International Journal of Social Robotics (2023) 15:969–982
https://doi.org/10.1007/s12369-023-01013-0

Hey Robot, Tell It to Me Straight: How Different Service Strategies Affect Human and Robot Service Outcomes

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Accepted: 27 April 2023 / Published online: 17 May 2023

Abstract
With robots already entering simple service tasks in shops, it is important to understand how robots should perform customer service to increase customer satisfaction. We investigate two methods of customer service we theorize are better suited for robots than human shopkeepers: straight communication and data-driven communication. Along with an additional, more traditional customer service style, we compare these methods of customer service performed by a robot, to a human performing the same service styles in 3 online studies with over 1300 people. We find that while traditional customer service styles are best suited for human shopkeepers, robot shopkeepers using straight or data driven customer service styles increase customer satisfaction, make customers feel more informed, and feel more natural than when a human uses them. Our work highlights the need for investigating robot-specific best practices for customer service, but also for social interaction at large, as simply duplicating typical human–human interaction may not produce the best results for a robot.

Keywords Human–robot interaction · Customer service · Social strategies · Human–robot comparisons

1 Introduction

Robots are being developed for a number of jobs that will require social interaction, such as museum guides [1, 2], retail workers [3, 4], and receptionists [5]. Research has already demonstrated how even simple social interactions in these tasks is possible for robots and helpful to people. In these interactions, robots have traditionally been programmed to follow best practices of human–human interaction, such as being polite, responsive, and deferential (e.g. [6, 7]). This typical strategy (copying polite human behavior) is received positively by people in general [6, 8–11] and is a good base design for social human–robot interaction. However, it is unclear if there are better behaviors for robots than those copied from human–human interaction.

In customer service and other social situations, it is sometimes important to convey information that may be difficult to communicate politely. For example, if a shopkeeper knows the outfit a customer picked may not be appealing, the shopkeeper may want to guide the customer to new clothes that suit them better so that the customer will be happier with their purchase. This is typically done in an indirect way, not stating the critical information directly, but perhaps by suggesting the customer "take a look at these other trendy clothes you might like." Such indirect customer service is effective for human shopkeepers, and has been developed over years of retail research [12, 13]. It is yet unclear, though, if this is a good strategy for a robot performing a similar customer service role, or if an even more effective strategy is possible that differs from the typical strategies used by people.

There is some evidence that traditionally acceptable human behavior is not always the best choice for robots [14, 15]. The research demonstrates how a robot can take advantage of behavior that may be regarded as rude or strange when done by a human, and may be acceptable because the robot and its actions are not perceived identically to a human [14, 16]. People may also react differently to robots, such as not being as self-conscious when judged by robots [14, 16, 17]. We ask if there are also communication strategies that are typically not as effective when used by people, but

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more effective when used by robot, particularly in customer service contexts.

For example, in the earlier clothes retail example, a shopkeeper could instead directly tell the customer their choice is unfashionable, or describe data about the fashion choice (Fig. 1), but this may be considered rude or unnatural when done by a normal human shopkeeper. However, such clear and direct communication may be more acceptable and clearer from a robot shopkeeper. We explore different types of communication strategies for customer service, directly comparing their effects when performed by a human or robot.

We conducted 3 online experiments with a total of over 1300 people and find that, when witnessing a robot using direct customer service strategies, people feel more customer satisfaction, feel better informed, and felt more natural than when a human uses the same methods. We further find that traditional customer service strategies are perceived as better when a human shopkeeper does it when compared to a robot. Thus, when using direct methods that may be more typically perceived as rude, robots are seen as more competent shopkeepers than people using the same methods. These results illustrate the importance of exploring new, robot-specific best practices for customer service, but also social interaction at large, instead of stopping at copying human best-practices.

2 Related Work

2.1 Robots Affecting Emotions and Perceptions

A robot's behavior during interaction can shape perceptions and emotions about the robot and situation. For example, robots could evoke different emotions by gestures [18], sound [19, 20], changing color [21, 22], or physical positioning [23]. Similarly, an interaction can also be designed to make people perceive a task our outcome in a certain way. For example, a robot could make people feel more motivated [24], or like they performed well or poorly at a task [25]. Robot behavior design can therefore affect how people feel about a situation, and we explore how to design robot-specific behaviors to improve feelings about customer service.

2.2 Persuasive Robots

There is extensive research on a robot's ability to persuade or recommend courses of action for people. For example, a robot can be framed to have a specific social [26–29], physical [9, 23, 30, 31], or emotional qualities [18, 32, 33] that it can leverage to be convincing.

In general, persuasive robots are designed to help people make better choices, such as with robots that promote exercise or better habits (e.g. [17, 34]). However, on purpose or by accident, they can also be used to promote less positive or beneficial behaviors in people [31, 35–37], implying robots should be designed carefully. By understanding how different behaviors can affect user impressions and choices (such as in a customer service situation), we can design robot behaviors to be appropriately persuasive for the situation.

2.3 Robots and Non-polite Behaviors

Social human–robot interaction work has typically studied socially acceptable and polite behaviors for robots. These behaviors are usually preferred by people, and result in people liking robots more, performing better, being happier, and intending to interact with robots more in the future [6, 8–11]. Due to these results and the arguably common-sense notion that robots should be polite, this robot research is broad and well understood, and is known to be a good guide for robot design.

In contrast, there have been recent works that explored less positive interactions. For example, people have studied how people react when robots cheat [8, 38], give blunt advice [11], use controlling language [39] and judgmental behavior [10, 14, 15], or administer punishments [40]. Interestingly, while negative interactions often have negative outcomes, applying this type of behavior in the correct context or problem these behaviors can have net-positive results [14, 15]. On the other hand, positive and polite robots do not always achieve better results [16, 41, 42], or can even reduce someone's performance [15, 42]. We explore how potentially rude robot behaviors could end up benefitting customer service results.

2.4 Robots in Customer Service

In the introduction, we already described how robots are a promising technology to help reduce the workload of employees in a number of sectors, including retail. Research has already demonstrated the ability of even simple robots to help in retail [3, 4, 31, 43, 44], deliveries [45], or engage in receptionist work [5]. In industry, the robot Pepper, has been used in numerous stores, helping people search for products.

There are many open questions for customer service robots, especially related to interaction with customers and how those are perceived and eventually impact the customer service experience [46]. One potential direction is investigating how machine-like or human-like the robot and its actions should be for better customer service outcomes [47], as well as results showing how the robot dialogue in interaction can affect customer service experience [48, 49]. However, most works replicate typical human behavior in robots and find positive results. We explore how other, less human-like strategies can influence perceptions of both robot and human shopkeepers.

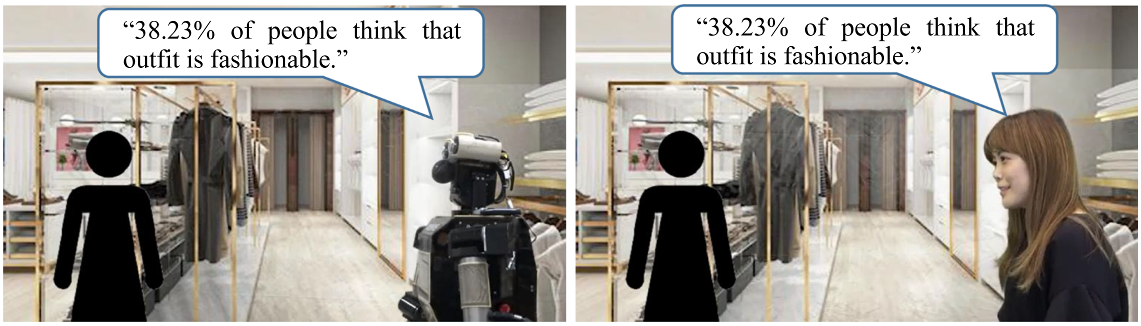

Fig. 1 An overview of our experiment. A shopkeeper suggests a customer may want to try other clothes by describing data about the purchase. We found this type of direct customer service is as effective as traditional, polite communication when used by robots, even though the same behavior is less acceptable for humans

2.5 Summary

Our work lies at the center of these research areas. We investigate the effects of typically impolite customer service strategies robots in customer service on customer satisfaction, and perception of the experience and robot.

3 Design: Customer Service Strategies

In customer service, one of the main goals is an increase in customer satisfaction [12, 13]. High customer satisfaction, even without purchases, can lead to repeat visits, more customer loyalty, and good public image due to word-of-mouth advertisement [13]. This is generally achieved through positive and polite behavior by human shopkeepers.

Polite customer service has been shown to be a good default for robots in general (e.g., [6, 8–11, 44]). However, it is unclear if other strategies may suit a robot better in some situations. For example, a human shopkeeper may wish to help a customer buy a better outfit, but criticizing the outfit the customer has picked may be perceived as rude. Thus, human shopkeepers sometimes engage in positive, but indirect persuasion to guide the customer to what they believe will be the better product and increase customer satisfaction. This indirect and roundabout communication style may not convey the information correctly [50], potentially wasting the advice of the shopkeeper and leading to poorer customer service impressions. Further, this indirect and vague communication can be difficult to implement on a robot without accidentally miscommunicating information to a person. We believe robots may be able to clearly and directly convey this information to provide the customer with the most accurate information, without appearing rude.

Robots have been shown to deliver typically rude behaviors without the same consequences a person would experience. For example, an exercise assistant robot may criticize a person's effort, which results in people working harder and feeling competitive [14]. Alternatively, a robot could provide some sort of negative feedback to encourage specific behaviors (a sort of persuasion) [15]. These works demonstrate that there may be benefits for robots to sometimes engage in non-polite interaction.

We hypothesize that a robot could deliver information directly with fewer negative social consequences than a person. In our earlier retail example, the robot could directly inform the customer that their current choice is not suitable. This may result in the person feeling better informed and have more customer satisfaction than if a human shopkeeper tried the same direct behavior, which may upset the customer.

3.1 Three Customer Service Strategies

We designed three customer service strategies that we used to explore how people react to different types of rude or polite communication. Two are based on direct communication, and the third is a traditional, indirect customer service method. We note that we do not intend to find one "best" customer service strategy; rather, we expect each to have situations they perform better in for both a human and robot. In particular, based on the earlier arguments, we expect a different customer experience when either a robot or human uses any customer service strategy. Our research investigates whether our strategies suit either type (human or robot) shopkeeper.

For the direct strategies, we developed *straight* and *data-based* communication. The *straight* customer service strategy is to provide information that is potentially critical of the customer in a straightforward manner. As previously explained, this is a form of communication that can sometimes be thought of as rude, especially when the content is critical of someone. For example, our robot said "the clothes you have selected are not trendy." This may potentially upset the customer as it could imply that the customer has poor

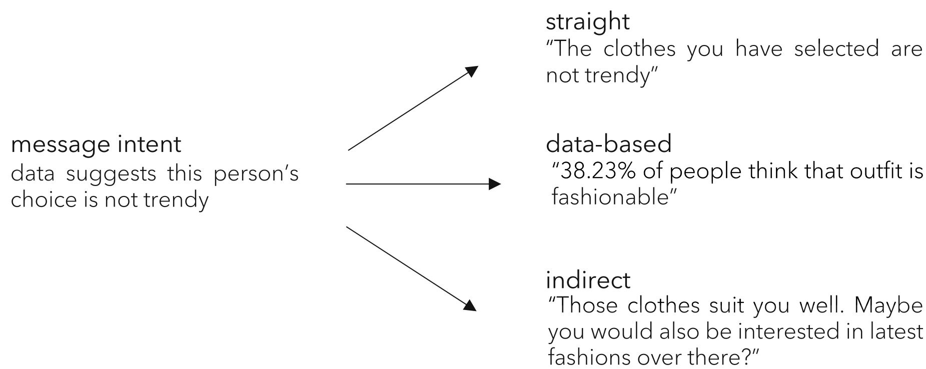

Fig. 2 An illustration of our communication strategies we tested in individual experiments. The core message to the customer is always the same, but the strategy changes how it is said

fashion sense, does not look good, or that fashionable clothes do not suit them.

The *data-based* customer service strategy informs the customer of the critical information but frames it as a purely statistical observation. For example, "surveys showed 38.23% of people thought those clothes were trendy," (Fig. 1—we always used 2 decimal places for increased feelings of precision and technicalness). This is a technical way of communicating information, which we think may be more appropriate for a robot [51]. This framing also focuses on the data and does not explicitly frame the information as an opinion of the robot.

We also designed a traditional customer service dialogue based on *indirect* communication: couching the language with euphemistic, circular, or indirect phrasing to soften the message [52]. For example, our shopkeepers say, "I think those clothes look very nice, however, maybe you would like to see these other clothes that are the latest fashions," (Fig. 3). This complements the customer, but subtly steers them to choices that may make them happier with their purchases in the long run.

It is important to note the strategies all convey the same core message: that the person's outfit choice is not trendy. The strategy is simply a certain mode of communication (Fig. 2). The customer service strategies were confirmed to be direct or indirect in a prior pilot described in Appendix 1.

We investigate the effects of each strategy over a series of three experiments.

4 Experiments: Comparing Multiple Communication Strategies Between Robots and Humans

Fundamentally, our research is investigating the differences in customer service results between robots and people when using different customer service strategies. We compare three customer service strategies over three experiments, each comparing interaction effects between a robot or human shopkeeper using that communication strategy. This section details the common structure of the experiments, and then the results of each experiment separately.

4.1 Task and Online Format

We created an task where participants were asked to role-play a customer trying to buy a new outfit for themselves to wear this year. While presented with two chances to pick an outfit (see Procedure, Sect. 4.3), their only goal was to pick the outfit they wanted to most buy for themselves.

Because of the potential differences in clothes preferences between different genders and ages, we decided to focus on a single demographic. Moreover, expecting further noise from differences in fashion opinion, we decided to recruit a large number of participants (see subsection xxx). Due to the COVID-19 pandemic, it would be difficult to recruit this number of a specific demographic to an in-person experiment, so we instead created an online study. Participants shopped with outfit images and watched videos of sample interactions for participants to imagine themselves in (See Procedure, Sect. 4.4).

4.2 Conditions

We had one variable with two levels: shopkeeper type (human, robot). The participants were distributed randomly to each experiment to create roughly equal samples for each (human or robot using one customer service strategy).

4.3 Procedure

Participants were first given a brief explanation of their goals in the study: they were to imagine themselves as a customer who is looking for clothes they would like to buy for the new season. They would then watch a video interaction with a shopkeeper, imagining themselves as the customer, and confirm or change their outfit choice.

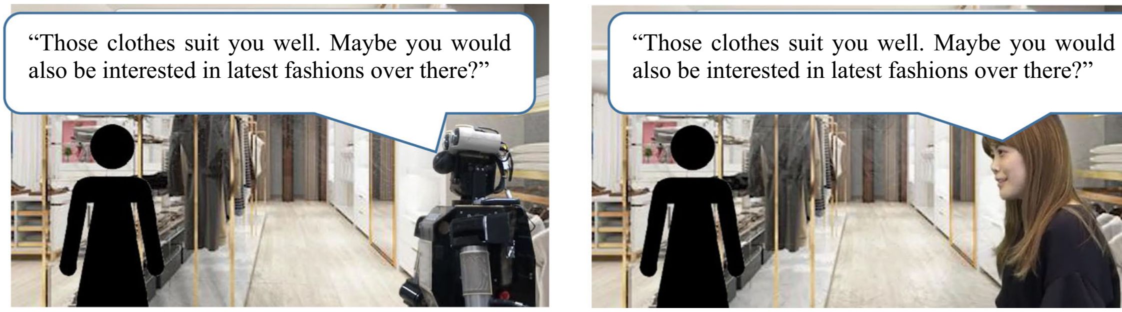

Fig. 3 A sample scene of traditional customer service, performed by a robot and a human shopkeeper, in our online experiment. Here, the shopkeeper complements the customer's choice and say it suits the customer, before suggesting they may want to check out the latest trendy clothes before making their final decision. This is trying to indirectly persuade them to instead buy other clothes

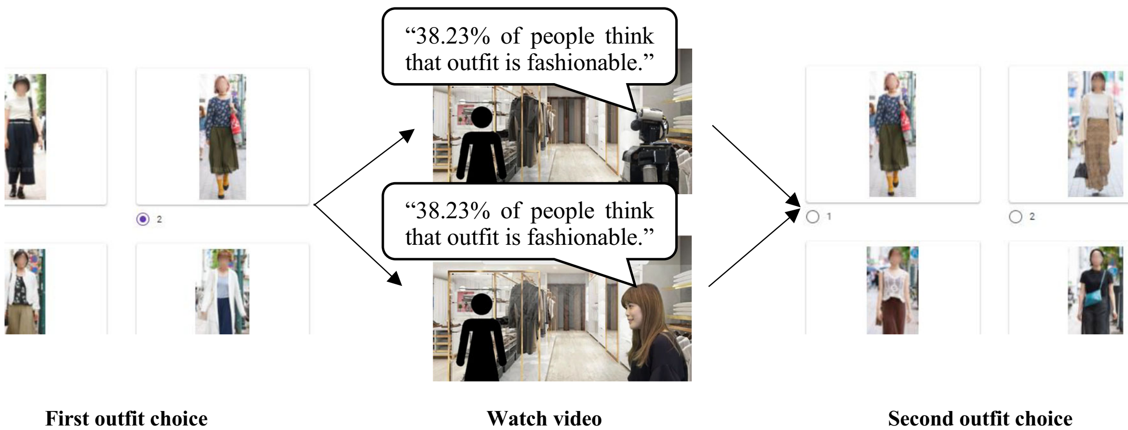

Fig. 4 Our experiment flow (translated). (Left) The participants are presented with the first outfit choice (less trendy clothes). They then watch a shopkeeper interaction (robot or human with one customer service strategy) that tells the customer they should consider clothes that are more trendy. Participants then make a second choice from new, trendier clothes, with the option to keep their first choice. Outfit photos are reproduced with permission of owner

Participants were instructed to view a list of images of clothes and select one of them Fig. 4, left) they would like to buy. They were then shown a video of a sample interaction with a shopkeeper (robot or human). The shopkeeper was either a humanoid robot, or a woman who has experience in customer service and who was a similar age to our participants (to make the human interaction more natural, Fig. 3).

The shopkeeper would use the customer service strategy to inform the user that there were fashionable outfit choices they may want to check before their final decision.

After watching the interaction, participants were presented with four new outfits, as well as the one they had picked from the original set (Fig. 4, right). After selecting their original choice or one of the new outfits for their final selection, participants confirmed their choice and filled out our questionnaire.

The outfits for the participant's first choice were from a set of somewhat trendy outfits (from less recent years). The second choice asked them to stay with their first choice, or to select from a new set of trendy outfits from recent years (to fit our scenario of criticizing the trendiness of the participant's choice). Appendix 2 details how we selected these outfits as well as the percentage numbers for the data-based strategy.

Our procedure was approved by our institution's ethics review board.

4.4 Materials

We used a Robovie R3 robot which is a humanoid robot that can move, perform gesture with its arms and head, and listen to and produce speech. The robot's dialogue was synthesized with a female-like voice. The human shopkeeper was a Japanese woman with customer service experience. The shopkeeper interaction videos were recorded with a green screen with software to overlay a more natural shop background. Both shopkeepers were recorded to appear roughly the same size, move in similar ways, and have roughly the same amount of their upper body showing in the video. Dialogue was identical between the robot and shopkeeper. The videos were all approximately the same length of interaction (straight: 33 s, indirect: 31 s, data: 40 s). Small, 1–2 s differences in length were allowed between shopkeeper lines. All materials were in Japanese.

4.5 Measurements

We measured three qualities of the interaction deemed important for quality customer service:

1. Naturalness
2. Feeling informed
3. Satisfaction

We wanted to have a reasonable baseline behavior to understand how people rated both human and robot shopkeepers using typical indirect (polite) behavior, and compare to the standard approach of copying human behavior [53]. Thus, to understand if direct communication is better for robots, we should also test normal customer service strategies, both as a comparison point for robots, and a baseline understanding of how well indirect strategies work.

Each was measured with a Likert-like scale, from one to seven, with seven being positive. Such simple scales are useful in measuring the quality of customer service (e.g., [12, 13]).

In addition, we recorded the participants' first choice in a given shopping interaction, and what they chose after viewing the shopkeeper interaction (measuring whether the customer service strategy successfully changed the customer's decision or not).

4.6 Experiment 1: Comparing Straight Customer Service Between Robots and Humans

4.6.1 Hypothesis

We hypothesized that direct customer service strategies would be more effective for robots than humans. In particular, telling a person critical information in a direct way is typically perceived as rude, but this consequence may be mitigated when performed by a robot [14], or make the robot's suggestions more effective [15] (Sect. 3). From this previous literature, we believe such direct customer service will be perceived as more natural when performed by a robot. Because the information is clearly stated, we also believe this will result in people feeling more informed. In total, this should result in better perceived customer satisfaction.

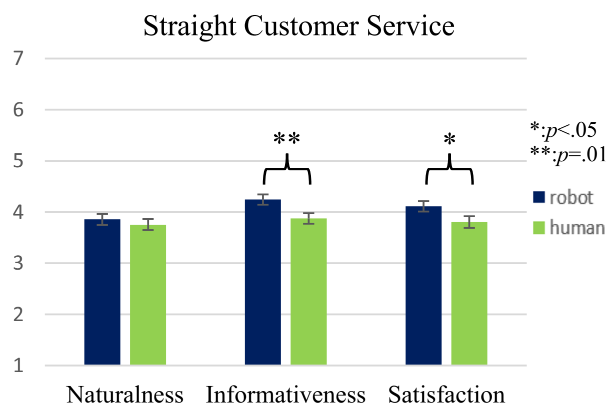

Fig. 5 Straight communication results. Error bars show standard error

H1 Robots that use a *straight* communication strategy will (a) produce higher customer satisfaction, be perceived as more informative, be seen as more natural, and (b) convince people to change to the recommended outfit more often, than when a human uses the straight strategy.

4.6.2 Participants

Using an online service, we recruited 432 Japanese women between the ages of 20 and 29 (217 in the robot condition). Outside of this age range, no age statistics were gathered. The age range was chosen to allow a wide sample of behavior while still maintaining some generational consistency for fashion preferences. This also enable us to only prepare one set of fashion images (instead of creating and balancing multiple outfits for multiple demographics).

4.6.3 Results

We ran t-tests to compare the effects of shopkeeper type (human, robot) on naturalness, informativeness, and satisfaction. Testing hypothesis 1a, we found a significant effect of shopkeeper type during straight communication on informativeness ($p = 0.010$, $t = -2.597$, $d = -0.250$), and satisfaction ($p = 0.043$, $t = -2.034$, $d = -0.196$). Naturalness was non-significant ($p = 0.499$, $t = -0.677$, $d = -0.065$). See Fig. 5. Thus, our data partially confirms H1a, that people experience better customer service when a robot uses straight communication, compared to a human.

To test H1b, we performed a chi-squared test on shopkeeper type, seeing if the participant changed their choice (yes/no category). We found no main effect of shopkeeper type for straight communication ($p = 0.163$, $x^2 = 1.945$, robot mean: 87.6% changed, human mean: 82.8% changed), Thus, while the direction of the mean change is as we predicted for straight and indirect communication, we did not find sufficient evidence, and thus our data better supports the null hypothesis for H1b: we did not detect that people change their outfit choice based on shopkeeper type for the straight customer service strategy.

4.7 Experiment II: Comparing Data-Based Customer Service Between Robots and Humans

In a separate experiment, we investigated the effects of another direct customer-service strategy: data-based.

4.7.1 Hypothesis

Similar to straight customer service, our data-based strategy is also considered direct and potentially confrontational (Sect. 3.1), our hypothesis was similar: data-based customer service will benefit the robot shopkeepers the most. However, people do not normally speak data out loud in this way, so we expect this to be even less natural for human shopkeepers than robot shopkeepers.

H2 Robots that use a *data-based* communication strategy will (a) produce higher customer satisfaction, be perceived as more informative, be seen as more natural, and (b) convince people to change to the recommended outfit more often, than when a human uses the data-based strategy.

4.7.2 Experiment Details

Our experiment duplicated the conditions, procedure, materials, measurements, and analysis methods of Experiment I. The main difference is the participants we recruited, and that the customer service strategy is now data-based for both shopkeeper types.

4.7.3 Participants

Using an online service, we recruited 467 Japanese women between the ages of 20 and 29 (218 in the robot condition) that did not participate in Experiment I. Outside of this age range, no age statistics were gathered.

4.7.4 Results

Testing hypothesis 2a with t-tests, we found a significant effect of shopkeeper type during data-based communication on informativeness ($p = 0.007$, $t = -2.724$, $d = -0.253$), satisfaction ($p < 0.001$, $t = -4.819$, $d = -0.447$), and naturalness ($p = 0.004$, $t = -2.921$, $d = -0.271$). See Fig. 6. This confirms H2a, that people experience better customer service when a robot uses data-based communication, compared to a human.

To test H2b, we performed a chi-squared test on shopkeeper type for if the participant changed their choice (yes/no category). We found no main effect of shopkeeper type for data-based customer service ($p = 0.663$, $x^2 = 0.19$, robot mean: 84.4% changed, human mean: 85.8% changed). Thus, we do not have evidence supportingH2b.

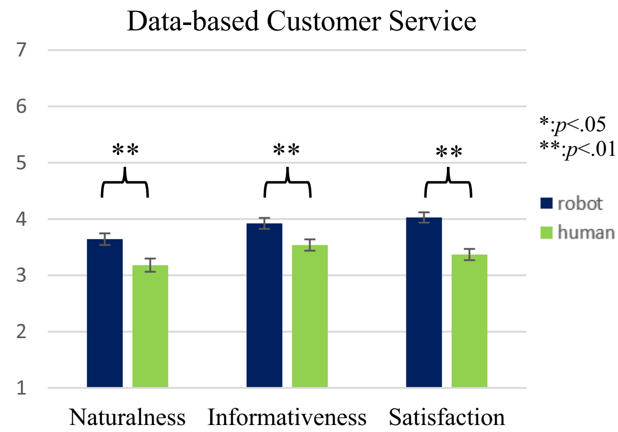

Fig. 6 Data-based communication results. Error bars show standard error

4.8 Experiment III: Comparing Indirect Customer Service Between Robots and Humans

We conducted our final experiment, comparing human and robot shopkeepers using a more typical indirect (polite) communication strategy.

4.8.1 Hypothesis

We wanted to have a reasonable baseline behavior to understand how people rated both human and robot shopkeepers using typical indirect behavior, and to compare to the standard approach of copying human behavior [53]. Thus, to understand if direct communication is better for robots, we should also test normal customer service strategies, both as a comparison point for robots, and a baseline understanding of how well indirect strategies work.

H3 People that use an *indirect* communication strategy will (a) produce higher customer satisfaction, be perceived as more informative, be seen as more natural, and (b) convince people to change to the recommended outfit more often, than when a robot uses the indirect strategy.

4.8.2 Experiment Details

Our experiment duplicated the conditions, procedure, materials, measurements, and analysis methods of Experiment I and II. The main difference is the participants we recruited, and that the customer service strategy is now indirect for both shopkeeper types.

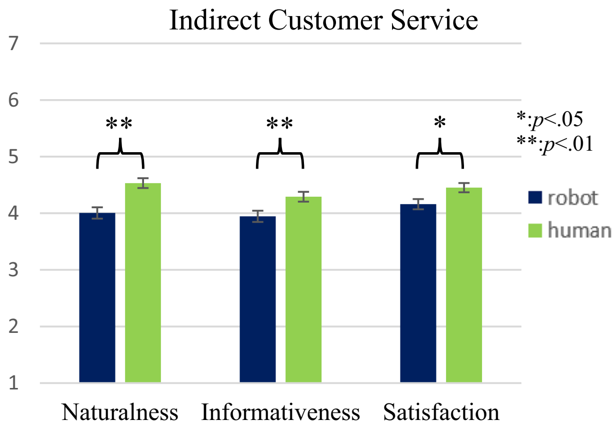

Fig. 7 Indirect communication results. Error bars show standard error

4.8.3 Participants

Using an online service, we recruited 456 Japanese women between the ages of 20 and 29 (219 in the robot condition) who had not participated in Experiments I and II. Outside of this age range, no age statistics were gathered. Our recruitment motivation is the same as described in Experiment I.

4.8.4 Results

Testing hypothesis 3a, we found a significant effect of shopkeeper type during indirect communication on informativeness ($p = 0.009$, $t = 2.633$, $d = 0.247$), satisfaction ($p = 0.017$, $t = 2.399$, $d = 0.225$), and naturalness ($p < 0.001$, $t = 3.998$, $d = 0.375$). See Fig. 7. This confirms H3a, that people experience better customer service when a human uses indirect communication, compared to a robot.

To test H3b, we performed a chi-squared test on shopkeeper type for a given strategy on if the participant changed their choice (yes/no category). We found a trend for straight ($p = 0.067$, $x^2 = 3.345$, robot mean: 79.4% changed, human mean: 84.9% changed) strategies on if participants changed their choice. Thus, while the directions of the mean change are as we predicted for indirect communication, we did not find sufficient evidence to confirm H3b.

5 Post-hoc Analysis

As a secondary analysis, after completing our main three experiments, we decided to compare which strategy was more effective for each shopkeeper type, for each of our measures (naturalness, informativeness, and satisfaction). As the experiments are separate and not designed to be compared within a shopkeeper type (e.g., data-based strategy includes more and finer-grained information), we only provide these as an additionalanalysis to provide insight only. All tests here were corrected with the Bonferroni correction for post-hoc tests to be conservative.

We performed a 1-way ANOVA (analysis of variance) on the effects of communication strategy on *naturalness* when controlling for a given shopkeeper type. For the human shopkeeper, we found a main effect of customer service strategy ($p < 0.001$, $F_{2,1349} = 43.0$, $\eta^2 = 0.110$). To further understand which strategies performed better, we conducted post-hoc pairwise comparisons. We found that the data-based strategy was perceived as less natural than the straight ($p < 0.001$) and indirect ($p < 0.001$) strategies, and that the straight strategy was perceived as less natural than indirect ($p < 0.001$). Performing a similar analysis for the for the robot shopkeeper, we found a main effect of communication strategy ($p = 0.046$, $F_{2,1349} = 3.09$, $\eta^2 = 0.009$). In post-hoc comparisons, we found that the data-based strategy was perceived as less natural than the indirect ($p = 0.041$). Other pairwise comparisons were not significant (data vs. straight, $p = 0.432$; indirect vs. straight, $p = 0.947$). Thus, it appears there was at least some effect of communication strategy on *naturalness* for both human and robot shopkeepers, with data-based likely being the least natural strategy for both types—see Fig. 10.

We performed a 1-way ANOVA on the effects of communication strategy on *informativeness* when controlling for a given shopkeeper type. For the human shopkeeper, we found a main effect of customer service strategy ($p < 0.001$, $F_{2,1349} = 15.8$, $\eta^2 = 0.043$). To further understand which strategies performed better, we conducted post-hoc pairwise comparisons. We found that the data-based strategy was perceived as less informative than the straight ($p = 0.044$) and indirect ($p < 0.001$) strategies, and that the straight strategy was perceived as less informative than indirect ($p = 0.008$). Performing a similar analysis for the robot shopkeeper, we found a main effect of communication strategy on informativeness ($p = 0.038$, $F_{2,1349} = 3.30$, $\eta^2 = 0.010$). In post-hoc comparisons, we found only a trend for the data-based strategy being perceived as less informative than the straight ($p = 0.065$) and a trend for the indirect strategy being perceived as less informative than straight ($p = 0.098$). Other pairwise comparisons were not significant (data vs. indirect, $p = 1.0$). Thus, we found evidence of least some effect of communication strategy on *informativeness* for both human and robot shopkeepers, with data-based likely being the least informative strategy for both shopkeeper types. For human shopkeepers we observed that indirect strategies may be more informative, while for robot shopkeepers it is possible that straight communication is seen as more informative (though further experiments are needed to confirm the latter trend)—see Fig. 8.

We performed a 1-way ANOVA the effects of communication strategy on *customer satisfaction* when controlling for a given shopkeeper type. For the human shopkeeper, we found a main effect of customer service strategy ($p < 0.001$, $F_{2,1349}$

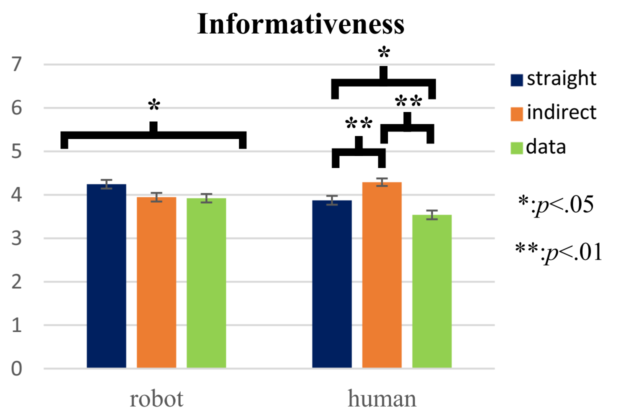

Fig. 8 There was a significant main effect of customer service strategy for both shopkeeper types

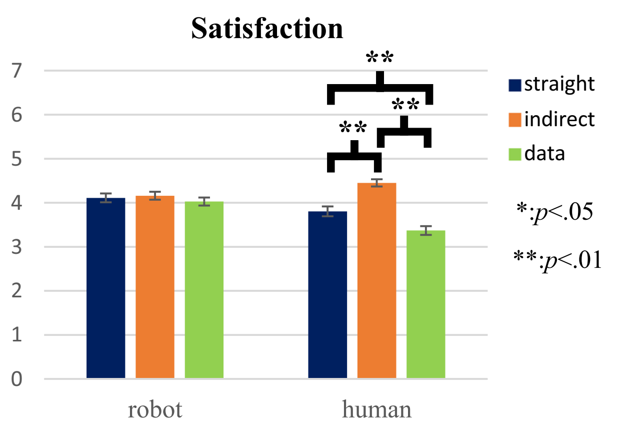

Fig. 9 There was a significant main effect of customer service strategy and shopkeeper type on satisfaction for human shopkeepers

$= 32.0$, $\eta^2 = 0.084$). To further understand which strategies performed better, we conducted post-hoc pairwise comparisons (Bonferroni corrected). We found that the data-based strategy was perceived as less satisfactory than the straight ($p = 0.006$) and indirect ($p < 0.001$) strategies, and that the straight strategy was perceived as less satisfactory than indirect ($p = 0.008$). For the robot shopkeeper, we did not find a main effect of communication strategy on customer satisfaction ($p = 0.603$, $F_{2,1349} = 0.51$, $\eta^2 = 0.002$). Thus we found evidence that a human shopkeeper's communication strategy could affect customer satisfaction, but we did not observe evidence for the same effect for robot shopkeepers—see Fig. 9.

After our main analysis, we were interested, post-hoc if there was evidence that the rates of behavior change (participants changing their choice due to watching the interaction) were equivalent. Thus, we performed a post-hoc Equivalence Bayesian Independent Samples T-Test comparing the frequency of participants changing their clothing choice between shopkeeper types. With the default Cauchy scale of 0.707 and an equivalence interval including small effects (− 0.01 to 0.01), we found moderate evidence for no effect in the straight (BF = 3.8) and data style (BF = 8.5), with weak evidence for no effect in the indirect style (BF = 2.1).

We emphasize all analysis in this section is a post-hoc analysis and requires independent study to verify, we only provide these as a secondary analysis to provide additional insight.

6 Discussion

Across our experiments, our results were that, on average, the robot performed better customer service than the human shopkeeper when using a direct communication strategy (better customer satisfaction, informativeness, and perceived naturalness). We confirmed H2a—that the data-based strategy would be perceived as better when performed by a robot, and partially confirmed H1a—that the straight strategy would be perceived better when performed by a robot (we did not detect a difference in perceived naturalness). On the other hand, the human shopkeeper produced better customer service than the robot for the indirect, traditional communication strategy, confirming H3a. We found no evidence to support change in behavior due to our conditions (H1b, H2b, H3b).

At first, it may appear that the differences in perception of the human shopkeeper's communication styles were large enough to cause these effects. In our post-hoc analysis, we saw that communication style was indeed a main effect on our measures for the human shopkeeper, we also found that within just the robot shopkeeper data, there was a significant main effect of communication style on informativeness and naturalness. Interestingly, the effect sizes for the robot shopkeeper were smaller than the human shopkeeper, leading our results to imply that while customer service effects do occur when both the robot and human change communication styles, a robot may be able to change how it conveys information with fewer consequences than people.

6.1 Design Implications

Our results suggest it is more acceptable for a robot to use direct communication than a person (See Figs. 5 and 6), and can sometimes lead to better impressions than when using traditional less direct communication (Fig. 8). More specifically, if a shop wants to use robots for customer service, a change from a traditional customer service strategy (of always indirect communication) should be considered. If a shop wants a robot to be more informative, they could consider using the straight communication style (Fig. 8), but switch to indirect when wanting to appear more natural (Fig. 10). This is different from the human shopkeeper, who was always preferred in all measures when using the

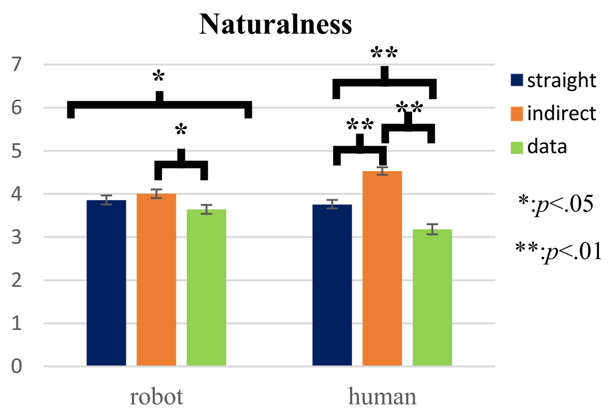

Fig. 10 There was a significant main effect of customer service strategy on naturalness for both shopkeeper types

indirect (traditional) strategy. Thus, robot behavior designers should not simply copy traditional human communication strategies in customer service and expect similar results with a robot. This claim is supported by Experiment I and II, which found robots perceived as more natural (except for straight communication), informative, and satisfying than a person when using direct communication, and Experiment III with the post-hoc analysis supporting that indirect methods are preferred in all cases for humans, and for robots wanting to appear more natural.

Looking to the post-hoc analyses, while communication strategy did affect impressions of the robot, the robot shopkeeper benefited from (e.g., for informativeness) or was penalized less (e.g., naturalness) when using direct communication, as demonstrated by the smaller main effect sizes in the analysis. Even considering that a human may start at a higher customer service rating, as we saw, it is still interesting that impressions of the robot dropped less for similar behaviors. Thus, if direct communication would be beneficial, for example to clarify a point that may be misunderstood if communicated too indirectly, that interaction would result in a smaller drop in impressions when provided by a robot, than with a human shopkeeper (supported by Experiment I and II).

7 Future Work

One future direction for our results is for improving the effectiveness of a human–robot shopkeeping team, sending a robot when direct communication is needed, and sending a person when indirect communication is better. This team-based strategy (choosing who to provide information based on if direct and indirect is better) could be further used in other social situations, but this human–robot teaming approach requires additional research. Human–robot teaming is already an active research area (e.g. [54]) and these results could contribute to those applications.

Robots are sometimes assumed to be truthful, and just using sensors and data [14, 55]. If this is the case in our scenario, the indirect robot that used polite comments or throwaway compliments may have been believed as truthful instead of simply following social conventions. While we do not know this occurred in our study, confirming it with future work is important as it could have implications for designing indirect robot dialogue, such as for situations where believing that the robot is speaking the truth is important (perhaps for persuasive applications, like encouraging better health habits, taking medications as instructed, or educational applications of robots).

It is sometimes acceptable for people to tell half-truths for the sake of politeness (like our indirect condition that opened with a compliment, even though the shopkeeper intended to direct them to a different purchase). We do not yet know if it is perceived as ethically or morally acceptable to program a robot to use such methods. This opens even more questions, such as robots working in situations in which diplomacy is required (e.g., conflict resolution, or business situations). Work in robot ethics is required to investigate these issues, but may justify the use of potentially impolite, but not deceptive, direct communication from a robot in service contexts or beyond.

7.1 Limitations

While we controlled many aspects of our experiments closely, there are caveats that limit the generalizability of our results. In terms of direct comparisons between our customer service strategies (our secondary analysis), the intentions of each were similar (to convince the customer to check other fashions), but the actual dialogue was not similar at all. This may have confounded the comparison somewhat, and contributed to us treating the within-shopkeeper post hoc analysis as speculative analysis. Future experiments focused more on the advantages and drawbacks of a strategy for a specific type of shopkeeper (e.g., focusing just on a robot shopkeeper) would want to carefully design the dialogue to be more similar between strategies.

While we found interesting differences between how people react to robot and human shopkeepers using different customer service strategies, our measurements, or lack of qualitative methods, led us to find a difference, but lack explanatory power as to why that difference (robot or human shopkeeper) has its effect. For example, the novelty effect may mitigate negative evaluation of robots. Alternatively, the effects may have been because the shopkeeper was not human, not because it was a robot (e.g., any non-humanoid robot or technology may have similar results when using the same strategies). While our hypotheses were based on prior work that led us to suspect it is the robot nature itself that causes the differences (e.g., [14, 31]), we cannot rule out these alternative explanations without further study.

Most obviously, we made significant choices in our experiment design that limit our study results. The video study is potentially a large factor. We instructed participants to imagine themselves role playing as the customer in the video, but we cannot rule out people felt or responded more as observers of an interaction. While an in-the-wild study would be best, there are ethical concerns about persuading people on how to spend their money and potentially harming shop-customer relations. Fashion preferences themselves are also noisy and personal, so in addition to the pandemic restrictions, this led us to the video study which gave us the benefit of recruiting a large number of participants from a specific demographic. This very specific demographic: younger Japanese women, was to fit our specific context of our study of fashion shopping (i.e., Japanese men may have responded very differently to choosing outfits for women, or older women may have different fashion preferences). What is acceptable or good customer service is also a cultural idea, and our participants' single culture opens the possibility that the effects we found are specific to people of Japanese culture.

These factors, and more, add a significant amount of potential variability to our results. Due to these decisions and uncontrolled factors, we wish to emphasize that our lack of finding a significant behavior difference does not mean there is no effect, but these factors may have interfered with participants' decisions in a variety of ways. While we found, post-hoc, weak evidence that there may be no actual effect, further study is needed to specifically clarify this.

8 Conclusion

Alongside developing the technology for robots to engage in simple social interaction, robots have been designed to broadly copy human behavior which has led to generally likeable, natural, and positive results. However, there may be behaviors that are better for robots to use than typical human behaviors. We explored this question with an online video study with 1351 participants in a role-played retail scenario. Our results demonstrate that a robot can use direct, typically rude behavior to communicate with customers and have better customer service outcomes than when people try those same strategies. Further, robots using direct styles of communication may sometimes outperform a robot using traditional indirect style. Our results also suggest that robots may have different tradeoffs when switching between strategies than when people, who we saw benefit from always using traditional communication methods. These results demonstrate the need for more research into robot-specific behaviors, and encourage the exploration into robot behaviors that may be intuitively negative if a person were to use them. While robots may do well copying human behavior, it does not always bring about the same results.

Funding This research was in part supported by JST CREST grant number JPMJCR17A2, Japan. This work was also in part supported by JST Moonshot R and D under Grant Number JPMJMS2011, Japan.

Data Availability The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

Appendix 1: Developing Customer Service Dialogue

We conducted a small, in-lab pilot study to develop dialogue that matched our design goals of being direct and indirect. Our hypothesis was that robots will be able to use dialogue that is socially unacceptable (rude) for normal people because it is delivered in a direct manner (Sect. 3). Therefore, we designed several direct criticisms for outfit choices (relevant to our task) and measured if they would be perceived as unacceptable for normal human use. We also developed several indirect phrases to suggest customers investigate other options to compare to the traditional human–robot interaction approach of copying human behavior.

We had 14 participants rate each dialogue item as rude or polite (similar to the dialogue pilot method in [14]) on 1–7 point Likert-like scales, with 1 being very rude, and 7 being very polite, and 4 being neutral. We only used dialogue for the straight case if it was rated as 3.5 or ruder (lower value), and 4.5 and higher (more polite) for the indirect case. This means the dialogue was perceived as socially unacceptable for the direct dialogue, or acceptable for the indirect dialogue.

By interviewing the participants about their preferences for the persuasive dialogue, we found confirmed lines were rated rude because of them being very direct. We used the feedback and interviews to pick the dialogue for each customer service strategy. These were used directly in our main experiment (Sect. 4).

Appendix 2: Determining Trendiness of Fashion Images

As we planned to criticize the trendiness of a participant's choice, we wanted to make sure this advice aligned with participant expectations. Our goal was not only to find fashionable clothes as agreed upon by a wide variety of people, but also fashion that the average participant would like to wear. This is because we didn't want people to simply change their decision because of the shopkeeper insisting, but because they genuinely thought the clothes were desirable to wear.

In addition, we wanted the criticism given to be true to our scenario. In other words, when the shopkeeper told participants (directly or indirectly) that their choice was less fashionable than other outfits, we wanted participants to likely agree with the shopkeepers comments upon viewing the new outfits. In other words, we wanted the customer service contents to be perceived as genuinely useful, and thus be judged on the customer service strategy used to provide this useful service. Thus, we ran this pilot to collect outfits that were still fashionable, but not too recent for the first outfit choice, plus a set of more fashionable outfits for the shopkeeper to present post-interaction.

We gathered fashion images of street fashion (pictures taken of real people out in the world who are dressed fashionably) found online, categorized by year. We note that all images are of young Japanese women, around the age we recruited for this pilot and the main experiment. We gathered 50 images, spread roughly evenly across: the current year (summer, 2021), last year (summer, 2020), 3 years ago (summer, 2018), 5 years ago (summer, 2016), and 7 years ago (summer, 2014). We then had participants rate the fashion on a 1 to 5 Likert-like scale where 1 was "very not trendy," 5 was "very trendy," and 3 was "neither trendy nor untrendy." We also had them rate if they would like to wear the outfit, with 1 as "I really do not want to wear this," 5 as "I very much want to wear this," and 3 was "Neither want to wear or not want to wear this."

We surveyed 50 women with an online survey company. Each participant rated all images in a counterbalanced order. This resulted in a set of images that participants rated as fashionable and desirable to wear, on average. Due to variations in average preferred styles between genders and age ranges, we recruited only Japanese women in the age range of 20–29.

We selected four images less recent years that were still rated as desirable but not as trendy as recent fashions. The 4 final images from earlier years had an average trendiness rating of 2.59 ($SD = 0.963$) with 54.9% of participants rating it 3 or higher. These images also had an average desire to wear rating of 2.31 ($SD = 1.16$) with 38.7% of participants rating it 3 or higher.

We also selected four images from recent years that were rated as desirable and trendy. In contrast, the 4 selected images from recent years had an average trendiness rating of 3.46 ($SD = 0.926$) and was rated as 3 or higher by 91.2% of participants. These images had an average desire to wear rating of 3.03 ($SD = 1.13$) and was rated as 3 or higher by 66.2% of participants.

We used the trendiness percentages (what percentage of people rated the outfit as 3 or higher trendiness) in our data-based condition to make the condition more believable.

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