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Guo, Peicheng; Smit, Iskander

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Towards an Active Predictive Relation by Reconceptualizing a Vacuum Robot: Research on the Transparency and Acceptance of the Predictive Behaviors

Peicheng Guo^(✉) and Iskander Smit

Department of Industrial Design, Delft University of Technology, Delft, The Netherlands
guopshing@outlook.com

Abstract. With the development of Artificial intelligence, the connected objects are extended with the predictive capabilities and the character of things can change to “things that predict”. If a connected device is able to embrace a predictive system that not only profiles for scripted behavior but could also use the knowledge co-created by all the other similar devices and their users that encounter similar situations, the predictions can be generated based on that. In this case, a new type of interplay between humans and things called “predictive relation” is created. However, before this future takes place, it is required to find out appropriate patterns to address challenges such as the transparency and users’ acceptance of predictive behaviors of connected products. The research in this article takes a vacuum robot as a reference product for the study. The research starts by collecting users’ daily practice with vacuum robots through 4-day diary booklets. And then the booklets serve as sensitizing tools to envision the possible predictive capabilities and lead the discussion on the acceptance and transparency of general predicting things. From the creative sessions we propose 1) design qualities for the acceptance of the predicting things, and 2) a model of generating predictive behavior that enhances the transparency. Eventually, we also propose the idea of “Designers as the facilitators of the human-robot collaboration”.

Keywords: Internet of Things · Artificial intelligence · Human-robot interaction · Transparency · Acceptance · Robot autonomy

1 Introduction

1.1 Predictive Relations & Knowledge

For some time now, things are becoming connected, such as electronic consumer products, being able to connect to each other directly and through the Internet, and things can interact without human interference [1]. By implementing sensors, things can exchange data and combine products into a decentralized system. This system of connected objects is referred to as the Internet of Things (IoT). With the development of Artificial Intelligence and Machine Learning capabilities, the connected objects are now extended with

predictive capabilities and the character of these things is changed to “things that predict” [2]. If a connected device is able to embrace a predictive system that not only profiles for scripted behavior but can also use the knowledge co-created by all the other similar devices and their users that encounter similar situations, predictions can be generated based on that. In doing so, a new type of interplay between humans and things called “predictive relation” is created (shown in Fig. 1). Commonly, there will be a feedback loop when users interact with a product or service. According to experiences from the past ($t-1$), the users will form a mental model ($t+1$) to understand and foresee in what way the product will perform. For example, a user considers an object as a cleaning tool based on his/her past experience with the tool and expects it to clean up the floor accordingly. When intelligence is added to the object, like sensors and algorithms equipped by the factory and schedule for performing tasks set by the users, this profile will also influence the anticipations of the users. Moreover, as a smart object fed with the predictive knowledge generated from the decentralized system, the profile will be formed by the knowledge on predicted futures and then indirectly shape the user’s perception of the product.

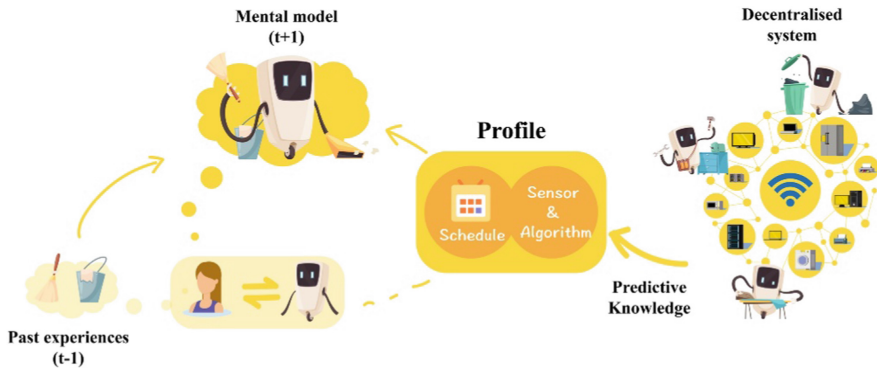


Fig. 1. An image of predictive relations and knowledge [2]

1.2 Current Issues and Related Work of AI & the Connected Objects

Acceptance. When we envision how promising a new concept or a new technology can be to enhance our lives, we still reserve the right to decide for ourselves whether to accept this new technology, especially when it will significantly change our existing lives. As everyday objects are implemented with predictive capabilities and become complex systems, one of the possibilities is that we will lose the control that we currently have on the objects. At that time, how shall we adapt to this shift in role, or how can robots help us accept them equipped with this new technology? Therefore, a successful implementation of a new technology would not be achieved without the investigation of user acceptance.

Apart from the theory such as Technology Acceptance Model (TAM) [3] focusing on the measurable factors of a concrete and realized system like perceived ease-of-use, the Domestication Theory [12–14] uses the metaphor of taming a wild animal into the

home environment to investigate how a new technology is being integrated and adopted in users daily life. Thus, the acceptance qualities of an immeasurable and unrealized technology such as things becoming predictive, are easier to be investigated through the Domestication Theory. The Domestication Theory provides a model which is divided into 4 dimensions:

- **Practical domestication:** This dimension points out the interactions that are physical and observable with the technology. This can refer to how the technology can be used, such as a button on the product to push.
- **Symbolic domestication:** This refers to what the technology means for the users after having it in their life, illustrating the unobserved after-effects of adopting the technology.
- **Cognitive domestication:** are the mental practices associated with the use of technology, e.g., how the users learn from and through the technology and how the technology changes the users in return.
- **Social domestication:** refers to how technology is influenced not only by individuals but also through a diversity of actors who hold agency in how the technology is applied to the lives of users and others around them.

Transparency. When the thing is able to predict and make decisions autonomously as a “black box”, it’s hard to explain why and how it reached certain outcomes. Sometimes the users can immediately realize that the predictions can perfectly meet their needs, while sometimes its predictive knowledge may achieve users’ potential demands that they are not yet aware of. Moreover, the predictive knowledge may take over the decision making and the reasons for the predictive decision are sometimes missing, leaving the user with passive use. To open up the “black box”, many have called for creating artificial systems with explainable and transparent qualities that humans can trust [4, 5]. Many well-known digital examples have come up with some solutions on transparency, such as Explainable AI of Google cloud which provide a set of tools and framework to help the customer learn and interpret predictions made by the Artificial Intelligence [18], but cases are few when looking into the IoT products [2].

Robot Autonomy and the Level of Robot Autonomy. Robot autonomy is considered highly relevant to the capability of the smart system to perform its own tasks and actions. In the field of human-robot interaction (HRI), robot autonomy plays a crucial role, since it will influence the performance of the tasks, the way and density of interaction with humans, and the reliability of the performance in an environment. A scientific basis of study on the autonomy of robots can help designers to understand the features and tasks of the smart objects and identify which actions and tasks should be assigned to humans or robots [6]. Over the years, the studies on the definition of robot autonomy have been discussed from the perspective of psychology and engineering [7–9]. The term is applied to characterize varied aspects of robotics, from the ability of the robot to manage itself to the level of required human intervention. In Beer’s study [6], they proposed a more detailed definition, which integrates current generally accepted definitions of autonomy and indicates common characteristics of autonomy (i.e., sense, plan, act, task-specific goal, and control): “*The extent to which a robot can **sense** its environment, **plan** based*

on that environment, and act upon that environment with the intent of reaching some task-specific goal (either given to or created by the robot) without external control.” This definition helps deconstruct the behavior of an autonomous robot into 3 dimensions—Sense, Plan, and Act, and indicates that the characteristics should be taken into account when researching robot autonomy. Views on how autonomy impacts human-robot interaction are different. In the case of Huang’s research team, they hold the view that the level of robot autonomy (LORA) has a negative linear relationship with the frequency of HRI, which means that the higher LORA, the lower the frequency of HRI [10]. The LORA also reveals that autonomy is not a binary allocation: either human or robot is allocated to a specific goal and action, but a continuous category that splits between the human and robot, indicating the degree of dynamic control of the tasks. Beer’s team [6] highlights that the robot’s autonomy is in a state of fluctuation, which may switch between levels over time according to the interaction, task, and environment.

1.3 Research Direction

With the predictive knowledge added to the interplay we have with the connected objects, there is no sufficient reference to validate if the interplay meets the requirements when the relation is linked to the future. So, before the future takes place, it is required to find out appropriate patterns to address the challenges such as the transparency and users’ acceptance of predictive behaviors of connected products. It is urged to have an active and valid dialogue to understand the now and the future at the same time, and this leads to the question: ‘how to design transparent and acceptable predictive relations for the things that predict?’ Therefore, to investigate the question, the research in this article takes a vacuum robot as a reference product of the study, including the following contributions:

- From vacuum robots to general predicting things:
 - Design qualities for the acceptance of the predicting things
 - Model of generating predictive behavior that enhances the transparency
- The idea of “Designer as the facilitator of the human-robot collaboration”

2 Methods

A creative session is conducted to dive deep into the context of the user and the vacuum robot to envision what kind of capabilities can be applied to the vacuum robot as predictive capabilities. Taking vacuum robots as the reference products, the research also focuses on exploring the general qualities that can help the predicting robots perform appropriately and integrate into our lives. Besides, based on the envisioned predictive capabilities, we also discuss how the predictive knowledge is being generated in individuals’ contexts and how can it be explainable and transparent to the users. In conclusion, three research questions for the qualitative study are set up as follows:

- What predictive capabilities could be applied to the vacuum robot in the future?

- From vacuum robots to general predicting things, what qualities can help the predicting robots become acceptable in our life?
- How does predictive knowledge generate in the individual context that can enhance transparency?

The creative session consists of 2 parts. In the first part, 4 users of vacuum robots and 2 experts from the robotic and design fields were invited and they were provided with a 4-day diary booklet to record their daily individual practices of cleaning and their relationship with the current vacuum robot. After that, they were asked to bring their diary booklets together to present and discuss their experience with vacuum robots. In the second part, a 1-h creative session was conducted through sketching and discussion to envision the predictive capabilities of vacuum robots and identify the design qualities for acceptance of general predicting robots. Besides, in a holistic view, we summarize the predictive behaviors envisioned in the creative session to a model indicating how a predictive behavior is being generated in the individual context. All participants were provided and asked to sign up for the consent forms before the study (Table 1).

Table 1. The structure of creative session

	Activities	Theories	Outcomes
Part 1	Investigating the daily practices with the vacuum robots through 4-day diary booklets	Path of expression [11]	Daily individual practices of cleaning and their relationship with the current vacuum robots
Part 2	Envisioning the possible predictive capabilities based on the current context of use and identifying the design qualities	The Domestication Theory [12–14]	<ul style="list-style-type: none"> • Categories of predictive behaviors • Design qualities for the acceptance of the predicting things • Model of generating predictive behavior that enhances the transparency

2.1 Sensitizing the Expression of Participants: Path of Expression

To help the participants envision the predictive knowledge of vacuum robots in the future, the study follows the path of expression [11]—ask about the present and the past before asking about the future. It enables participants to connect to what their concerns are from their past and present experiences and use that to trigger their feelings and ideas about the future. Thus, the study starts by recording participants' experiences and feelings about the present and past through the diary booklets and then discusses the future scenarios of predictive behavior of vacuum robots. In addition, as a sensitizing tool, the diary booklet also follows the path of expression to help the participants record

and present their personal experiences on the booklet. It not only asks about participants' current and past experiences but also requires them to think about the vacuum robots' possible connections with other objects in the future (Fig. 2).

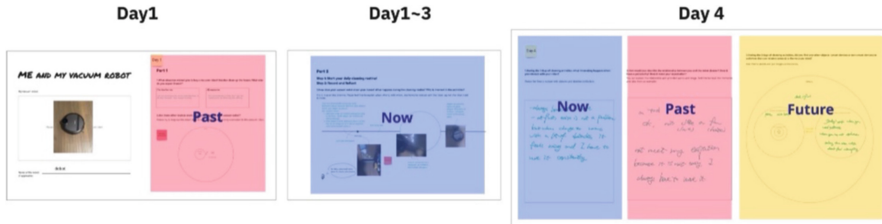


Fig. 2. An example of the diary booklet

2.2 Sensitizing the Findings: Domestication Theory

To answer the research question: what qualities can help the predicting robots perform appropriately and become acceptable in our life, the Domestication Theory [12–14] is applied to lead the questions during the creative session and sensitize the participants to find out the qualities from the predictive capabilities they envisioned that help the predictive behaviors become acceptable.

3 From the Current Vacuum Robot to the Predicting Vacuum Robot

3.1 The Main Tasks of the Current Vacuum Robot

To summarize the daily practices of current vacuum robots, the data collected by the 4-day diary booklets are categorized into groups of main tasks. The tasks are described from the human perspective and clustered as: 1) preparing for the cleaning, 2) opportunistic cleaning, 3) planned cleaning, 4) solving the problems when cleaning, 5) after cleaning.

- **Preparing for the cleaning:** Usually, before the robot is able to clean, some components, such as an empty dust box, should be installed. Sometimes, users must preclean up the cables scattered on the ground to prevent robots stucking and overturning.
- **Opportunistic cleaning** is the type of cleaning task that is temporary and unscheduled [15]. Sometimes the users and vacuum robots may need to carry out some unexpected cleaning tasks, such as cleaning up specific areas and rooms that are covered by scattered nuts with spot cleaning and room cleaning mode.
- **Planned cleaning:** The cleaning activities that are regularly carried out, such as weekly scheduled cleaning, cleaning in the condition of leaving home, are categorized as planned cleaning [15].

- Solve the problems when cleaning: The robot may encounter problems in the cleaning route. Solving problems, such as getting rid of stucking, are common activities in the cleaning routine.
- After cleaning: When the cleaning is complete, the robot will automatically go to the charging base and switch to the Sleep Mode. Also, to maintain the robot and obtain new features, users are required to replace the consumables and update the system regularly.

3.2 Categories of Predictive Behaviors

Summarizing from the perspective of the starting point of the predictive behavior, the scenarios envisioned by the participants can be categorized as follows: 1) Predicting starts from sensing the environment, 2) Predicting directly starts from the knowledge generated from the cloud users.

Predicting Starts from Sensing the Environment. In this situation, the predicting robot first senses the surrounding environment, then matches the collected information with the data from the cloud to trigger the predictive actions. The predictive behaviors in this situation can start from sensing the elements of the scene: the human actions (e.g. users' commands and emotions), and recognizing the object (e.g. dust, etc.).

Predicting Directly Starts from the Knowledge Generated from the Cloud Users. The other way to trigger the predictive knowledge is that the predictions directly start from the cloud. Instead of triggering predictive behavior through the surroundings where the robot is embedded, in this situation, predictions are executed by obtaining knowledge directly from the cloud. For example, the predicting robot performs actions because of weather information and news reports (Fig. 3).

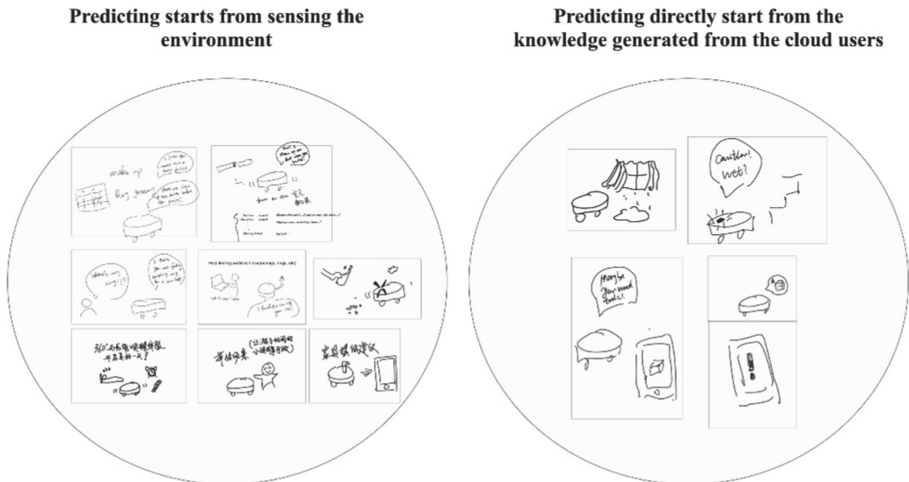


Fig. 3. The categories of predictive behaviors sketched by the participants

4 From Vacuum Robots to General Predicting Things

To identify the qualities that help the predicting robot become acceptable in our daily life, the Domestication theory is applied in the creative session to sensitize the findings. Based on the theory, the findings are classified into 4 dimensions.

4.1 Practical Dimension

Able to Show Context-Related Information. The ability to help the user to learn the reason behind the predictive behavior is crucial for the things that predict [2]. The Human-AI interaction guideline from Microsoft [16] indicates one of the ways to express the reasons for predictions is to show the information that is related to the user's current environment and activity. This also can be proved from the creative session. Without guidance from the interviewer, the interactive dialogues with the predicting robot created by 4 participants all include the contextually relevant information to explain the robot's behavior. For example, the robot provides the information that it is detected from the user's current behavior—smoking, and asks for permission to clean. Another situation that came up from the participants shows that the robot points out the user will have a party and recommends cleaning in advance.

Able to Provide Room for Negotiation on the Decision Made by the Robot. When robots become intelligent or even able to predict, it is inevitable that they will need to make decisions autonomously at various degrees. These decisions may not always fit perfectly with the user's wishes. At this point, robots need to be able to negotiate, to revise their behavior, and even more advanced, to convince users to accept and understand their behavior. The negotiation process can also stimulate the user to provide the robot with more information to learn.

Able to Easily Dismiss Undesired Services. Robots are required to have the quality of being able to easily cancel the services they provide. One of the participants addresses the possible impact of the predicting vacuum robot: "*The robot may over-speculate my behavior.*" In his vision, the predicting robot is like a student eager to update his knowledge pool through learning. The robot will constantly compare the data from the cloud with the scenario being served, which may offend the user or over-provide the service. Therefore, robots need to have the ability to easily dismiss undesired services.

4.2 Symbolic Dimension

Be a Surprise but Still Relate to the Individual's Knowledge of What the Robot Should Do. Take a vacuum robot as an example, unlike the current vacuum robot, which can only perform basic cleaning tasks, participants expect more comprehensive housekeeping from a robot that can gain more knowledge about household chores from other users. For example, based on reports of an increase in slip and fall accidents due to slippery floors, the vacuum robot issued a slippery floor warning. Also, one participant drew a scenario describing the vacuum robot that keeps pets away from

broken cups, etc. All of these indicate a shift from the robot, which now represents a guarantee of completing basic tasks, to a symbol of providing unanticipated knowledge or even surprises. However, no matter how intelligent and predictive a robot becomes, the predictive behavior should still relate to the individual's knowledge of what the robot is supposed to do.

P6: *"I know that when this technology turns out to be a reality, he will give me a lot of surprises, and even know how to do the cleaning better than I do, but his behavior should still be in line with my key expectations of this product, I mean, like, saving my time on cleaning the floor."*

Able to Foster New Lifestyle. Based on the fact that users now have a need for pre-cleaning (removing the objects that the vacuum robot will easily get stuck) before launching the vacuum robot, one participant suggested that through learning from the cloud, the vacuum robot is able to identify furniture and give suggestions on furniture placement to free up more sweeping space. Another participant proposed that predicting robots can hint and stimulate users to buy more smart devices in a proper time. The participants' expectations for the predicting robot were no longer limited to better work, but extended to suggestions for new lifestyles, such as embracing new home layouts and new smart devices. They also said: *"(...) Compared to the current sweeper, I think if the predictive sweeper recommends new things to me from time to time, this will keep me fresh to him, so that the frequency of use may increase."*

4.3 Cognitive Dimension

Able to Motivate Users to Constantly Participate in Generating Predictive Knowledge for Other Users. Unlike current robots, predicting robot is not only a matter of encouraging users to be more involved, but also a matter of motivating them to pass on the knowledge they co-create with the robot to the cloud in order to enrich the knowledge base of the robot system to serve more people and make predictive behavior more relevant to people's demands. A participant from a robotics company said, *"(...) As a developer of the robot, it is also an important part of our job to effectively collect user preference and feedback to enhance our system (...)"* He added: *"(...) There are many ways to motivate users to donate their data, such as enabling them to understand what parts of the information they are about to share are desensitized. We also build a community of users to make them feel connected, and to let them realize how valuable their data donation is to the community (...)"*.

Able to Motivate Users to Provide Feedback in Order to Make the New (Predictive) Behaviors More Suitable in Their Own Context. This expert also said, *"(...) when the robot first predicts a new behavior through the cloud database, for example, that the robot predicts the user may need to clean the floor while smoking, the robot can ask for the user's opinion in a polite and questioning tone, and when this behavior is accepted by the user several times, the robot then performs the task with more initiative (...)"* This process also allows the user to understand the underlying reasons for the predictive behavior of the robot and to adjust the nuances of the behavior to their own situation,

e.g., sweeping the floor in a specific area around the user when the user is smoking. Through this process, the user changes from unfamiliar with this predictive behavior to familiar with it, and gradually delegates the initiative to the robot.

4.4 Social Dimension

No Social Comparison. When the robot starts to predict behaviors that it learns from networked users, the user will start to be influenced by social comparison. “(...) *it’s like when I’m browsing a certain t-shirt on an online shopping platform, and the website gives me information that the person who viewed this t-shirt also bought this pair of jeans. Then I will start to think....hmmmm...maybe having this pair of jeans to match the t-shirt would be nice. So, when I learn that prediction is learned from someone else, I will start to reflect on my own thoughts*”.

If a robot is trying to prove that its predictive behavior is reasonable, it is not a good idea to compare the individual’s situation with other users, even though the users know that the information is anonymous.

P7: “*Well, I understand that the robot will try to told me this information so as to make me feel that his decision was reliable and reasonable, but it also made me feel defensive. Why should I do the same just like others?*”.

P8: “*It’s like he has his own social circle with other robots, and I know he learns a lot from there, but I feel offended if he’s always comparing my situation to others*”.

5 Discussion

From the study, it is not hard to notice that, in the future, the process of defining products—what the products should do and how to do it, has shifted from the stage of the design process to the stage where users use the product. In the predictive system, the roles of planning the tasks and justifying the appropriate initiative are highly dependent on the knowledge generated from similar and networked users. In this system, users are not only engaged as the ones using the products but also as the ones participating in the evaluation, making the predictive behavior more appropriate and suitable for more people through the involvement of a wide variety of users.

In the following paragraph, we first reflect on the identified design qualities that enable predicting things to become acceptable. Then, in a holistic view, we summarize the predictive behaviors envisioned in the creative session to a model indicating how a predictive behavior is being generated in the individual context. Besides, we also discuss that the proposed model reveals the users’ learning and adapting process. And thus, we argue the way to generate the predictive behavior in our proposed model can enhance transparency. Finally, we discuss the shifting role of designers when things become predictive and reflect on the value of the creative session.

Table 2. The design qualities identified from the creative sessions

Dimensions	Qualities
Practical	-Able to show context-related information -Able to provide room for negotiation on the decision made by the robot -Able to easily dismiss undesired services
Symbolic	-Be a surprise but still relate to the individual's knowledge of what the robot should do -Able to foster new lifestyle
Cognitive	-Able to motivate users to constantly participate in generating predictive knowledge for other users -Able to motivate users to provide feedback in order to make the new (predictive) behaviors more suitable in their own context
Social	-No social comparison

5.1 Design Qualities for the Acceptance of the Predicting Things

Our main findings from the creative session are conceptualized in Table 2, where we summarize the qualities that enable predicting things to become acceptable in 4 dimensions.

It can be concluded that, when things become predictive, the predicting thing change the role from a command follower to a collaborator who is expected to have the qualities of bidirectional communication and negotiation. Therefore, in the practical dimension, the predicting robot should provide ways for users to actively argue whether the predictive behaviors are appropriate and easily cancel the undesired services. Besides, reasonable and appropriate information such as context-related information provided by the predicting robots can help users understand how the prediction is being generated and thus and thus enable the predictions more likely to become acceptable.

Different from existing robots that represent performing defined and scripted behaviors, the predicting robots symbolize bringing new and unanticipated knowledge to the user. In this manner, the user can learn about other networked users' daily practices through the predicting robot, thus changing his or her own lifestyle. However, the knowledge of a predicting robot cannot expand without rules. The predictive knowledge still needs to comply with ethics and be restricted to the robot's domain of duties. For example, a domestic predicting vacuum robot should vacuum inside the house instead of going out to the garden to sweep the leaves. Further research is required on how to define the scope of predictive knowledge.

The development of predictive knowledge is co-created by all the networked users and robots. To expand this cloud-based knowledge pool, in the cognitive dimension, the predicting robots need to be able to motivate their users to generate new knowledge continuously and actively for the community in the cloud. Similarly, in the individual context, the predicting robots are required to have the capability to motivate users to provide feedback in order to customize the predictive behaviors more suitable and acceptable to the individual.

When the users are aware that the formation of predictive knowledge is a co-creation process with other users, inevitably, the users may attribute social properties to their relationship with the predicting robots. For example, because of the potential social comparison, the users may resist the robots' predictive behaviors which perform based on networked knowledge. Therefore, as a predicting robot the behavior should be performed in a way that minimizes the impact of social comparisons. For instance, do not argue that the prediction is reasonable with the results of comparing individual situations with the cloud users.

5.2 Model of Generating Predictive Behaviors that Enhances the Transparency

The process of generating predictive behaviors is highly automatic. According to the definition of robot autonomy [6], the process can be divided into 3 parts——Sense, Plan, and Act. With this concept in mind, based on the predictive capabilities summarized from the creative session, we propose a model of generating predictive behavior to reveal how the predictive behavior is being developed in the individual context (shown in Fig. 4).

Sense. In the Sense part of the model, according to the findings in Session 3.2, there are 2 ways to trigger the prediction: 1) starting from robots sensing the environment and the users' command, 2) directly starting from the knowledge generated from the cloud users. As Fig. 4 shows, the only difference between these two processes is that the former has one more step than the latter one, i.e. sensing the user's environment and command.

Plan & Act. After the predicting robot sensing the environment or the prediction directly starts from the cloud, the predicting robot will match the collected information with the data from the cloud to interpret and understand the scene. Based on the cloud knowledge and the user's past experience, the robot will determine the initial autonomy level when this predictive behavior first takes place in the context and perform actions with the corresponding level of automation. The interaction between humans and robots will create a loop of co-performance [17] where human performers and robot performers together judge and shape the appropriate performance under individual situations. Through the co-performance, the predictive behavior will be gradually adjusted and adapted to the specific circumstances, and the data generated from this loop will also feed forward the profile in the cloud.

Kuijjer and Giaccardi [17] define the co-performance in the view that things have equal roles with humans to learn and judge the tasks in the interplay. In the traditional procedure of developing smart things, the performances of the devices are determined in the design process. However, in the concept of 'co-performance', the process of defining the performances of the things is shifted to the everyday use practice, which creates an open space for humans and things to learn and adapt to the appropriate performances in their daily practice. The distribution of the agency and the robot's autonomy, however, are the result of this dynamic learning and adapting process.

In the loop of co-performance, humans and robots will learn and adapt to the behavior of each other, and the labor distribution between humans and robots will be dynamically changed throughout the interplay. For instance, the human judges whether a particular

predictive behavior is appropriate, and through the interplay with the robot, the predictive behavior becomes more in line with the personal expectations. In this process, the distribution of activities between humans and robots is also changing, thus implicitly affecting robots' autonomy. Also, since the interplay reveals the learning process, the reasoning and the generating process of the predictive behavior can be explained in this loop, thus enhancing the transparency of predictive behaviors.

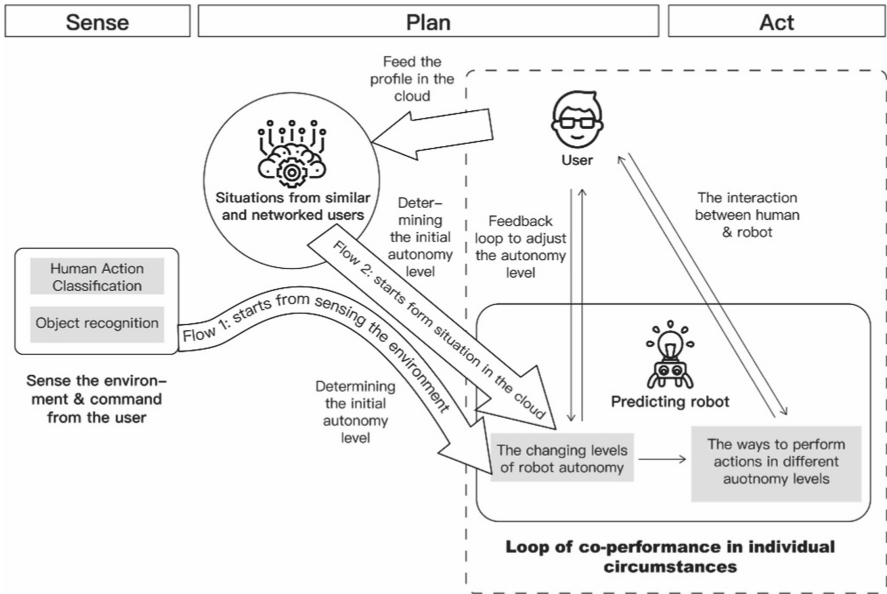


Fig. 4. Model of generating predictive behaviors

5.3 The Shifting Role of the Designer When Things Become Predictive: Designers as Facilitators of Human-Robot Collaboration

The creative session eventually led to discussions and reflections on the shifting roles of designers and developers when designing the predicting things in the future. Some participants thought that the designer should be the one to help the user set up a proper expectation of the robot's capabilities. Admittedly, robots empowered with Artificial Intelligence have great potential, but there are still limitations to what they can accomplish. The designer, therefore, has the responsibility to help the user understand what the predicting robot can do and how well it can do. In addition, when robots are equipped with the abilities of self-awareness and self-determination, their role changes from the command's followers to a collaborator on equal footing with humans. At that time, humans are no longer in the state of outputting one-way commands to robots, but humans and robots are in a state of bidirectional communication, or even bidirectional negotiation and compromise. By then, the focus of designers and product developers will be extended to

how to guide the users and the predicting robots to form a well-coordinated partnership and how to lead this partnership to co-create reliable and meaningful knowledge. Therefore, this article proposes the view that: when the connected things become predictive, one of the roles of the designer is to facilitate the collaboration between humans and robots. The designers here are the ones who help to bring in the background knowledge and the patterns of the predictive relation and indicate the ways for humans and robots to co-perform reliable and meaningful daily practice in their partnership.

5.4 The Creative Session as Speculative Trigger to Open up the Discussion About the Future Where the Things Become Predictive

The creative session stimulated debate and discussion between the participants and the researcher about the future of the everyday product, and the most fruitful of which was the discussion about what qualities should the predicting things have. Some participants said that this speculative discussion helped them imagine the predicting thing more clearly and feel accessible, which no longer made them perceive it as a surrealistic thing, and their fear of this relatively advanced technology was relieved.

P2: “I think the fear that people used to have about the development of robotic things was probably that they would worry that these things would completely replace humans. For example, most typically, humans are afraid that Artificial Intelligence will completely replace their careers and jobs. But through the discussion, I would think that in the future people and robots are more like in a closer and more cooperative relationship, and I can still see the value of humans and their irreplaceability.”

6 Conclusion

This article presents qualitative research on the acceptance and transparency of predicting things by taking vacuum robots as reference products. The qualitative research was shaped in the form of a 2-part creative session that envisioned the possible predictive capabilities of the vacuum robots and discuss their possible impacts.

From vacuum robots to general predicting things, we identify design qualities for acceptance based on the Domestication Theory and are divided into 4 dimensions. Besides, from the creative session, we also propose a model of generating predictive behaviors and argue that the loop of co-performance in the proposed model can reveal the learning and adapting process, thus enhancing transparency. Finally, we propose the idea of “Designers as facilitators of the human-robot collaboration” when things become predictive. In the coming future, the designers can be the ones who help to bring in the background knowledge and the patterns of the predictive relation and indicate the ways for humans and robots to co-perform reliable and meaningful daily practice in their partnership.

Further research can be conducted on evaluating the effect and impact of the proposed design qualities and model. The design qualities and the model can be integrated into the prototype using method such as “Wizard-of-Oz” to engage the participants to experience and test the predictive relation. Besides, regarding the idea of “Designers as facilitators of the human-robot collaboration”, there is still much room for more systematic exploration,

such as designing a systematic pre-sales and after-sales service system for predicting robots to facilitate collaboration.

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