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The effect of rejection strategy on trust and shopping choices in robot-assisted shopping*

Matthias Rehm[1], Antonia L. Krummheuer[2] and Carlos G. Cubero[1]

Abstract— **In this paper, we investigate how a customer-facing service robot can support decision making in shopping interactions. In this role, a robot needs sometimes to reject a customer's choice. Thus, we investigate different rejection strategies with the goal of changing customer behavior. The implemented strategies have been developed based on an ethnographic study on assisted shopping and tested in a lab experiment with 31 participants. The experiment showed significant differences in trust ratings and decision-making depending on the employed strategy.**

I. Introduction

There is an agreement that in light of a more sustainable future we need to change our behavior, esp. our consumer behavior. The UN's sustainable development goal (SDG) 12[1] aims at ensuring sustainable consumption and production patterns with target 12.3 working for halving the per capita global food waste at the retail and consumer levels and target 12.8 working for that people everywhere have the relevant information and awareness for sustainable development and lifestyles. At the same time, the focus for introducing new technologies like customer-facing robots in the retail sector is usually economy driven, i.e. selling more or decreasing costs. We argue that the potential of robots to form relations with customers opens up for a more transformative role of robots to drive or at least support consumer behavior change. The argument is based on the acknowledged characteristics of service robots in relation to their performance expectancy and decision making support [1]. But instead of using these characteristics for increasing sales, we investigate how robot-assisted shopping can empower the customer in behavior change instead.

We draw inspiration from an analysis of assisted shopping, which is a well-known practice in health care institutions. Thus, we understand assisted shopping as an interaction between a customer and a robot, where the robot provides decision support to the customer. One crucial aspect of this support is the rejection of customer choices if they do not adhere to the previously defined agenda, e.g. to shop more sustainable products. Thus, trust is a crucial parameter for relying on the robot's support and accepting the rejection of the robot. This paper presents three main contributions for the further development of service robots:

- Discussion on transformative role of robots by saying "no" to the user
- Impact of rejection strategies on user behavior
- Impact of rejection strategy on trust towards the robot

II. Related Work

Shopping robots: Currently the term shopping robot spans over a range of different systems like telepresence robots for collaborative shopping experiences (e.g. [2]), mobile robot carts, often for supporting older customers (e.g. [3]), companion robots in online shopping (e.g. [4]), or customer facing robots in physical shopping environments (e.g. [5]). In this article, we focus on the latter, where a direct multi-modal interaction between the robot and the customer is taking place.

Stakeholder perspective: Shopping robots are first and foremost service robots that have to be purchased and deployed in physical shopping environments (malls, individual shops) by the respective management and shop keepers and then subsequently interact with potential customers in these environments. Thus, different perspectives on the usefulness and goals of shopping robots can be expected from these stakeholders and from prospective customers.

Tuomi, Tussyadiah, and Stienmetz [6] present a first classification of the different roles of customer facing robots from a stakeholder perspective: (1) Supportive role: The robot takes over restricted tasks, e.g. helping a customer checking in at a hotel. (2) Substitute role: The robot takes over the work of a human service staff for a whole service transaction. (3) Differentiating role: The robot is used for attracting customers and showcases the business as modern. (4) Improving role: The robot increases the efficiency of certain tasks, e.g. quality control or demand prediction. (5) Upskill role: The robot takes over repetitive tasks and thus allows human staff members to concentrate on higher value tasks.

As a main motivation for the deployment of shopping robots, increased sales and decreased costs are mentioned [7], [8]. Brengman and colleagues [9] give a classification of the effects of shopping robots that stem form this motivation: (1) Stopping power: The ability of the robot to stop potential customers that are passing by is the first step in the sales interaction. (2) Engaging power: Using multi-modal behavior the robot can then engage the potential customer in a sales interaction. (3) Attraction power: By building up a relation to the potential customer, the robot can guide the potential

[1]Faculty of IT and Design, Aalborg University, Rendsburggade 14, 9000 Aalborg, Denmark matthias@create.aau.dk, cgcu@create.aau.dk [2]Faculty of Humanities, Aalborg University, Rendsburggade 14, 9000 Aalborg, Denmark antonia@hum.aau.dk
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[1]https://sdgs.un.org/goals/goal12#targets_and_indicators

customer into the shop or towards specific products. (4) Selling power: The last step then is to sell a product to the customer.

As mentioned earlier, robots allow for multi-modal interactions making it easy to relate to this physical entity that uses human interaction channels like gestures and speech and that often comes in humanoid form. For instance, Chen et al. [10] present a facial recognition system that enables a social robot to infer shopping interest and thus create a more emotional retail interaction with the aim of increasing sales. Similarly, Song et al [11] show how a teleoperated robot in a shopping mall can be used to influence customer buying behavior and increase sales in retail.

Burg et al. [12] investigate if a robot assistant can be used to convince customer's to overspend their budget. To this end, they test different interaction strategies (robot-led vs human-led) and different design patterns (manipulative robot vs supportive robot), showing that a manipulative robot leads to more rejected items during the interaction but nevertheless succeeds in nudging the user to spend more money overall. At the same time, participants preferred robot-led interactions and attributed higher intelligence to the system.

Customer perspective: Niemelä and colleagues [8] investigated the acceptance of a robot in a shopping mall across customers and management. As mentioned above, the mall stakeholders were focusing on the robot's selling power and the potential decrease of costs (i.e. less human employees) whereas customers were expecting among other things, information and guidance from the robot, including physical guidance as well as decision making support (e.g. what to buy a 14-year old boy for birthday). Similarly, Subero-Navarro and colleagues [1] show that one of the relevant factors influencing the use of social robots in retail scenarios is performance expectancy, i.e. the assumptions that a robot is beneficial for the shopping task, e.g. will improve decision making.

Golchinar et al. [13] were interested in the factors determining the use of social robots in retail from a customer perspective and run an experiment with a Pepper robot as an information service point in a mall. Their analysis revealed that the most relevant factor in relation to the user experience are the hedonistic qualities of the interaction. Edirisinghe et al. [14] present large scale field trial of customer support robot that guide customers and use admonishing behavior to prevent unethical behavior. The robot behavior was designed based on analysis of the practices of shop workers to fit into the shop environment. Heikkilä and colleagues [15] develop a robot for physical guidance at a shopping mall, based on investigations of human guiding behavior. In four different studies they develop guidelines for the design of such robots that include the use of multi-modal communication such as the use of gestures and gaze.

All these examples on shopping robots are still developed under the stakeholder premise of selling more and providing a friction-less shopping experience. When the interaction behavior of the robot is in focus, it is related to spatial guidance or recommendations of products.

Interaction perspective: Although robots allow for rich multi-modal interactional behavior, apart from Burg et al that focus on increased sales, we could not find studies on shopping robots that take into account how the interaction with the robot supports joint selection and decision-making in shopping activities. Therefore, we take a look at studies that use video recordings and multi-modal interaction analysis to explore the sequential and embodied unfolding of joint shopping interaction [16], [17], [18], [19].

In this paper, we are very much interested in exploring the potential of shopping robots for the benefit of the customer, e.g. allowing the customer to follow his/her agenda. Thus, when we investigate shopping interactions, we are not restricted to sales conversations. Of special interest is the work on assisted shopping from Krummheuer [18], [19], which explores the situated and interactional management of assistance in shopping interaction of a woman with acquired brain injury (ABI) who is accompanied and assisted in her shopping activities by a carer.

Krummheuer differentiates five phases of the selection and decision-making processes: (1) The construction of a mutual focus in a certain area in the shop (e.g. a certain shelf), which is thus marked as being relevant for a next action. (2) The mutual identification or selection of an object which is thus marked as as 'potentially buyable product' [16]. (3) The inspection of the object, e.g. feeling it or reading the label. (4) The decision whether or not to put the object in the shopping basked or back on the shelf. (5) Disentanglement of the joint focus and orientation to a next activity (see also [16], [17]).

Two main types of assistance are identified: *Instrumental* assistance directed to the physical manipulation of objects by the carer, e.g. fetching the requested object, and *moral assistance* directed to guide the person with ABI in her decision-making, e.g. by commenting on the shopping choice or rejecting it. This is an example of a joint decision making process, where the carer tries to allow for as much free choice as possible while at the same time providing decision support in regard to an institutional agenda (e.g. prevent too many unhealthy choices like sweets and alcohol).

The role of trust: Trust has been shown to be an important factor when it comes to using robots (e.g. [20]). Trust in human robot interaction has become a relevant topic over the last few years, where more and more chance encounters with robots happen, e.g. in shopping malls, at airports, or other public places. Hancock [21] distinguishes between human-, robot- and environment-related factors influencing trust and thus interaction behavior in such encounters. In this paper, we focus on robot-related factors, specifically different robot behavior in shopping interactions as a trust factor. Our assumption is that user are more likely to follow the decision support by the robot when they trust the robot. We further hypothesize that different rejection strategies during the shopping interaction will increase or decrease trust of the user towards the robot.

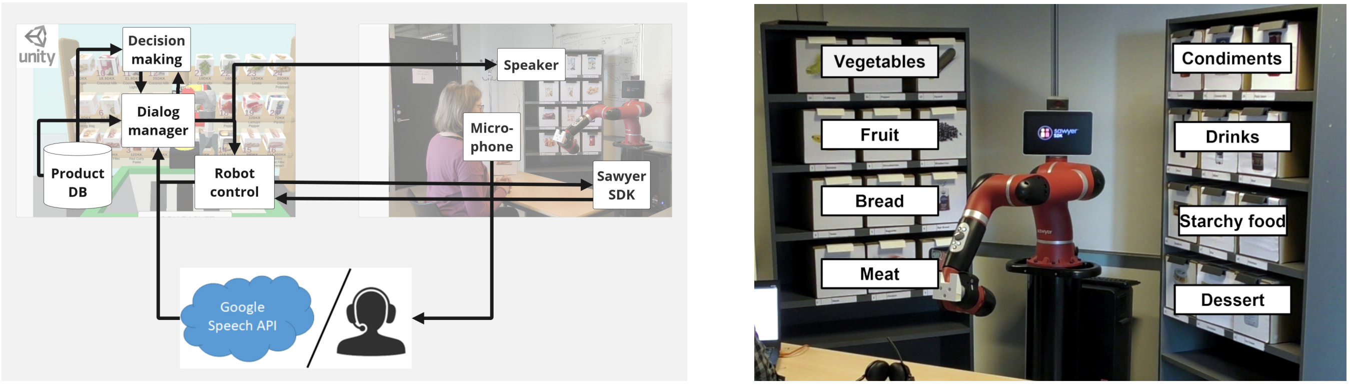

Fig. 1. Left: System architecture; Right: Food categories on the shelves. During the experiment, participants select one item from each category.

III. Assisted Shopping

A. Transfer of Insights to the Robot System

For the development of the assistive shopping robot we took inspiration from Krummheuer [19] (multi-modal behavior and strategies for rejection), Burg et al. [12] (robot initiative vs user initiative), and Hancock et al. [21] (robot-related trust factors). In our scenario, the user interacts with the robot that fetches products from a shelf while at the same time providing decision support for a previously agreed agenda, e.g. buying healthy, cheap, or sustainable. Figure 4 shows the final setup, with the user placed in front of the robot.

Based on [19], we implemented a positive and a negative rejection strategy for the robot. Krummheuer observed that rejections were accompanied by explanations accounting for the rejection, e.g. the proposal of alternatives was combined with the presentation of a certain quality of the alternative product. This was transferred to the design of the robot. During the **positive rejection** the robot provides the user with an alternative product and provides agenda-based arguments to support the decision making, e.g. "This is a better choice because it is a regional product". The **negative rejection** strategy focuses on the chosen product and provides agenda-based arguments why this product is not compatible with the agenda, e.g. "This product has been transported several hundred kilometers across Europe." Apart from verbal behavior, the robot's multi-modal behavior includes bodily interactions, following the analysis in [18] on how a care person uses her body to orient towards the chosen object in a shelf. During the positive rejection, the robot orients its manipulator towards the alternative product, during the negative rejection is moves towards the chosen product.

The positive and negative rejection are closely related to Burg et al.'s [12] strategies of robot and user initiative. Positive rejection provides the user with an alternative product simplifying the decision making process for the user and can thus be seen as robot initiative. Negative rejection provides arguments against a product but leaves the choice of alternatives to the user and resembles thus the user initiative. Based on the results presented in [12], we thus assume that positive rejection will have a positive effect on the acceptance of the robot suggestions compared to the negative rejection strategy.

Finally, the two implemented strategies relate to two robot-related trust factors from Hancock et al. [21]. Level of autonomy of the robot is higher in the positive rejection because the robot is selecting a different product by itself, instead of waiting for the user to select a new product. Transparency is seemingly equal in both rejection strategies because the same type of argument is presented in both versions. But because the level of autonomy is higher in the positive rejection strategy, transparency might seem more useful in this condition because being presented with a reason for choosing a different product makes it easier to follow the suggestion. Based on this analysis, we assume that trust ratings will be positively influenced by the positive rejection strategy compared to the negative rejection strategy.

B. System Architecture

The system architecture is depicted in Figure 1 (left). The assisted shopping system utilizes a collaborative robot arm (Rethink Sawyer) mounted on a static platform, positioned between the retail counter and shelves containing various products from different food categories (see Figure 1 right). The robot is equipped with audio input and output devices, enabling voice-based communication with customers, as well as an end-effector for grasping and dispensing items to customers over the counter.

The voice recognition system uses the Google Speech-to-Text (STT) API to capture and transcribe verbal input from customers, and provide this information to the dialog manager. For the experiments, the voice interaction is realized as Wizard of Oz to prevent unintended interactions due to recognition errors.

The robot's control system is implemented on a separate computer through a digital twin in Unity3D that communicates with the robot via the proprietary Sawyer SDK. The control software is responsible for coordinating interactions and executing a series of pre-determined movements, including inverse kinematics calculations, to accurately grasp and present products to customers. The control software makes

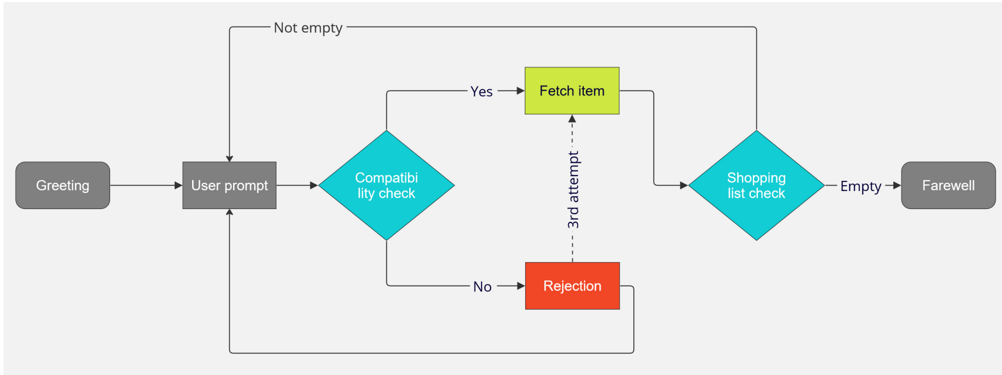

Fig. 2. General interaction flow

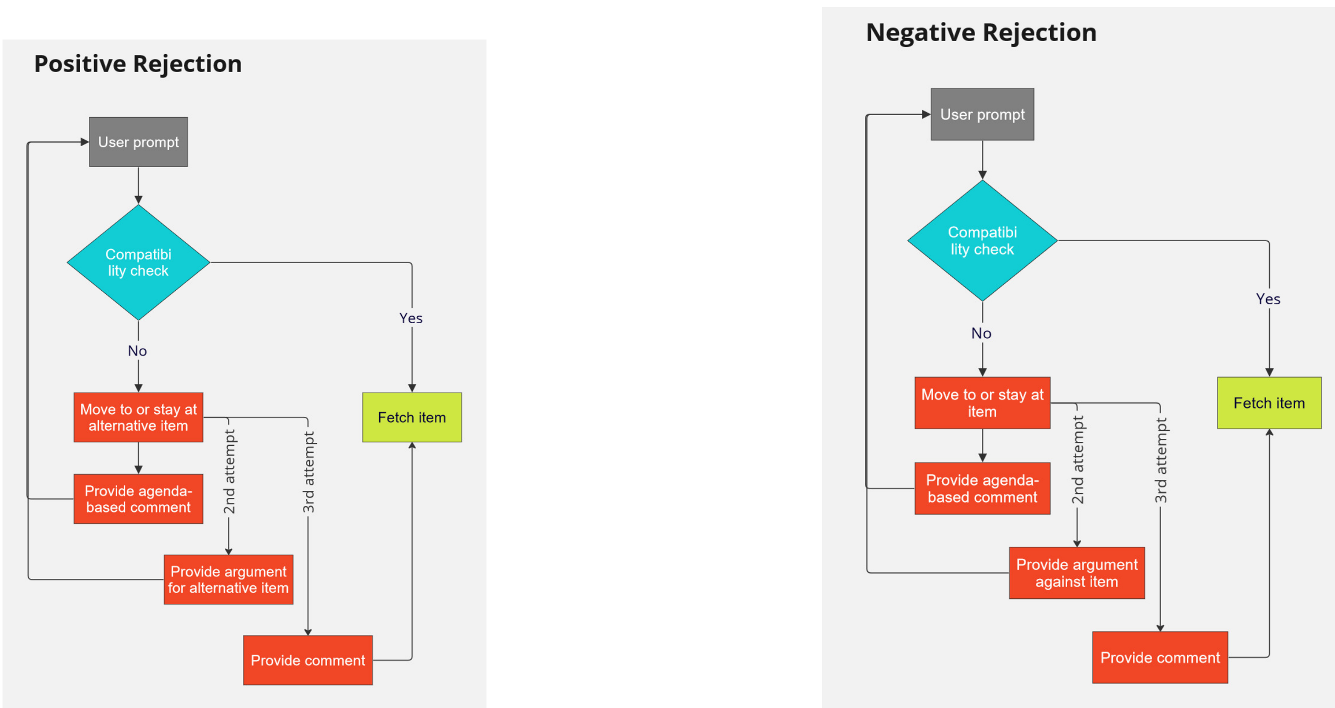

Fig. 3. Detailed interaction flow for positive and negative rejection strategies.

use of the Unity2Sawyer[2] interface. The control system is triggered by the dialog manager that keeps track of the enfolding interaction with the user and triggers the correct actions depending on the interaction design described below (Section III-C).

The product data base contains all information about the available products, including the comments and arguments for and against products that are used in the positive and negative rejection strategies.

C. Interaction Design

Before the interaction starts, the user is provided with an agenda – in our example to buy sustainable – and a shopping list that contains one item from each of the eight different food categories. The categories can be seen in Figure 1 (right) and include e.g. vegetables and dessert. The shopping agenda is used to argue for and against different products. The general interaction protocol for the assisted shopping system is presented in Figure 2 and is as follows:

1) Greeting by robot: The robot initiates the interaction by introducing itself and inviting the user to request a product.
2) Prompt for user to specify item: The user provides the name of a product.
3) Check for compatibility with agenda: Upon receiving the user request, the robot employs a decision-making process to determine if the product matches the criteria given by the shopping agenda.
   a) If compatible, deliver item: The robot acknowl-

[2]The software is available from Github: https://github.com/HRI-AAU/Sawyer-Unity_Interface_VM. An introduction video can be found here: https://youtu.be/fXiOQ_ko_sI.

edges the request with a positive statement, such as *Good pick* and proceeds to navigate to the designated product, grasp it, and transport it to the counter.

b) If not compatible, initiate positive or negative rejection: The interaction design for the rejection strategies is described below.

4) Goto 2) until all items from the shopping list have been acquired

Figure 3 gives an overview of the interaction design for the positive and negative rejection strategies. For both rejection strategies, the robot will accept the user choice in the third attempt, i.e. if the user insists on a product, s/he has the possibility to override the robot's rejection of this choice.

Positive Rejection: During a positive rejection, an alternative product from the same food category is offered that is compatible with the shopping agenda. The robot navigates to this alternative product and presents it as a better option, providing a comment such as *These apples are a better choice because they are more sustainable*. If the user follows the robot suggestion, the item is fetched and delivered. If the user insists on buying the original item, the robot will stay at the alternative item and provide an argument, why this item is the better choice, e.g. *These apples come from a local farm*. If the user still insists on buying the original item, The robot acknowledges the request with a negative statement, such as *If you insist* and proceeds to navigate to the selected product, grasps it, and transports it to the counter.

Negative Rejection: During a negative rejection, the robot navigates to the selected product without fetching it and instead provides a comment such as *These strawberries are not a sustainable product*. If the user chooses a different item from the same food category, then this item is fetched and delivered. If the user insists on buying the original product, the robot will not move and provide an argument, why this item is not sustainable, e.g. *These strawberries have not been produced in Europe*. If the user still insists on buying the original item, the robot acknowledges the request with a negative statement, such as *If you insist* and proceeds to grasp the selected product, and transports it to the counter.

For both rejection strategies, the user is in full control of the interaction and can always decide to try a different item from the shopping list. The system keeps track of specific items and will recognize if the user tries to buy the same product at a different time and will resume the rejection strategy at the previous point of exit.

IV. Evaluation

A. Design

The system is evaluated using a dependent measures design, where participants test both the positive and negative rejection strategy. The order of the two conditions is counterbalanced, participants are randomly assigned. Positive rejection presents the user with a suitable alternative to his choice based on the shopping agenda (robot initiative, higher level of autonomy and transparency) whereas the negative rejection leaves the decision to the user (human initiative, lower level of autonomy and transparency).Based on the analysis presented in Section III-A, we investigate the following hypotheses:

Fig. 4. User interacting with robot

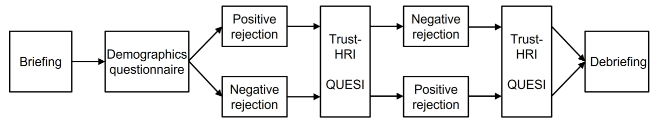

Fig. 5. Procedure of the shopping experiment.

H1: Positive rejection elicits significantly higher trust in participants than negative rejection.

H2: Positive rejection results in significantly higher sustainable shopping choices than negative rejection.

H3: Positive rejection has significantly higher usability ratings than negative rejection.

B. Participants

A convenience sample was recruited on campus from students that were present in the building on the days of the experiment. 31 students were recruited (12 female, 19 male), with an average age of 23.87 (SD = 3.03). Seven participants had previous experience with robots, either programming robots or participating in other experiments with robots.

C. Apparatus

The experiment was run with a Rethink Sawyer robot, which is a one-armed collaborative robot. The robot is controlled through the Unity2Sawyer interface. Trust is measured with the short version of the Perception of Trust-HRI questionnaire by Schaefer [22], which consists of 14 items. Usability is evaluated with the QUESI questionnaire by Naumann and Hurtienne [23], which is a questionnaire with 14 items that are evaluated on the five subscales of subjective mental workload, perceived achievement of goals, perceived effort of learning, familiarity, and perceived error rate.

D. Procedure

The experimental procedure is presented in Figure 5. After an introduction to the experiment and collection of informed consent, participants fill out a short Demographics questionnaire after which they are distributed in one of two groups. They receive a shopping list with eight items, one from each category (see Figure 1 right). They start interacting with one version of the robot (either positive or negative rejection) following the interaction protocol outlined in Section III-B. To ensure equal experience for each participant, the robot rejects half of the items on the list according to the following pattern (A: accept choice; R: reject choice): A A R A R R A R. After all items from the shopping list have been acquired, participants fill out the Trust-HRI and QUESI questionnaires, while an assistant re-stocks the shelfs. For the second interaction, participants receive a new shopping list and the interaction is repeated with the other version of the robot. After all items have been acquired, the participant fills out another Trust-HRI and QUESI questionnaire, after which participants are debriefed and receive some sweets as compensation for their participation.

E. Results

A Levene test shows that the data from the Trust-HRI questionaire is not normally distributed ($p < 0.001$). Thus, a non-parametric test was used on the trust data. Wilcoxon signed-rank test reveals higher trust ($V = 143$, $p = 0.04$) towards the robot that uses the positive rejection strategy ($Mdn = 0.71$) than towards the robot that uses the negative rejection strategy ($Mdn = 0.68$).

The number of items that were accepted have been logged during the interactions. A Levene test shows that the data is not normally distributed ($p = 0.028$). A Wilcoxon signed rank test ($V = 33.5$, $p = 0.02$) reveals that the robot that uses positive rejection is significantly more successful ($Sum = 58$, $Mdn = 2$) than the robot that uses the negative rejection strategy ($Sum = 37$, $Mdn = 0$).

Similar to the trust data, a Levene test revealed that the usability data from the QUESI was not normally distributed ($p = 0.014$). A Wilcoxon-signed rank test shows a slight tendency towards higher usability of positive rejection ($Mdn = 4.43$) over negative rejection ($Mdn = 4.29$), $V = 145$, $p = 0.12$. No significant differences are found for the subscales apart from learning effort, which also shows a tendency towards lower learning effort for positive rejection ($Mdn = 4.67$) compared to negative rejection ($Mdn = 4.33$), $V = 76.5$, $p = 0.1$.

F. Discussion

Hypothesis 1 is retained, i.e. the robot that rejects the choice of the user by providing arguments for an alternative item elicits higher trust in the user, while a robot that just provides arguments why a product is not a good choice in relation to the user's selection is eliciting lower trust in the user. The robot showing a higher level of autonomy and transparency in terms of explaining the rationale for the autonomous decision making process is seen as more trustworthy.

Hypothesis 2 is also retained, i.e. users accept the robot's rejection more often, when it uses a positive rejection strategy. This confirms the results from Burg and colleagues [12] that robot initiative is preferred by the user. While the negative rejection strategy provides arguments against a product but leaves the decision what to take instead to the user, the robot with the positive rejection strategy provides the user with an alternative solution and thus takes over the decision making process. Positive rejection thus results in significantly higher sustainable shopping choices.

Hypothesis 3 is rejected, i.e. there is no clear difference in the usability of the two different versions of the robot. There is a slight tendency towards the positive rejection strategy having a lower learning effort, which could be explained by the fact that the user does not have to make an active decision for choosing an alternative product.

The results clearly show that depending on the strategy, we can influence the customer's buying decision. While we argue here that this helps the customer to follow a desirable agenda, in this case buying more sustainable products, there is of course the possibility to use the same strategies to further what we called earlier the stakeholder perspective of just buying more or more expensive products. For really creating robots that support change, the use of such strategies needs thus to be integrated in the larger societal discourse on sustainability. This is also necessary because the robot's arguments focused on the relative sustainability of the products on the shelf, but it was never defined for the users what that meant. Also, it is unclear what sustainable consumption means for the use as this might imply ecological sustainability but could also mean economic sustainability to name just two interpretations. An important next step is thus to gain more information about the layman's discourse around sustainable consumption to create more relevant arguments for individual consumers. The limitation of the study at this point is the experimental nature of the interaction in the lab, which lacks ecological validity for the shopping experience. Thus, a field test in a supermarket is an obvious next step.

V. Conclusion

This paper investigated rejection strategies in service robots as a means to support decision making of the customer focusing on a customer perspective, i.e. supporting the customer in keeping to a predefined agenda, e.g. buying healthy, economical, or sustainable. The implemented strategies were modeled based on an ethnographic study in an assisted shopping context. The results show show that positive rejection, i.e. rejection suggesting alternatives and providing agenda-based arguments for the alternatives, elicits more trust in the system. This can be linked to trust-related factors of higher autonomy and transparency. The positive rejection also results in greater acceptance of the robot's suggestions and thus seems to be the better choice for decision support.

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