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SURVEY

User-Adaptive Interaction in Social Robots: A Survey Focusing on Non-physical Interaction

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Abstract
This work presents a survey on the usage of user-adaptive techniques for human interface with Social Robots, with focus on non-physical interaction. The work is based on an analysis of a number of recent scientific works, and aims to uncover existing scientific and technological gaps which can serve as basis for future research and development work. User-adaptive systems consist of autonomous agents that are able to use some manner of information on their user in order to adapt to them. Through their adaptive nature, these systems have been shown to be easier to accept by end-users, and to lead to improvements in a myriad of objective and subjective performance measurements. Thus, in the context of a growing domestic Social Robot industry, it becomes of key importance to study the scientific and technological frontiers of this field. In order to uncover potential lines of future research, we propose a taxonomy for the classification of works, which we use to analyse the works under survey, exposing the current scientific frontiers of the area. Aiming to establish the overall readiness of the field, we also analyse the maturity of the works under survey, exposing the current technological level of the techniques at hand and discussing a number of technological challenges.

Keywords User-adaptive systems · Social robotics · User modelling · Survey

1 Introduction

This article presents a survey of user-adaptive techniques used to implement human interfaces with Social Robots, with focus on non-physical interaction. The main aim of this text is to establish the scientific and technological frontiers concerning non-physical user-adaptive systems in Social Robots, in order to support future research and development endeavours.

As robots move from factories into homes, the study and optimization of HRI becomes an increasingly important factor. Whereas in industrial environments the users adapt to the characteristics of the robotic equipment they must use as part of their activity, domestic users must *adopt* and *invest* in these technologies of their own volition. Thus, the issue of technological acceptance becomes central to the success of the Social Robots of the future.

Human–computer interaction (HCI) studies the issues that arise from the interaction between a computerized system, such as a computer or smart device, and a human, using their limited interaction modalities: keyboards, touchscreens, occasional voice input, *etc*. In this context, it has long been established that user-adaptive interfaces lead to significantly improved acceptance when compared to non-adaptive ones [61]. Social Robots, on the other hand, can use any natural communication channel employed by their users, resulting in much higher potential for user-adapted behaviour. Thus, it becomes interesting to study the phenomenon of user-adaptiveness in the context of HRI.

To provide a comprehensive overview of the field, we have collected a number of recent scientific works, narrowed down from a large-scale initial sample by our inclusion and analysis methodology. The works are discussed in a bisected way, first from the scientific perspective, and then from the technological maturity perspective.

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1.1 Role of User Models in Adaptive Systems

User-adaptive systems are based on information on the users, usually (but not necessarily) contained in user models. These models are, conceptually, akin to those constructed by humans when interacting with each other, allowing us to "get to know" and familiarize with each other, an effect that can be exploited by user-adaptive systems. User models encode the attributes of the user that are relevant to the operation of the system, such as the user's expertise level or preferences. This information is used by the system to generate behaviour that conforms to the idiosyncrasies of the user, resulting in a system that conforms to the user it is interacting with, boosting user satisfaction and acceptance levels.

The usage of these techniques has the potential to enable a Social Robot system to interact on the same performance level with a multitude of different users. This is analogous to the autonomous characteristics exhibited by systems that are able to adapt to different operational conditions, employing techniques that allow for context analysis and to adjust their operation accordingly. Thus, we dub this characteristic of user-adaptive robots as *autonomy in interaction*: user-adaptive systems generate autonomous behaviour in the context of an interaction with a particular user who is different from all others and, as a consequence, are able to interact equally well with all users.

1.2 Applications of User-Adaptive Systems

User-adaptive technology can easily be found in everyday devices. Systems such as smartphones and tablets, personal computers and even cable TV systems incorporate user-adaptive facilities to enhance their user's experience. Cloud-based services such as Google Assistant, Apple's Siri or Amazon's Alexa, learn from their users usage of their devices in order to improve the future interactions they share with their users. These systems enjoy widespread use and commercial success, even if they are seen as gimmicky or useless by some users. We have found a limited number of technologically-mature social systems that are also user-adaptive in their function, which we present in this section.

The Paro robot [64], also discussed in [84] and other research papers, is a seal-like therapeutic robot aiming at helping depressed patients. It communicates solely via its movements and chirping sounds, reacting to the user's touch and voice. It employs a reinforcement learning algorithm to gradually adapt to the user's preferred behaviours, for instance learning the name that the user prefers to call it by, not necessarily relying on a user model *per se*.

The Jibo [67] robot is a personal assistant robot, aiming at aiding users in their day-to-day activities, such as ordering food or taking pictures. It is not mobile, but does employ moving joints for expressiveness. Information on Jibo's inner workings is scarce, but it is able to learn the user's preferences regarding the robot's actions, as well as their habits. In terms of user-adaptiveness, and assuming that the system is able to autonomously gather the data needed to perform its function, it is on-par with some of the most intricate systems since it needs to, at least, create a static model of the user's preferences in order to operate.

Similarly, Buddy [31] intends to be a personal assistant for the home. Unlike Jibo, it is mobile and able to roam around the house. In terms of user-adaptiveness, it seems able to get to know its users in much the same way as Jibo, learning their schedules, names and habits, and we postulate that it operates on a static user profile that it builds in the first or first few interactions with the user.

Pepper [2] is a humanoid domestic robot, which aims at interacting with its users emotionally. It is able to recognize the user's emotional state from their voice and facial expression, and adapts to the state the user is in. In terms of user-adaptivity, Pepper uses immediate information to reactively adapt its actions to the user's state and, to the best of our knowledge, this is the only user-adaptive ability of this robot. Naturally, the robot is also *adaptable*, which means it can be configured by the user to act as they want, namely via the installation of *apps*. This represents a relatively limited form of user-adaptiveness, when compared to some of the systems analysed before. However, this simplicity allows the system to be robust and, as such, more suitable to the target environment and users.

Despite the technological maturity of the systems discussed in this section, most of them are not actually available to the general public yet. Indeed, with the exception of Pepper, these systems are locked behind pre-order, crowd funding and issues with product delivery, resulting in apparent commercial success but low actual user adoption.

1.3 Key Definitions

In order to ensure the clarity of the technical terms used throughout the remainder of the text, this section presents the definitions of the main terms used.

Adaptivity We define adaptivity as a system's ability to perform its function in different scenarios by automatically changing its operational parameters accordingly. These parameters can be any controllable aspects that affect the performance of the system, e.g. an air conditioning machine can *adapt* to the outside temperature by changing the velocity of its cooling fan.

User-adaptiveness User-adaptiveness is defined as the system's ability to adapt to its user's characteristics. This definition falls in line with previous work [54,61]. User-adaptiveness can be observed in systems that deal with differing scenarios that emerge from a switch in user-related conditions, such as the user's identity, preferences, expertise, *etc*.

User model As seen in [54], a user model can be seen as an explicit repository of knowledge on the user, which can be used by an adaptive system to retrieve the information needed for adaptation. User models can be represented in many different ways, ranging from a single attribute representing some relevant characteristic of the user, to probabilistic models that combine the representation of the model with its inference. In our view, user adaptivity does not require a user profile, as a system can adapt to its user simply by changing its operational parameters on the fly to suit the user. Model-based systems, on the other hand, explicitly maintain a cache of data on the user that can be, at every step, used to fine-tune the system's mode of operation.

1.4 Structure of this Manuscript

This article is structured as follows. Section 2 presents the taxonomy employed to classify the surveyed works, as well as our analysis methodology. Section 3 presents a short description of the works under survey. Section 4 discusses these works according to our methodology from the scientific perspective, uncovering a number of research gaps. Section 5 analyses the works from the technological maturity perspective, exposing a number of technological challenges and opportunities. Section 6 presents a summary of our findings and concluding remarks.

2 Taxonomy of User-Adaptive Systems

In this section we present a taxonomy, inspired by early surveys [14,54,61], which is used to categorize the works under review. These categories will be used throughout the remainder of the text, namely in Sect. 3, for describing, analysing and discussing the systems under survey as groups. The categories are presented considering two key factors: the existence of an explicit user model, and its persistence in time. They are enumerated as follows:

1. **Adaptive systems with no user model** these systems are characterized by a reactive behaviour with respect to the user's immediate feedback. They do not keep an explicit cache of information on the user;
2. **Systems based on static user models** these systems use predefined information about the user's relevant attributes, making use of this explicit knowledge for adaptation;
3. **Systems based on dynamic user models** like the previous, these systems maintain an explicit model of the user, tailored to the task at hand. Additionally, these systems update user information as they operate.

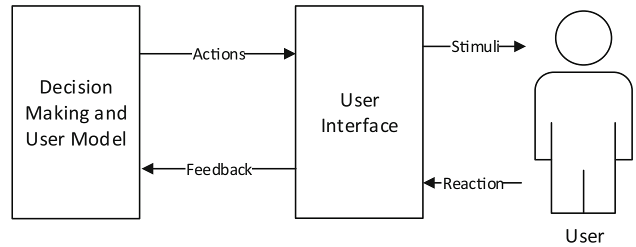

Fig. 1 An illustration of the generic user-adaptive framework

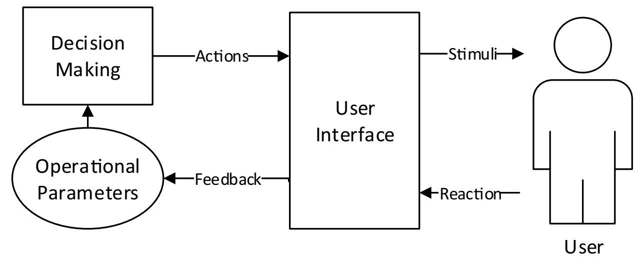

Fig. 2 An illustration of the general architecture of an adaptive system that does not rely on persistent knowledge on the user. The user's feedback is directly employed in changing the behaviour of the system

The enumerated categories aim to represent different variants of a user-adaptive system. We aim to advance beyond the methodology of recent surveys [53,69] by providing a more in-depth analysis of the works under survey, as well as an additional discussion on technological maturity.

Figure 1 illustrates the generic framework for a user-adaptive system. The framework is generically composed of two main components.

– *Interface* the layer where the information exchange between the system and the user occurs. It is constituted by sensors and actuators that perceive and deliver stimuli to the user.
– *Decision making module* The layer where decision algorithms [25] take as input the perceived information, and generate a future response action that will be synthesized by the interface.

As seen in [61], in order to be a user-adaptive system, having *information about the user* is key. This information is usually kept in the form of a *user model*, describing the aspects pertaining to the user that are of importance towards the operation and adaptation of the system. This has led to the birth of the field of *user modelling*, of which we can find an early survey in [54], a field concerned with the organization, representation and acquisition of information on a system's user.

The user's model can be implicit in the design of the adaptive system itself [54]. This results in a system that is able to achieve adaptive behaviour without persistent information on its user, as illustrated in Fig. 2.

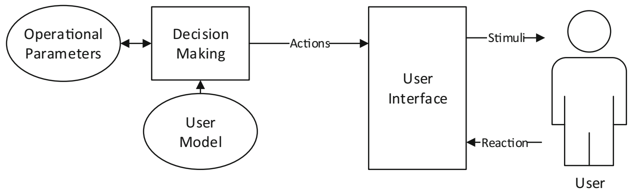

Fig. 3 An illustration of the general architecture of an adaptive system that relies on a user model for user-adaptiveness

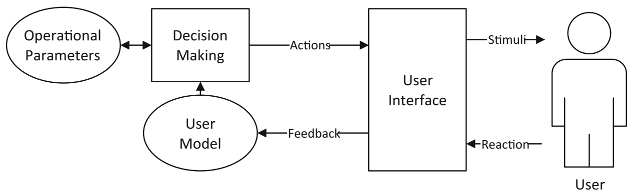

Fig. 4 An illustration of the general architecture of an adaptive system that relies on a user model for user-adaptiveness. The user's feedback is employed in building and refining a cache of data on the user, which is then used to refine the system's behaviour

These techniques perform *reactive adaptation* by adapting their behaviour to immediate information on their users, such as their intention or walking speed. Changes in the user's behaviour that the system is monitoring trigger immediate changes in the system's operational mode, and are not stored or updated in a model of the user.

A system can be user-adaptive using a static, immutable view of the user during the whole interaction period, as illustrated in Fig. 3. This static user model can be obtained by the system using two different mechanisms: (1) the model is created by the system itself during the beginning of the interaction or (2) it can be provided *a priori* by an external agent, for instance, using a questionnaire or a form. These category of systems is unable to dynamically learn the user's characteristics.

Systems endowed with Dynamic User-Models have the ability to change their view of the user through a feedback mechanism, adapting to new circumstances, as illustrated in Fig. 4. In this case, the user's feedback is used to trigger updates to the existing user model, thus allowing the system to evolve with the user. Systems with these characteristics have been suggested as the best (yet most complex) solution for user adaptiveness [54,61].

2.1 Inclusion Criteria and Analysis Methodology

To focus the effort of studying and analysing the surveyed works, this article has two key inclusion criteria:

- **Autonomous systems** This paper analyses systems that adapt to the user in an autonomous manner, as opposed to solutions which are designed with the user's needs in mind [40,55,56,65] or that have to be manually configured [18] in order to act in an adapted manner.
- **Human–robot interaction (HRI)** The focus of this survey are works that deal with Social Robots (embodied artificial agents) as opposed to other frameworks and pure computational solutions, even if possibly applicable to Robotics.

We have gathered a sample of recent works that propose Social Robots of many kinds which exhibit user-adaptive characteristics, which was narrowed down from an initial sample of over 400 works. The surveyed works are analysed considering the following aspects:

- **Taxonomy** does the work use an explicit model? What sort of data and representation does it use?
- **Adaptive parameters and decision making** what parameters of the system are adaptive? How do they decide how to adapt?
- **I/O interface** What type of input and output does the system take advantage of?
- **Maturity** What is the technique's Technology Readiness Level? How is it tested, by whom and where?

These four analysis dimensions allow establishing an overview over the current state of the art and to carve potential future research lines.

3 Survey on User-Adaptive Systems

In this section, the surveyed works are divided in subsections, according to the categories defined in Sect. 2.

3.1 Adaptive Systems with no User Model

The authors of [78] present an system for aiding the user in their mobility. The system, consisting of an intelligent wheelchair or walker, is able to determine the user's intended goal on a map, and their satisfaction with the current path that the system is taking, encoding these variables as hidden states in a POMDP. None of this information is kept in a user model *per se*, but is instead used to adapt the system's actions according to the user, thus achieving user-adaptiveness. The users do not evaluate the system with respect to its adaptiveness, instead demonstrating only that the system does indeed work.

In [52], the authors present a system based on a robotic wheelchair, able to carry its user to their intended destination. The system employs Bayesian techniques to estimate the user's intended goal, which it then uses to guide its navigational efforts. The user's intention is not kept in a user model, and is instead represented solely by its belief. The system was not tested in realistic conditions, but the authors show that it is indeed able to infer a user's goal from the user's input.

The authors of [13] present a system based on an intelligent walker, able to adapt to a user's walking speed. The system constantly monitors the user's walking speed, through odometry force sensors located in the system's handlebars, which it uses to modulate its speed, thus adapting to the user's characteristics. The system was tested in demonstrative trials, and shown to be able to accomplish its goal.

Similarly, the authors of [57,62,63] present a system, integrated in the MOBOT project [19] and making use of its robotic walker platform, aiming a aiding the user in walking. The system infers the user's intention using their inputs and their movements, as measured by an LRF. The system is able not only to infer the user's intended goal when going through crossroads and intersections, but is also able to be teleoperated hands-free, from behind, with the user walking behind the device. User tests were carried out with 35 participants, demonstrating the system's operation.

In [21], the authors present a system, integrated in the SPENCER project [80], intended to adaptively guide a user to a location. The system monitors the user's movements, and adjusts to their walking speed and engagement level, proactively engaging the user if needed. The system makes use of a hierarchy of Mixed Observability Markov Decision Process (MOMDP) that subdivide the decision-making process into smaller chunks, thus making it computationally tractable. In a demonstrative trial, the authors show that the system was able to improve the user's engagement and reduce both the mean and variance of the distance to the user, indicating successful adaptation.

The authors of [39] present a robotic vacuum cleaner that is able to adapt to its user's preferences. The robot does not keep an explicit model of the user, but identifies the user's commands and any obstacles it finds on its map, and determines the times of the day where these areas are best accessible, thus adapting to its users' occupancy of the environment. The authors do not present any experiments with users, but validate their mathematical solution.

In [30], the authors present a system that aims at helping a user gather the ingredients for a recipe. The user selects the items by pointing at a board with drawings of the items, and the robot adapts to the user by estimating their intention, from their gaze and speech, speeding up the delivery of the item. The authors employ Bayesian techniques, and show that this proactive attitude on the part of the robot significantly speeds up the process, in a set of tests involving 26 participants.

The work presented in [48] exploits the *entrainment* effect, wherein two or more people have a tendency to adjust their prosodic characteristics are they become closer. The system aims at teaching basic mathematics to users, and adjusts its pitch as the interactions with the user progresses, progressively matching that of the user. The system was evaluated with 48 participants, who indicated that they experienced a much higher social presence when interacting with the adaptive system.

Similarly, the authors or [73] present a robotic tutor for aiding diabetic children in learning to judge insulin dosages based on food intake. The system observes the user's answering pattern and adapts its difficulty depending on the number of correct answers. The authors show that the adaptive system is able to surpass the novelty effect, and achieve higher levels of intrinsic motivation in the user past the initial interaction.

The authors of [11] present a study on the impact of the inclusion of user intention and explicit time dependency as hidden variables in a POMDP framework. The authors argue, without explicitly discussing user-adaptiveness, that the inclusion of the user's intention can improve the quality of the interaction. Indeed, a study with 35 participants, where participants were interacting with a simulated robot in a driving experience, shows that the users do indeed prefer the adaptive system, and it is able to achieve significantly higher rewards over time.

Similarly, the authors of [45] present an assistive driving system which is able to determine when the user is distracted and to compensate by taking control of the vehicle for a short amount of time. The system learns models of non-distracted drivers in an off-line step, which it then applies to each user to determine their state at each moment. The system uses Bayesian techniques to maintain a set of beliefs over the state of the driver, which it uses to estimate when the driver needs help. The system was tested with an undisclosed number of participants, and the authors show that the system was able to prevent a number of accidents in a driving simulator.

The authors of [77] present a study on the adaptation of the CADENCE turn-taking system to a user-adaptive version. The system monitors the interaction with the user's state and adapts to the user's cadence of active/inactive status. A study with 15 participants shows that the system was able to elicit the same social response as the non-adaptive version could, with the crucial difference that the adaptive version was able to automatically achieve results within a single interaction, whereas the original system have to be manually tuned between interactions.

In [76], a study the impact of user-adaptiveness on users, namely on the impression of rapport, is presented. The authors implemented a humanoid robot that mimics the user's gestures while speaking, via an estimation of synchronism between the user and robot. A study with 23 participants shows that most users preferred interacting with the adaptive version of the system,

3.2 Systems Based on Static User Models

In [17], a system that makes use of Personas for adaptation is presented. Personas, also used in [49] in the context of HCI, consist of a set of manually-built user profiles that, combined, aim to represent a large portion of the potential user base. Each persona represents a number of users, and new users can be quickly matched to a known persona, with adaptation taking place in accordance to the matched persona. In this work, the authors have defined the Personas with basis on tests with 28 users. This technique eschews the usage of large learning dataset, and favours the usage of experts in building the Personas. In this work, Personas are gathered through questionnaires, and the authors show that the system is able to adapt to new users.

The authors of [4] explore the adaptation of a robot's synthesized personality to the personality of its user. The user profile is constituted by the user's personality, which is estimated at the beginning of the interaction and remains static throughout the interaction. The robot communicates through gestures and speech, and the authors have found that users interacting with the adaptive robot have found it to be more expressive.

The work presented in [41] aims at assisting a user in dressing themselves. The system maintains a list of poses that the user cannot reach, thus adapting to their limitations. This model does not evolve during normal execution, but is learned by the robot in a specific interaction, during which the user is asked to position themselves in a variety of poses. The system adapts by compensating for the positions the user cannot reach, and the authors have found that the system, in its adaptive operation, is faster at accomplishing its goal.

In [24], a system which aims at assisting a user in dressing themselves is presented. The system maintains a model of the user's mobility, namely the positions achievable by their joints, which is learned in dedicated tests. The system adapts to the user's limitations by compensating for the lack of mobility of the user. The authors do not provide a comparison with a non-adaptive system, but have demonstrated that the system is able to achieve its function.

The authors of [68] present a study on the usage of an adaptive robot for teaching dance lessons for children. The system interacts with children one-on-one, and maintains a static model of their personal information, as well as of the history on interactions they have shared before, which it uses to adapt its speech and gestures to the child it is interacting with. The authors perform a thorough study of the effects of this system on the children, and note that the system was able to teach the lessons, and be perceived by the children as a peer or a sibling, instead of a tutor or teacher.

The HOBBIT system, presented in [22], is able to provide several services to elderly users. Its adaptivity relies on an initialization phase, during which the user provides the robot with their preferences, such as speech volume and voice, to which the robot then adheres in future interactions. The authors do not compare their system with a non-adaptive version, but demonstrate its functionality in a number of trials involving elderly users.

The work presented in [1] exploits crowd-sourced information to determine its user model. The system focuses on organizing shelves according to user preferences, and these preferences are learned, via collaborative filtering, from data gathered from a number of participants. The robot is then able to organize the shelves by representing the user's preferences as constraints, and using an optimization process to violate as little constraints as possible when placing objects on containers. The system is not compared with a non-adaptive version, but is able to organize the shelves.

3.3 Systems Based on Dynamic User Models

A *proactive* system is presented in [29], integrated in the ACCOMPANY project [5]. The system maintains a state of the user, and a set of rules that cause that state to evolve. The goal of the robot is to keep the user in a "good" state. By observing the environment and the user's choices, the robot identifies opportunities for action that can divert the user from reaching an undesirable state. For instance, in the example presented in the work, the system detects that the user has not taken their medication, despite the robot's warning and, knowing that this can lead to an undesirable state, the robot takes action and fetches the user's medication, thus compensating for their attitude. In this demonstrative trial, the authors show that the system can indeed identify opportunities and act proactively.

The authors of [26,27] present a robotic Intelligent Tutoring System (ITS), first presented in [6,28], that aims at aiding a child in learning how to read. The system maintains knowledge on the user's reading level, which it periodically evaluates and updates using an Active Learning technique. This information is then used to adapt the serious game that the child and system are playing, with the goal of enhancing their learning performance. The authors show that the system is able to interact with children of varying ages, and that children interacting with the adaptive system were able to learn more effectively.

Similarly, the authors of [7] present an empathic robot aiming at aiding a user learn Geography. The system keeps track of the user's skill levels, such as compass reading and map symbol knowledge, and adapts its actions to these levels. The authors gauged the user's perceived enjoyment, mutual understanding and trust, and found significant improvements in all measurements.

Joint tasks, tasks performed cooperatively between user and robot, are explored in [60]. The system, applied to the problem of moving a table out of the room, monitors the user's level of adaptability to the robot's optimal plan, and adjust its actions accordingly. As the user complies, or not, with the robot's suggested change of plans, the robot adjusts its model of the user and, thus, its actions. The system employs a Multi-Agent Markov Decision Process for decision making, and the authors have found that user preferred interacting with the adaptive version of the system, and found it more trustworthy.

Similarly, the authors of [16] present a system that aims at performing a joint task with the user. The system maintains a Theory of Mind representation of the user, namely of their task and beliefs. This representation is updated as the interaction takes place, with the robot also aiming at minimizing explicit instructions between it and the user. The authors evaluate the system in a table cleaning scenario, in tests with an undisclosed number of users, and conclude that the adaptive system can perform the task much faster than the non-adaptive alternative.

The authors of [8] present a system that aims at alleviating the workload of an operator behind a Wizard of Oz. The system maintains a model of the Wizard's action policy, i.e. when and how the user acts, which is updated as the user uses the system. Gradually, the system refines its representation of the user, to the point where it is able to replace them. The authors have used a two-robot setup, simulating an assisted learning scenario, for validating their technique, and have shown that the system does indeed alleviate the workload on the user while maintaining the same results in terms of child-robot performance.

In [9,10], the authors present a system that aims at adapting the coloured lights in a robot to the tastes of the user. The system relies on three basic preference profiles, which are adapted to each user via a technique akin to Reinforcement Learning. The authors did not test their approach with users, but have demonstrated its functionality in simulated scenarios.

User-adaptivity is explored, as a primary task, in the work presented in [34], which was also presented in [35–38]. The system learns the user's preferences, which are updated using interaction traces obtained as the robot repeatedly interacts with the user. The system makes use of an MDP formulation to recalculate its policy according to the user's preferences. Tests with 17 participants have shown that the users believe that the system can indeed adapt to its user, and that it progressively adapts to their needs.

The authors of [72] present a system that aims a cooperatively performing music with the user. The system makes use of Context-Free Stochastic Grammars, and is taught a baseline user profile in a dedicated interaction. During interaction with the user, the user can inform the system that they dislike the robot's musical decisions, which triggers a change in their preferences profile, and thus the system's actions. The authors performed tests with users, who reported that they found decreasing difficulty in producing music with the system, indicating the successful adaptation of the system to the users.

The Dialogue Manager of the SERROGA system is presented in [58,59]. This manager implements turn-based dialogue, which is made adaptive by the incorporation of the user's feedback on the Bayesian-like Dynamic Factor Graph of the system, adapting it to the user's preferences. The system was tested with real users in a 10-day test, and the users noted that the system was indeed able to change in accordance with their preferences.

A robotic recommender system [43] is presented in [47], aiming at aiding users in learning English. The system operates on the principles of classic recommender systems: it builds and maintains a preferences profile of the user, maintained in an ontology, regarding the serious games used for learning. This profile is updated during interaction via n-gram analysis of the events. The system relates this data with both data from the same and from other users to provide better suggestions to the user. A study with 12 participants has shown that the usage of this system improves the users' performance when learning.

An evaluation of various interactions is presented in [74], relying on a system that aims at learning from the user, eventually being able to carry out commands without explicit orders. The system maintains a model of the user's preferences, which evolves at every interaction. The system was tested with 25 non-expert users, and the authors conclude that the users prefer the adaptive system over the non-adaptive one.

4 Analysis and Research Gaps

In this section, we discuss the works presented in Sect. 3, uncovering research gaps to support future work. We perform our analysis according to the key system characteristics identified in 2.1, and present research gaps in each of the relevant dimensions.

4.1 Taxonomy Trends in User-Adaptive Systems

Figure 5 and Table 1 present an overview of the taxonomy in User-Adaptive HRI systems, complemented by an overview of the usage of psychological information on the user. It is visible that most works apply user models for adapting to the user. Furthermore, systems tend to gain their own information on the user, with the portion of works that are given the user model beforehand being relatively small. As seen in Fig. 5c, most of the systems update their user model during execution. Thus, most of the works surveyed fit the architecture of Fig. 4.

We have observed, in Sect. 3.1, that techniques that do not require a user model to operate tend to focus on a sin-

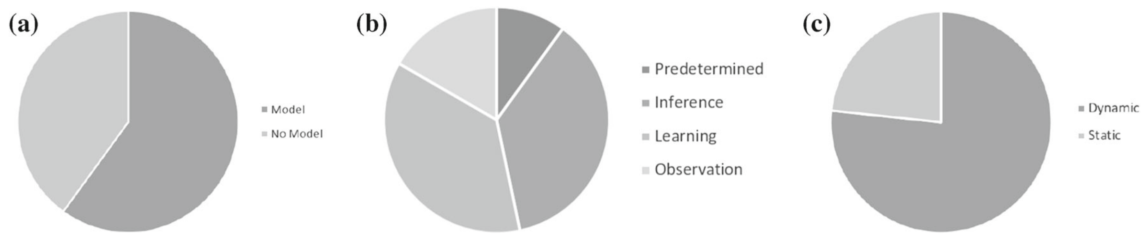

Fig. 5 Pictorial illustration of the usage of user models in the works under survey. **a** Usage of user models, **b** source of user data and **c** user data persistence

Table 1 User model types, source, persistence and usage of emotions and personality in user models

References	Data source	Persistence	Emotions	Personality
(a) Techniques with no user model				
[21]	Inference	Dynamic	No	No
[11]	Inference	Dynamic	No	No
[13]	Observations	Dynamic	No	No
[30]	Inference	Dynamic	No	No
[39]	Inference	Dynamic	No	No
[45]	Inference	Dynamic	No	No
[48]	Observations	Dynamic	No	No
[52]	Inference	Dynamic	No	No
[57]	Inference	Dynamic	No	No
[76]	Observations	Dynamic	No	No
[77]	Observations	Dynamic	No	No
[78]	Inference	Dynamic	No	No
[73]	Observations	Dynamic	No	No
References	Source	Persistence	Emotions	Personality
(b) Techniques with static user models				
[4]	Learning	Static	No	Yes
[41]	Learning	Static	No	No
[17]	Predetermined	Static	No	Yes
[22]	Predetermined	Static	No	No
[24]	Learning	Static	No	No
[68]	Predetermined	Static	No	No
[1]	Learning	Static	No	No
(c) Techniques with dynamic user models				
[8]	Learning	Dynamic	No	No
[10]	Learning	Dynamic	No	No
[16]l	Inference	Dynamic	No	No
[27]	Learning	Dynamic	No	No
[29]	Inference	Dynamic	No	No
[34]	Learning	Dynamic	No	No
[47]	Learning	Dynamic	Yes	No
[60]	Inference	Dynamic	No	No
[72]	Observations	Dynamic	No	No
[59]	Learning	Dynamic	No	No
[74]	Learning	Dynamic	No	No
[7]	Inference	Dynamic	Yes	No

gle attribute for adaptation. Furthermore, these techniques tend to adapt to the user in a reactive manner, continuously measuring the characteristic of relevance and updating their decision-making routines to compensate. Thus, these techniques tend to make use of decision-making techniques into which the user's attributes can be seamlessly integrated, examples of which include the POMDP, where the status of the user can be encoded as a hidden variable of the model.

These techniques lack the ability to distinguish users from one another, operating with complete ignorance as to the identity of the user. This results in, effectively, a generalization of user characteristics, according to the reactions they display to the stimuli generated by the system. In other words, if different users display the same reactions to the stimuli offered by the system, the system will operate in the same manner, regardless of user identity.

Systems based on user models, seen in Sect. 3.2, overcome this shortcoming by employing a model of the user which is given or inferred during the interaction, or in dedicated experiments. This model can be built in a personalized manner for each individual user. Thus, these systems gain the ability to adapt to different users and, if necessary, to adapt to different users according to their identity.

We can observe, in Fig. 5, that many of the systems surveyed are given part or the whole of the information used for adaptivity, and that this information remains static throughout execution. These techniques based on static models are unable to adapt to the changes of their users, or to evolve as they do. Information on the user is gained only once during the experiment, and cannot be changed to accommodate for the changes that the user may undertake. Therefore, these techniques appear to be better capable of dealing with larger numbers of differentiated users but are, at the same time, unable to deal with long-term interactions with single users.

This fact does not necessarily represent a drawback: some information on users changes very slowly or unnoticeably throughout the duration of the interaction, even if it lasts for long periods of time. For instance, systems based on personality, such as [79], can argue that this particular aspect of the user is subject to little change with age [81]. However, systems based on more transient aspects of the user, such as their preferences and habits, need to be able to readjust these characteristics to ensure long-term viability.

Lastly, systems based on dynamic user models, presented in Sect. 3.3, gradually learn and adjust the relevant characteristics of their users. These techniques represent the combination of the best qualities of both the other categories of systems: they are both able to adapt to several users, and to keep adapting as their users change. These systems have the additional advantage of not requiring a setup phase for profile determination or definition, nor manual gathering and introduction of user information.

Furthermore, systems based on dynamic user models are able to continuously improve their perspective of the user as time changes. This represents increased autonomy and robustness for the system: even if the user does not change, the system's initial perception of them may be partially incorrect, and these systems have the possibility of improving upon those errors. Thus, these systems are, in our view, the most appropriate for long-term interaction: as users grow and age, these systems have the potential to grow and age with them.

4.1.1 Research Gap: Psychological Trait Modelling

As seen in Table 1, there is very little attention dedicated to adapting systems to a user beyond the general usage of personal and behavioural data. However, characterizing users on a deeper, psychological level, can yield unprecedented satisfaction and acceptance levels[3]. Psychological measures on the user can include, for instance, their personality [83] or their emotional state [66].

The usage of Personality in Affective Computing, and thus HCI, is becoming a popular trend [82], but its presence in user-adaptive Social Robots seems to be relatively restricted. Very few of the works surveyed take into account the user's personality or emotional state, but those that do achieve positive results. This exposes research gap in the refinement of personality and emotional information to achieve higher levels of adaptation.

No technique that we have found combines the knowledge of the user's personality with the knowledge of other aspects, such as routines and preferences. Thus, psychological and behavioural analysis of the user seem disjointed in the literature, constituting another research gap. The combination of behavioural and psychological information can result a *holistic* profile of the user, which could be the bases for unprecedented adaptivity levels.

4.1.2 Research Gap: Learning New Users

As the user-adaptive system interacts with multiple users, it continuously learns their models. This process can potentially take large amounts of time and data. If the robot interacts with an unknown user, it will have no information on this user, and will have to adjust their model from the beginning. A solution for this problem is the matching of a new user to an existing model that exhibits the same initial characteristics as the new user. In practice, the system would use an existing model as a starting point, enabling the system to quickly adapt to an approximate view of the new user.

At first, this will result in a user model that suffers from an approximation error. However, as the system interacts with the user, it should be able to continuously adapt and, thus, correct the initial error. Furthermore, optimized learning strategies can be used for efficiently learning new users. Techniques such as Active Learning [12] and techniques based on Information Theory could be useful to optimize the information gathering procedure.

4.1.3 Research Gap: Big Data

Crowd-sourcing approaches are used by some techniques to improve their user-adaptive abilities. These works can be seen as a step forward, with respect to systems that learn solely from a reduced number of users, as they are able to leverage larger amounts of data for adapting to the user. A possible research line would be to explore the influence of Big Data and data mining techniques in the improvement of the adaptive abilities of embodied systems. Shedding the purpose-built model paradigm, a more generalized and extensible user model [42] could benefit from big data and data mining techniques by incorporating larger and more varied amounts of information on the user, potentially adapting to increasingly finer points of the user's characteristics. The Internet of Things may also be an instrumental addition to this paradigm, by providing continuous streams of additional multimodal data into the systems, which can then analyse it and extract patterns that inform the system on the user.

This can lead to the problem of *over-modelling* the user, in which too much data on the user is kept and never used in any of the system's functions. A possibly interesting line of future work is the study of this trade-off: the determination of *how much* data on different aspects on the user is relevant for adaptation, and if a saturation effect is achieved after a certain number of aspects or volume of data.

An important aspect of user-adaptive systems in HCI, such as recommender systems, is the manner in which these systems make use of inter-user information. In recommender systems, users are, for instance, clustered in representative groups[44] which can then be used for extrapolating the characteristics of users on which there is relatively little information. Other systems, such as [85], even explore the latent social connections between users to increase the level of adaptivity of the system. An interesting line of research could consist of the application of these techniques on user-adaptive Social Robots.

4.2 Adaptive Parameters and Decision Making

As seen in Table 2, the majority of the works under review uses as single adaptive parameter the decisions made by the system. In other words, these works adapt to the user in *what* they do. This allows systems to achieve a manner of *functional adaptation*, wherein their choice of actions is influenced by their information on the user. This leads to systems that are able to, for instance, navigate autonomously to where they believe they can best interact with the user. In the case of these systems, the adaptive process is intertwined with the system's own function, and its goal can only be achieved through adaptation.

On the other hand, a number of works adapts in *how* they interact with the user. This manner of *non-functional adaptation* allows systems to adapt the parameters of their actions, which translates into changes in their current speed or prosody, for example. These systems can achieve higher levels of adaptation without affecting their main function, decoupling the adaptive process from their main goal, which can be achieved with or without adaptation.

A smaller number of works adapts in both of these perspectives, changing both *what* actions they take and *how* they are taken. In these cases, the robot is, for instance, able to adapt both the way it conveys information, and what information better suits the user at that particular time. These systems take the adaptive process to a higher level, truly adapting both to the problem and user at hand.

4.2.1 Research Gap: Continuous Adaptation

An important requirement for a companion Social Robot is long-term viability. In order to ensure viability, a long-term companion should be able to live and cooperate with its users for extended periods of time with no intervention from technical personnel. As such, it must be able to learn from its users and continuously adapt to the changes it observes on its users.

An important number of surveyed works do indeed continuously adapt to their users, iteratively re-evaluating their users characteristics. However, these systems are the least developed, often relying on single measurements of their users, or not storing this information in a re-usable user model. This line of research is, thus, ripe with opportunity for future work, and may be the key for enabling Social Robots to live with their users in the long term.

Additionally, long-term viability enables the system to build true relationships with its user, as seen, for instance, in the Paro [84] and in [32,33] experiments. The further exploration of these long-term adaptive interactions, with more complex and complete adaptive mechanisms, could also constitute an interesting line of research.

4.2.2 Research Gap: User Adaptivity as a Layer

The techniques surveyed in this work cover a wide number of application areas, showing the usefulness of user-adaptiveness in many applications. In these applications, being user-adaptive, as mentioned before, is seldom them main task of the system. In our view, user-adaptiveness can thus be seen as transversal to all areas in which HRI is involved.

Table 2 Adaptive parameters, I/O modalities, Decision Making and Evaluation of the Social Robots under survey

References	Adaptive parameters	Input modality	Output modality	Decision making	Evaluation metrics	Evaluation process
(a) Social Robots with no user model						
[21]	Robot Speed	User's pose and speed	motor control	MOMDP	Distance to user and speed difference	Measurements
[11]	Decisions (take left turn)	Physical controls	image and sound	POMDP	POMDP Rewards, driving performance, perceived control, naturalness, similarity to real world, social appropriateness	Measurements, Questionnaires
[13]	Robot Speed	Odometry, Physical controls	motor controls	Fuzzy control	n/a	n/a
[30]	Decisions (object to move)	Speech, Gaze	Robot arm movement	Rule-based	Projection accuracy, prediction accuracy, response time, perceived awareness and intentionality	Measurements, Questionnaires
[39]	Decisions (room to clean)	User locations, task success	motor control	Rule-based	n/a	n/a
[45]	Decisions (Warn driver or intervene)	Physical controls	image and sound	Hidden Mode Stochastic Hybrid System	Time in safe and unsafe conditions	Measurements
[48]	Voice pitch	User speech	Robot speech	Rule-based	Perceived social presence, rapport, persistence and learning gain	Questionnaires
[52]	Robot's Navigation Goal	Physical Controls	Robot Commands	Rule-based	Recognition accuracy	Measurements
[57]	Robot speed and path	Physical Controls	Robot Commands	Rule-based	n/a	n/a
[76]	Robot's gestures	Vision, Speech	Robot Commands	Rule-based	Information distance, perceived gesture recognition, perceived behaviour performance, perceived social interaction, enjoyment	Measurements, Questionnaires
[77]	Decisions (when to speak, what objects to move)	Speech, Vision, Depth	Speech, Robot Commands	Rule-based	User's speech time	Measurements
[78]	Decisions (navigation goal)	Physical Controls	Robot Commands	POMDP	Robot path, state variables, destination probabilities	Measurements
[73]	Decisions (difficulty of items to present)	Speech	Speech	GOAL	Intrinsic motivation	Questionnaires
(b) Social Robots with static user models						
[1]	Decisions (placement of objects)	Crowd-sourced data	Robot controls	Rule-based	F-scores	Measurements

Table 2 continued

References	Adaptive parameters	Input modality	Output modality	Decision making	Evaluation metrics	Evaluation process
[4]	Robot's speech and gestures	Speech	Speech, Gestures	Rule-based	Preference towards a type of adaptation	Questionnaires
[41]	Decisions (how to dress the user)	User's pose, speech	Robot Commands	Rule-based	Task completion speed	Measurements
[17]	Font size, interface complexity, warning levels, robot location	n/a	n/a	Rule-based	n/a	n/a
[22]	Sound volume, robot speed, speech output gender, robot's name	Speech, touch	Robot commands, speech	Rule-based	Perceived usability, acceptance	Questionnaires
[24]	Decisions (how to dress the user)	User's pose, speech	Robot Commands	Rule-based	Classification accuracy	Measurements
[68]	Sequence of dance movements	User's pose	Robot commands	Rule-based	Gaze position, facial emotion, body language, perceived bond, satisfaction, amusement, anxiety, enjoyment, observed leadership and expectancy	Manual classification, Questionnaires
(c) Social Robots with dynamic user models						
[8]	Decisions (what interactions to perform with the user)	Physical Controls	Robot Commands	Rule-based	Human intervention ratio, child learning rate	Measurements, Questionnaires
[10]	LED Colours	Physical Controls	LED Colours	Rule-based	Cumulative reward from users, estimation error	Measurements
[16]	Decisions (Adaptation to user's choice of sub-task)	Vision, Speech	Robot Commands, Speech	Rule-based	Number of communications needed to instruct the user	Measurements
[27]	Reading difficulty level	Speech, Touch	Speech, Images	Active Learning	Number of words learned	Measurements, Questionnaires
[29]	Decisions (when to render services)	Speech, Touch	Speech, Images, Robot commands	Equilibrium Maintenance	Relevant opportunities for services found	Measurements
[34]	Decisions (when to take actions, including services and parameter adjustment)	Gestures	Sound, Projected images	MDP	User satisfaction, perceived coherence, ease of use, originality, perceived helpfulness, perceived adaptivity	Questionnaires

Table 2 continued

References	Adaptive parameters	Input modality	Output modality	Decision making	Evaluation metrics	Evaluation process
[47]	Decisions (what content type to learn)	Speech, Physical Controls	LEDs, Robot commands	Rule-based	n/a	n/a
[59]	Decisions (dialogues to execute)	Tactile sensors, sound, touch	Image, speech, robot commands	Dynamic Factor Graph	User opinion	Questionnaires
[60]	Decisions (where to move a shared object)	Vision, Physical controls	Robot commands	MAMDP	Ration of participants who changes strategies, perceived trustworthiness	Measurements, Questionnaires
[72]	Decisions (sounds to make)	Physical Controls	Sound (music)	Context-Free Stochastic Grammars	Number of user interventions, perceived difficulty, engagement, conformity, progression, speed	Measurements, Questionnaires
[74]	Decisions (where to guide the user)	Vision, odometry, robot position, user Attention, speech	Robot Commands, navigation	Rule-based	User opinion (score)	Questionnaires
[7]	Decisions (positive, neutral or negative output)	Facial expressions, electro-dermal data, RGBD, touch screen	Images, speech, gestures	Rule-based	Perceived enjoyment, understanding, trust	Questionnaires

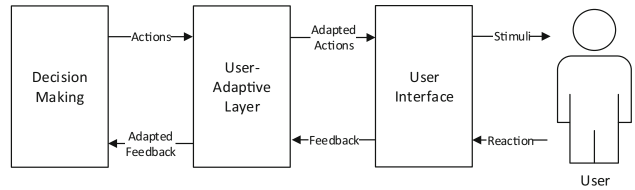

Fig. 6 User-adaptiveness as a layer in a generic system

As a future line of research, it could be interesting to explore the modelling of user-adaptive characteristics as a layer that can be applied to several HRI or HCI systems. This layer would be responsible for modulating the signals received from the user, and the actions decided by the decision-making modules, in a manner that was best adapted to the user. This comes as a natural consequence of the models presented in Sect. 2: user-adaptiveness can be seen as a layer between the user interface and decision-making blocks, as illustrated in Fig. 6. This paradigm would allow a larger number of systems and applications from benefiting from the advantages of user-adaptiveness.

4.2.3 Research Gap: Interaction with Multiple Users

Interactions with groups of users is becoming a trend in research. This type of interaction is an important factor in the integration of Social Robots as members of society, since group interactions among humans are very frequent. However, none of the surveyed work is able to interact with multiple users, which constitutes an important research gap.

4.2.4 Research Gap: User-Adaptive Robotic Perception

As noted in [61], user-adaptive behaviour can stretch beyond the synthesis of behaviour proper. Knowing the user more deeply can enable a system to better understand their actions and states, resulting in the application of user-adaptiveness not only to behaviour synthesis but also to *perception*.

Artificial perception is already a very active field of research [20], and it requires intricate systems to achieve interesting results. The addition of a user-adaptive layer to perceptive systems would likely increase their complexity, but would also likely significantly increase their performance, as seen in [86].

Some works on user-adaptive perception exist, such as [71] for colour description systems, but this line of research is, to the best of our knowledge, unexplored in interactive social robotic systems. Thus, endowing an adaptive robot with the ability to adapt its perceptive abilities as well constitutes a research gap.

4.3 I/O Interface

Regarding the user interface used by these systems, Table 2 presents the interaction modes used by the surveyed works. We can observe that, unlike systems dedicated to HCI, Social Robots employ a myriad of different interaction modalities. Social Robots can make use of natural communication channels to express themselves, resulting in the increased expressiveness noted, for instance, in [4]. Furthermore, we observe that a significant number of systems make use of more than one interaction modality, combining of speech and other channels.

We can observe that speech is, by far, the most popular choice of interaction modality. This trend is to be expected, since speech is one of the most natural communication channels for humans, and speech analysis and synthesis have been the focus of significant attention in recent years.

Humans also communicate through two additional channels, aside from verbal: non-verbal, usually consisting of gestures, and paraverbal, namely via prosodic changes. The paraverbal channel, as far as we know, has been seldom explored in user-adaptive robots, with only a few works making use of it. However, the non-verbal channel, namely gestures and physical interactions such as moving robots and objects on a table, seems to be gaining popularity among researchers, with a number of techniques adopting these modalities.

4.3.1 Research Gap: Physical and Haptic Systems

Physical interaction is an important aspect of human relationships, and is a hallmark of intimate interpersonal relationships. However, with the exception of the robotic walker systems of Sect. 3.1, we could not find any systems able to interact physically with the user *in an adaptive manner*, i.e. in which the physical interaction itself was adapted to the user's behaviour or characteristics, despite there being an important body of physical HRI work, such as [46]. While some systems do employ physical controls, as seen in 2, none of them employ touch as an adaptive parameter or adaptive output modality.

With the advent of haptic systems, it could be interesting to explore the impact of user-adaptive, touch-based physical interaction on the objective and subjective measurements employed in the evaluation of these systems.

5 Maturity of User-Adaptive Systems

In this section we perform an analysis of the maturity of current state of user-adaptive robots. We aim at determining the overall readiness of user-adaptive technologies, and in identifying the main obstacles impeding further progress.

5.1 Experimental Maturity the Surveyed Works

User skill level One important aspect of mature systems is the ability to deal with their end-users, as opposed to technical personnel. We can observe that solutions with no explicit model of the user tend to be tested with more end-users. This indicates a higher maturity of no-model systems when compared to the remaining classes of systems, which can be attributed to the fact that these tackle simpler problems, and constitute simpler solutions.

As seen in Table 3, the most popular test subject of these works is the non-expert user (e.g. students), i.e. users that, while not proper end-users, are also not part of the system's development. This points at a lack of readiness in the field: the prevalent use of students as test subjects indicates that the systems are not mature enough to be presented to the end-users. This constitutes a technological challenge.

This is not a problem of research *per se*, as the scientific principles in question can still be demonstrated on non-end-users. However, in order to progress technologically, it is important that the end-users be involved in the final stages of development, thus providing important insight into whether the systems under development *actually* fit their needs.

Long-term scenarios Long-term test scenarios are an unavoidable obstacle in the development of these systems. Passing a long-term test indicates maturity in the system, and is necessary, in our view, to classify a system as over TRL4. However, the very definition of "long-term" is of an ambiguous nature. For our purposes, we define "long-term" as a trial that takes place for over 5 or more consecutive days. Only one of the adaptive systems under review [59] has successfully performed long-term tests, albeit of only 10 days. In fact, the trend points to very short test sessions with the users, of only a few minutes, which last only long enough to provide insight into the principles at work. These short sessions tend to be sufficient to demonstrate the intended research, and are thus the most popular method.

However, in technological terms, long-term interaction is key for the maturity of HRI systems, namely domestic Social Robots. In this case, robots should be able to interact continuously or intermittently with their users for months or years of use, as is the case with current consumer electronics. This indicates another technological challenge in the field: long-term tests are demanding, from a technological standpoint, to orchestrate, leading to a tendency to produce proof-of-concept systems with little impact on society.

Relevant environments Another important aspect of a technology's overall maturity is its ability to be tested outside of the highly-controlled environment of a laboratory. However, we can observe that the vast majority of works has not yet left the laboratory. This fact reveals another technological

Table 3 Readiness metrics of the surveyed Social Robots

References	Environment	Participants	Participant expertise
(a) Social Robots with no user model			
[21]	Lab	1	Undisclosed
[11]	Lab	35	Non-expert
[13]	Lab	Undisclosed	n/a
[30]	Lab	26	Non-expert
[39]	n/a	n/a	n/a
[45]	Simulation	Undisclosed	Undisclosed
[48]	Lab	48	Non-expert
[52]	Simulation	n/a	n/a
[57]	Lab	35	End-users
[76]	Lab	23	Non-expert
[77]	Lab	15	Non-expert
[78]	Lab	1	Undisclosed
[7]	Target-like Environment	51	End-users
[73]	Target-like Environment	22	End-users
(b) Social Robots based on static user models.			
[4]	Lab	21	Non-expert
[41]	Lab	2	Undisclosed
[17]	n/a	n/a	n/a
[22]	Relevant Environment	49	End-users
[24]	Lab	3	Undisclosed
[68]	Relevant Environment	12	End-users
[1]	Lab	15	Non-expert
(c) Social Robots based on dynamic user models.			
[8]	Lab	10	End-users
[10]	Simulation	n/a	n/a
[16]	Lab	Undisclosed	Undisclosed
[27]	Lab	49	End-users
[29]	Lab	1	Undisclosed
[34]	Lab	17	Undisclosed
[47]	Lab	12	End-users
[60]	Simulation	69	Non-expert
[72]	Lab	8	End-users
[59]	Lab	16	Expert Users
[74]	Lab	25	Non-experts

challenge: these systems could benefit from technological transference into mature, commercial systems.

5.2 Metrics and Standardization

Adaptivity is seldom the main task of the described systems. Indeed, this is to be expected: user-adaptiveness in and of itself offers little utility to the user. However, this results in a well-observable disparity in the measurements used for evaluating the performance of the adaptive effort. The performance measurements used by the surveyed works (Table 2) can be split into three basic types:

- Introspective measurements, such as POMDP rewards or classification accuracy;
- Interaction measurements, such as speech time, automatic measurements that relate to the user's experience with the system;
- Subjective measurements, such as ease of use, assessing the user's experience with the system through questionnaires.

This results in a lack of standardization, and thus maturity, in the field.

Introspective measurements provide little to no information on the user's experience with the system. Mostly, these measurements show that the system was able to achieve some self-motivated goal, such as achieving a high POMDP reward, or a high confidence as to the user's characteristics. They typically demonstrate that the system's mathematical intricacies work as designed, and approximate reality as closely as the authors intended. However, these cannot be trivially related to the user's experience with the system, providing little insight as to the actual impact of the adaptive process on the user.

On the other hand, subjective measurements, such as user acceptance [15,74] and user satisfaction [50], are able to provide deep insight into the user's experience in the system, and provide objective and empirical information on the user impact of the adaptive system. Many of the works under survey employ questionnaires in some way or another, demonstrating that their adaptive processes do indeed produce the intended impact on the users, be it ease of use, perceived bond, among others. However, if a system's goal is to be as autonomous as possible while having measurements as to its own performance on user adaptiveness, these measurements suffer from a major flaw: they are not automatic, and require extensive human intervention, not only in their administration, but also in their interpretation.

On the middle ground, interaction measurements such as user intervention time provide limited insight into the system's impact on the user, and allow for further personalization based on those metrics. These measurements are able to close the interaction loop, providing the system with online information on how its action are influencing the user. Automatic performance metrics are a desirable trait of an autonomous system, since they enable the robot to evaluate its own performance, and apply, for instance, techniques for self-rewarding [75] and self-motivated reinforcement learning. However, they tend to be extremely domain-specific, and not generalizable to other types of interaction.

However, there is a lack of a unified metric, or standard set of metrics, that can objectively measure the performance of user-adaptive systems. Interaction measurements, measured automatically, can possibly constitute a viable first step towards a solution to this problem. Autonomy in this measurement is, thus, an indispensable requirement for the robot's overall autonomy. Thus, an interesting avenue of future work would be to automatize subjective metrics or, from the other perspective, devise interaction measurements that can be empirically validated.

For these reasons, we have opted for not including the results obtained by each individual technique in Table 3, as their comparison would be meaningless.

5.3 Open Databases

An important characteristic of mature research areas is the ability for different works to compare their results against one another. The standardization of metrics, discussed in Sect. 5.2 is an important factor in this comparison. Common datasets are also an important factor, as they provide the common basis upon which each system will work.

The surveyed works seem to each operate on their own data. This constitutes a problem when it comes to comparing different techniques, as it removes the important common ground for comparison. Thus, it may become important in the future to build a database of domestic usage of robots, such as those found commonly for Computer Vision [23] and Action Recognition [70].

5.4 Usability and Acceptance

The technologically-mature systems we can observe on the market today tend to exhibit the following characteristics:

- Ease of use;
- Low versatility: focus on a single function;
- Robustness and fault tolerance.

These characteristics stem from a simple design pattern that can be found across these systems: their interface is maximally simplified, allowing a large majority of users to use them successfully. By simplifying the interface design to a point where any person, regardless of expertise, is immediately able to understand how they can reap the benefits of the use of the robot. For instance, the user interface of the Roomba robot is reduced to a large button in the centre of the device labelled "CLEAN". This enables any user, from any demographic, to make use of the robot: they simply press the largest button on the device, and it works.

Similarly, the Paro robot, one of the most successful among our examples, also features a reduced interface. It communicates only via the non-verbal channel, and emulates, as closely as possible, the behaviour of an immobile pet. Since users are accustomed to interacting with animals, interaction with Paro becomes natural, despite the simplistic adaptive facilities of Paro. However, this simplicity comes at a price: Paro is not a versatile solution, although it is very successful at its single intended function.

This form of *interface reduction* can be seen as one of the ways to design a system for the majority of users, and it is currently one of the most successful strategies for ensuring wide acceptance and usage of user interfaces. However, it is impossible, except in very concrete cases, to lower the difficulty of the interface of a complex system to such a level where everyone can use it flawlessly. Furthermore, it is a relatively straightforward process to simplify the interface of a single-function device, but becomes increasingly harder as devices become more complex and versatile, as is the case for many robots.

We propose user adaptiveness as an alternative solution for designing systems for every user. By detecting (or learning) that a user is experienced in the usage of a device, a user-adaptive system can stimulate the user into learning more about the device itself and making use of more advanced functions. Thus the system becomes almost a "tutor of itself", potentially lowering the knowledge entry barrier of these systems to even lower levels than those that can be achieved by extremely simplified interfaces by exploiting the natural processes already in place in the human mind.

5.5 Ethical Considerations

A clear technological hurdle is the necessity of these systems to make use of personal data for adaptation. Indeed, some of the most intricate user-adaptive robots make use of extremely sensitive information, such as the user's personality and emotional patterns.

Users are naturally reluctant to supply this information to systems they do not know, and with no knowledge of how this information can be used in the future. This issue is tackled, in lab tests, by making data anonymous and employing transparent procedures in data collection and manipulation. However, as noted before, commercial systems are naturally opaque. This leads to opaqueness in the treatment of personal user data, akin to the phenomenon observed in services such as Google accounts.

The Paro robot has effectively side-stepped this issue. It has become a successful system while not employing identifying or personal information on its user. However, complex systems cannot take the same route, and will inevitably need to manipulate the personal data of their users.

Table 4 A summary of the research gaps uncovered in this analysis

Gap	Temporal Scope	Description
Psychological Trait Modelling	Short-Term	There is little work based on psychological constructs.
Learning New Users	Short-Term	There is a need for improved learning mechanisms for efficiently learning users.
Big Data	Short-Term	There is a gap in the application of Big Data techniques in this context.
Continuous Adaptation	Long-Term	No works have explored the long-term viability of user-adaptive robots.
User Adaptiveness as a Layer	Long-Term	Can user-adaptiveness be applied generically to all robotic tasks with users?
Interaction with Multiple Users	Short-Term	None of the works surveyed are able to interact with multiple users simultaneously.
User-Adaptive Perception	Long-Term	Little work is devoted to adaptive perception on robots.
Physical and Haptic Systems	Short-Term	Little work is devoted to user-adaptive physical interaction with the user.

On the other hand, the GrowMeUp Project [51] has opted for embracing its use of personal data, instead defining a protocol that adheres to the regulations of the countries involved in the studies conducted. This solution is suitable when there are regulations in place that account for the novelty of interactive robots. However, obsolete and restrictive regulation can hinder the performance of studies that could be of vital importance to the development of these technologies. This issue stretches beyond the domain of user-adaptive systems, and the solution to this problem will have to be found for personal and social robotics as a whole. This, the problem of privacy and data regulation pose yet another technological and societal hurdle that user-adaptive systems need to overcome.

5.6 Key Elements Towards Mature Systems

One of the main indicators of technological maturity is the demonstration of its functionality in the operational environment—the user's home, in the case of domestic systems Some of the systems under review already make use of target-like environments, such as purpose-built rooms. However, in order for technological progress to be achieved, these solutions need to operate autonomously with no supervision at the users' homes which, to the best of our knowledge, none of the surveyed systems has.

Furthermore, the system should be tested in operating conditions, which involve long-term presence in the home of the end-user. This poses a number of scientific and technological problems, namely the study of the long-term impact of Social Robots in human environments and the development of solutions able to operate for extended periods of time. None of the systems under review have been tested for extended periods of time in the homes of the end-users, thus exposing another technological gap.

Similarly, it is important to transition from non-expert users to end-users. Instead of employing non-expert users and corridor sampling techniques in their development, user-adaptive systems need to be tested with end-users. These tests allow for the gathering of crucial feedback that can be used to improve the technology towards the end-user, not necessarily towards scientific developments.

This technology is, thus, on the verge of achieving success. It needs only to overcome three main transitions: to the target environment, to operational conditions and to end-users.

6 Conclusion

6.1 Research Gaps in User-Adaptive Systems

Table 4 presents a summary of the research gaps uncovered on this survey. These gaps constitute one of the main outcomes of this analysis: the potential lines of future research that were uncovered by this work.

We can observe that a number of research gaps still remain to be explored. In general terms, user-adaptive robots need to evolve to match the developments that were observed in the field of HCI over the last few decades. Concretely, there needs to be an agreement among researchers as to the proper evaluation techniques of user-adaptive techniques, which consequently would lead to the creation of open databases for benchmarking. Furthermore, user-adaptiveness can be taken to the next level by the employment of user-specific psychological information, such as personality traits, mood or even psychological disorders, which would potentially extend the application range of these systems from the domestic to the clinical environment. Lastly, all of the surveyed works focus on user-adaptive *actuation* in some form. This leaves open the field of user-adaptive *perception*, which would allow a system to adapt its analysis of incoming data to the user it is currently interacting with, potentially improving the performance of state-of-the-art behaviour analysis systems.

6.2 Overall Readiness of User-Adaptive Systems

In order to determine the overall status of the field, in technological terms, we have performed a general TRL analysis of

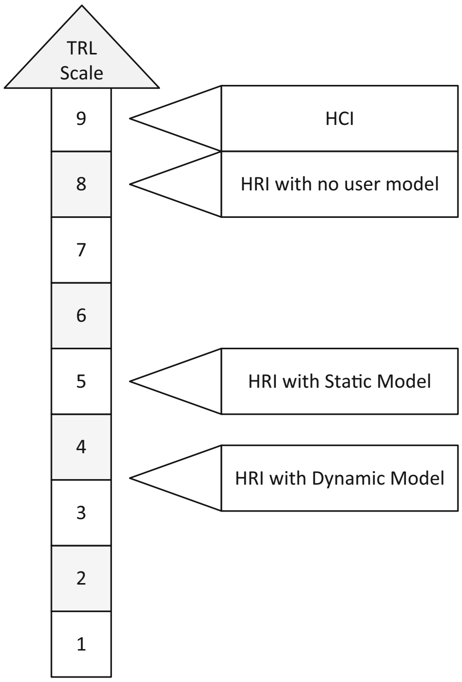

Fig. 7 Illustration of the general TRLs of the surveyed techniques

the systems described above. The categorization of mature systems is hindered by the opaqueness of the commercial systems under study. Since none of the mature systems have published, to the best of our knowledge, any details on how they handle their data on the user, it is impossible to categorize them unequivocally. For instance, the Buddy robot seems able to know its users' name and age, but *how* that information is gained, which constituted the tipping point of our analysis, is not disclosed. A notable exception is Pepper which, according to the information available, can be assumed to have a no-model adaptive interface based on emotions. As such we will not categorize the remaining systems in this discussion.

Systems that make use of no explicit user model for adaptivity, such as Pepper, are very close to mass public availability. Adaptive systems of this nature have been tested in relevant scenarios both in scientific and non-scientific scenarios, and have shown their ability to operate in a variety of scenarios. Systems of this nature are well-established in the realm of HCI, and are becoming so also in HRI. Taking into account the success of the Pepper robot, and the underlying scientific research on this category of systems, they can be classified, overall, as TRL 8.

Systems that make use of static models have been, as illustrated in Table 3, tested in target-like environments, such as model homes or controlled home-like environments. The absence of these techniques in technologically mature robots dictates the insertion of these techniques in TRL 5. Similarly, techniques relying on dynamic user models seem to never have left the laboratory and, as such, can be classified as TRL 3. This analysis is illustrated in Fig. 7.

6.3 Closing Remarks

In this work we have provided an overview of the state of the art on user-adaptive Social Robots.

We have performed a twofold exploration of the state of the art. Firstly, we have explored the scientific aspects of the field, and have enumerated and analysed a number of currently-published systems. Secondly, we have explored the technological status of the field, determining a number of technological hurdles that must, in our view, be surmounted in order to achieve technological maturity.

Indeed, by observing Table 3 and Fig. 7, we can conclude that all of the academic systems analysed in the previous sections inhabit TRL levels ranging from 1 through 5. Conversely, user-adaptive systems in HCI can be easily categorized as TRL 9, as there are already user-adaptive solutions in broad use, e.g. recommender systems. Thus, there is a clear technological gap between HRI and HCI in this matter, which can provide an interesting platform for future developments.

In general terms, we can conclude that user-adaptive systems are harnessing the attention of researchers from several fields, in an apparent renaissance of the field since its inception in HCI. We believe that user-adaptiveness in itself constitutes an interesting and rich field of research, and will aim to further scientific knowledge in this area in the future.

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Compliance with ethical standards

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

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