchical settings, using both hands to present items conveys deference, emphasizing the importance of recognizing social norms in robot behaviors. Conversely, in casual contexts like convenience stores, where efficiency is prioritized, such formalities may be superfluous. Finally, the support hand behavior can be used for small, lightweight objects that do not require two hands to hold. For large, heavy objects a two-handed grip is required, which is beyond the scope of our study.

7.4 Generalizability across Cultures

It remains an open question whether the support hand behavior can be applied to other cultures. However, our study provides preliminary insights and serves as a starting point for an extensive investigation into the use of idle hand motions in different cultures.

While this research was conducted in Japan, we believe that the support hand behavior shows potential for use in different cultural contexts. The use of both hands for handling objects signifies politeness, and this practice is prevalent in East Asian countries such as China and Korea [44]. Additionally, we asked several members of our lab with international backgrounds about their impressions of the support hand behavior. They responded that they had also observed the support hand behavior overseas (including North America and Europe). They felt discomfort when observing shopkeepers handle valuable items with a single hand, but did not mind in the case of inexpensive items.

7.5 Limitations

While revealing the importance of the support hand behavior, there are still several limitations to this work. First, we chose only handbags in the observation and evaluation; it is uncertain whether people would rate the robot differently with other objects regarding politeness and competence. Second, as the observation of shopkeepers' hand behavior and the experiment were conducted in a laboratory setting, the situation would be a bit different in a real-world environment. However, we believe our experiment design effectively captured the important factors of hand motions in object-based interactions, and the setup allowed us to focus on the hand motions and not other factors such as verbal interaction.

8 CONCLUSION

This study was motivated by the phenomenon in which robots keeping one hand fully idle during object manipulation gives the impression of weirdness, particularly in roles demanding social cues such as that of shopkeepers. Accordingly, we first observed how human shopkeepers served customers with both hands, identifying the supportive role of the idle hand during object-based interactions. We then developed a computational model to replicate the support behavior for the idle hand of robot shopkeepers. The experimental results indicate that robots implemented with support behaviors for the idle hand are perceived as markedly more polite and competent than those without such behaviors. We believe that the incorporation of the support hand behavior can drastically enhance social acceptance of robots, especially in roles like shopkeepers.

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