Encoding Guidelines for a Culturally Competent Robot for Elderly Care

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***Abstract*— The functionalities and behaviours of socially assistive robots for the care of older people are usually defined by the robot's designers with limited room for runtime adaptation to meet the preferences, expectations and needs of the assisted person. However, adaptation plays a crucial role for the robot's acceptability and ultimately for its effectiveness. Culture, which deeply influences a person's preferences and habits, can be viewed as an invaluable "enabling technology" to achieve such level of adaptation. This paper discusses how guidelines describing culturally competent assistive behaviours can be encoded in a robot to effectively tune its actions, gestures and words. The proposed system is implemented on a Pepper robot and tested with an Indian persona, whose habits and preferences the robot discovers and adapts to at runtime.**

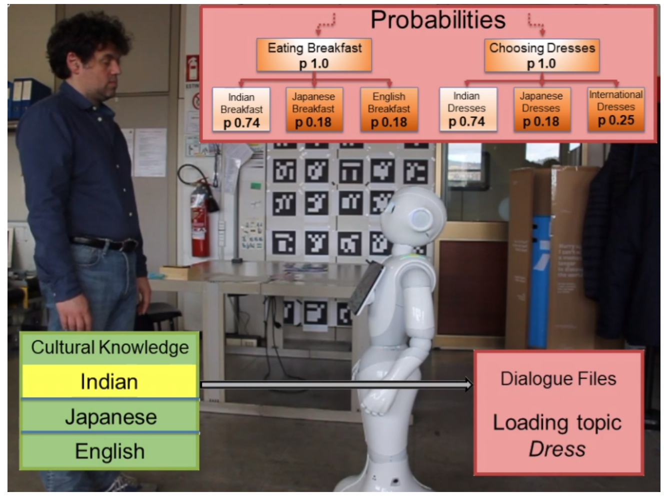

Fig. 1: The culturally competent robot meeting Kabir.

I. INTRODUCTION

The design and development of assistive robots for older people is a broad and long research avenue [6]. An analysis of the literature in the field suggests that two different, and complementary, approaches have been adopted.

Physically assistive robots focus on supporting the person in the execution of physical activities, usually identified starting from the Activities of Daily Living used by gerontologists to assess the level of autonomy of a person [14], [13]. Common functionalities for such robots include aiding mobility, eating, bathing, toileting, getting dressed, as well as performing basic household chores [16], [8], [5], while their social interaction capabilities are typically primarily devoted to facilitate the fruition of the offered services by the user.

Socially assistive robots, conversely, use social interaction as a mean in itself for enhancing health and psychological well-being of older people, e.g., motivating users to maintain a healthy lifestyle, guiding them in the execution of daily activities and providing companionship [4], [17], [1].

Recent works, stemming from the closer and closer interaction between roboticists, healthcare professionals and social scientists, tackle the problem with a user-oriented perspective, aiming at designing assistive robots with functionalities that have been proposed by or discussed with possible end-users, formal and informal caregivers, and medical personnel [3], [18], [20]. Identified functionalities include: reminding of important information (e.g., phone numbers) and events (e.g., birthdays); contacting relatives or medical help in case of emergencies; providing entertainment (with the robot possibly acting as a mediator towards other home appliances, such as the TV); providing step-by-step assistance in daily activities (e.g., reminding to take medications at the right time, guiding the user throughout the house to reach a specific room or object, displaying step-by-step instructions on how to perform an activity, as the robot in Figure 1 does about dressing); supporting the user in the interactions with friends and relatives (e.g., recognizing their faces, reminding of facts about them); proposing daily schedules every morning and revising them in the evening, in light of the day's events, to encourage people towards an active life and train their memory.

It is interesting to notice that most of the desired functionalities not only require the assistive robot to possess social interaction capabilities (such as reminding of information and events), but also, even more so, stress the importance of *personalized* social interaction, which requires the robot to know its user, his/her preferences, customs and beliefs, and adapt to them both its actions and modes, to be effective. Intuitively, the success of entertainment, a daily schedule, or a suggestion, evenly depends on how well the content fits with the user's preferences, habits and needs, and how familiar and appropriate the way in which the content is conveyed appears to the user. In line with this finding, an analysis of 86 studies in 37 different study groups [12] mentions person-centered care, multi-modal interaction and the modelling of cultural diversity among the key suggestions to improve existing socially assistive robots for older people and increase their effectiveness in enhancing the well-being of the person and reducing the burden on the caregivers.

Beside the above study, it is well-established that culture

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plays a key role in the context of *personalization*, since it influences individuals' lifestyles, personal identity and their relationship with others within and outside their culture [15], as well as with robots [19], [2]. As a consequence, endowing a robot with cultural knowledge makes it more aware of culture-related preferences, traditions and needs, and allows it to behave more competently, tuning its behaviour to meet the customs and expectations of the user [7].

As part of a joint effort towards the development of a culturally competent robot for elderly care[1], experts in Transcultural Nursing have led the development of guidelines defining the behaviour and functionalities of a culturally competent robot for older people, linking cultural knowledge and perceptual information to actions and utterances[2]. The guidelines are complemented by the $\mathcal{ADORE}$ model, allowing the robot to revise the cultural knowledge at runtime, to better tune its behaviour to the needs and preferences of the specific person it assists, avoiding stereotypes.

Building on that work, this paper presents a solution for encoding the guidelines and the $\mathcal{ADORE}$ model in the knowledge base of a robot, allowing them to effectively drive the robot's actions, gestures and words.

The article is organized as follows. Section II describes the guidelines and the $\mathcal{ADORE}$ model, while Section III details the solution we propose for encoding them in the knowledge base and interaction mechanisms of the robot. Section IV discusses an implementation case study involving the interaction between a Pepper robot and an Indian persona named Kabir. Conclusions follow.

II. Guidelines for Culturally-Competent Robots

Figure 2 illustrates with black arrows the procedure adopted for the definition and refinement of the guidelines and the $\mathcal{ADORE}$ model. As a first step, informed by the work of Hofstede [11] and Papadopoulos [15], researchers in Transcultural Nursing have developed a number of "scenario tables", describing a daily routine or situation and indicating the robotic capabilities needed to assist the older person in that case, in a culturally appropriate, sensitive and acceptable way. Convergence to suitable and feasible robotic capabilities (ideally, implementable on an off-the-shelf robot platform, possibly operating in a smart ICT environment) is achieved by iterative revisions incorporating feedback from roboticists and Transcultural Nursing researchers. The guidelines are then extracted by the researchers in Transcultural Nursing from the scenario tables, as a corpus of information and rules aimed at mapping the notion of cultural competence onto the data structures and algorithms defining the robot's behaviour, and iteratively refined integrating feedback from independent experts, observations in care homes, Transcultural Nursing and robotics researchers. Two types of guidelines can be identified: (i) information and rules describing the influence of one or more cultures on the robot's behaviour, that can be encoded in the robot offline (the actual *guidelines*); (ii) design principles and requirements for the procedures used by the robot online, to revise its knowledge and adapt to the user (the $\mathcal{ADORE}$ *model*).

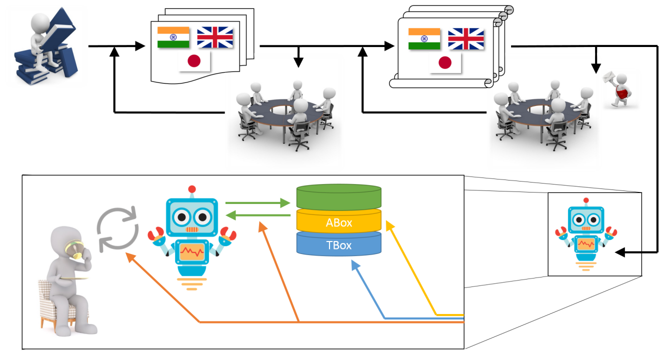

Fig. 2: The workflow (denoted with black arrows) adopted to devise, refine, and encode in the robot the guidelines. The zoom box highlights the contribution of this article. Culture-specific information encoded in the guidelines is mapped onto the TBox (blue) and ABox (yellow) of an ontology, and used by algorithms and structures for runtime Assessment & Adaptation to the user's preferences (green). The $\mathcal{ADORE}$ model (orange) influences both such algorithms and directly the way in which the robot interacts with the user (grey).

Concretely, the guidelines have been designed for a Pepper[3] humanoid robot interacting with elderly end-users of English, Indian and Japanese heritage, living in care homes located in the UK and in Japan[4].

A. Guidelines

Taking as a reference the robot's planning and sensorimotor capabilities, the guidelines include information and rules that have an impact upon the following main areas:

- *Goals*. The user always has the last word in choosing what the robot should do for her. However, the robot might proactively make suggestions, and some of them might depend on cultural factors. What activity should the robot suggest the user to engage in before lunch? Cooking – and what menu?, praying – and how? What will the user most likely want to be reminded of? Social or cultural events – and which ones?, TV shows?
- *Actions and their parameters*. Different cultures may use different actions to convey the same concept. How should the robot greet the user? Waving, bowing, or with a Namaste[5]? What volume would the user be comfortable with? What distance while interacting?
- *Norms*. Behaviours which are common in one culture might be unacceptable in others. Are there areas of the

[1]CARESSES, Culture-Aware Robots and Environmental Sensor Systems for Elderly Support: `https://caressesrobot.org`

[2]Detailed guidelines to achieve a cultural competent robot's behaviour can be found on the CARESSES website, in the Research section.

[3]Pepper is developed by SoftBank Robotics.

[4]This decision is motivated by the CARESSES experimental phase: Indian and English end-users will be recruited among the residents of the care homes of Advinia HealthCare, a UK partner of the project, while Japanese end-users will be recruited among the residents of the HISUISUI care home, located in Japan.

[5]A slight bow with hands pressed together, palms touching and fingers pointing upwards, thumbs close to the chest.

TABLE I: Examples of guidelines defining culture-specific goals, actions, parameters, norms and topics of conversation

Condition	Group	Topic/Rule	Questions	Sentences/Actions	$\mathcal{ADORE}$	Source	Likeliness
Mid-morning	Japanese	Engage in exercises	Can you see the instructor from here? Let's try a little harder!	[Imitate the motions of the instructor]	$\mathcal{A}$ssess, $\mathcal{D}$o	S+O	High
Mid-afternoon	Japanese	Sing a song	Let's sing a song together. Do you have something to sing? It's autumn, so how is "red dragonfly"?	[Sing songs]	$\mathcal{D}$o, $\mathcal{O}$bserve	O	High
Lunch-time	All groups	Remind about activities	Dear... it is lunchtime now. Would you like to walk to the dining table?	[Offer to accompany the user to the dining table]	$\mathcal{A}$ssess, $\mathcal{D}$o	S+O	High
Whenever nodding	Indian	Move the head side to side			$\mathcal{D}$o	L+O	High
Whenever nodding	English	Move the head up and down			$\mathcal{D}$o	L+O	High
Upon entering the bedroom	All groups	Ask for permission	May I come in?	[Act in accordance with the person's answer]	$\mathcal{A}$ssess, $\mathcal{D}$o, $\mathcal{O}$bserve, $\mathcal{R}$evise	L+O	High
Afternoon	English woman	Talk about hobbies	Do you have any hobbies? Do you belng to any clubs such as bridge, choir, women's club, book club?	I know that the Women's Association runs many local clubs and they do useful charitable work. I also understand that book clubs are popular with many women.	$\mathcal{A}$ssess, $\mathcal{D}$o, $\mathcal{O}$bserve, $\mathcal{R}$evise	S	High
Afternoon	Indian	Talk about movies	What is your favourite Hindi movie? Who is your favourite actor/actress? Do you like action movies? Or love stories?	I know that Bollywood movies are very popular. I know that Amitabh Bahchan is a famous Indian actor. Do you like him? I also know Shah Rukh Khan. What do you think about him?	$\mathcal{A}$ssess, $\mathcal{D}$o, $\mathcal{O}$bserve, $\mathcal{R}$evise	S+O	High

house that should be off-limits for the robot? Does the answer depend on the time of the day? What is the user likely to consider as private?

- *Topics of conversation*. Different cultures might have different histories, customs and traditions, which influence the lifestyle of people. What are the topics a user might like to talk about? Is she interested in sports, movies, politics or social activities? And if so, which sports, which types of movies could the robot suggest? Topics of conversation are also those activities in which the robot might assist the user, independently from any physical assistance it might also provide. Could the user be interested in discussing pizza toppings? Could this motivate her to bake a pizza herself? Or to call her friends for an evening out?

The above list discusses cultural factors which have a direct impact on the robot's behaviour, but culture might also play an indirect role. As an example, consider the appliances and furniture inside a house: they are influenced by cultural factors, and they influence the robot's perceptual system (Is it an emergency if the robot sees a person lying on the floor? What if there is a tatami on the floor?).

Table I reports a few examples of guidelines. Each guideline specifies the *Condition*(s) in which it is applicable (e.g., in the afternoon), the cultural *Group* it relates to, the corresponding *Rule* or topic of conversation, *Questions* and *Sentences* that the robot may use for engaging the user and acquiring new person-specific knowledge about her preferences. The $\mathcal{ADORE}$ column specifies the relation between the guideline and the steps in the model, and it will be discussed in the next Section. The *Source* column reports the source of the information used to produce the guideline (the *S*cenarios, direct *O*bservations performed by experts, *L*iterature evidence, etc.). Lastly, the *Likeliness* column provides an estimate of how likely it is that the guideline, written for a cultural group (i.e., encoding *culture-specific knowledge*), may be applicable to the person that the robot is interacting with, i.e., providing an estimate of how reasonable it is to encode this guideline as a-priori *person-specific knowledge*. As an example, the last guideline of Table I states that it is reasonable (highly likely to be true) to assume that an Indian person likes Bollywood movies, and defines suitable times, sentences and suggestions for the robot to bring up the topic.

B. $\mathcal{ADORE}$ model

Consider again the last guideline in Table I. However popular Bollywood movies are, it would be very wrong to simply assume that *all* Indian persons *surely* like them. As a consequence, the robot should know how to properly use this culture-specific knowledge at run-time, to drive its interaction with the user and the acquisition of person-specific knowledge. This is specified by the $\mathcal{ADORE}$ model, which identifies five steps:

- $\mathcal{A}$ssess the components of a *goal*, an *action* and its *parameters*, a *norm*, a *topic of discussion*, etc., with cultural awareness, knowledge and sensitivity;
- $\mathcal{D}$o / implement a *goal*, an *action* and its *parameters*,

a *norm*, a *topic of conversation*, etc., with dignity and cultural compassion;

- $\mathcal{O}$bserve the implementation of a *goal*, an *action* and its *parameters*, a *norm*, a *topic of discussion*, etc., with cultural awareness at visible levels;
- $\mathcal{R}$evise the components of a *goal*, an *action* and its *parameters*, a *norm*, a *topic of conversation*, etc., in partnership with the person;
- $\mathcal{E}$valuate the impact of the implementation of a *goal*, an *action* and its *parameters*, a *norm*, a *topic of conversation*, etc., with cultural competence through the application of ethical principles.

The $\mathcal{ADORE}$ model is "dynamic" and "spiral" in nature, playing a role similar to feedback-based models for autonomous agents behaviour (e.g., Reinforcement Learning): its steps shall be iteratively applied to refine the robot's assumptions and actions towards the ultimate production of behaviours that best suit the user's preferences and needs.

For example, culture-specific knowledge encoded in the last guidelines of Table I ($\mathcal{A}$) might drive the robot, one afternoon, to bring up the topic with its Indian user, inquire about her preferences and suggest her to watch a popular Bollywood movie ($\mathcal{D}$). On the basis of the person's response ($\mathcal{O}$), the robot might infer that its user doesn't actually like movies much ($\mathcal{R}$), and, as a consequence, reduce the probability of discussing that topic of conversation.

III. Encoding Guidelines in the Robot

The zoom box in Figure 2 shows the rationale for the encoding of the guidelines and the $\mathcal{ADORE}$ model in the robot. The core of the system is a Cultural Knowledge Base (CKB), whose main component is an ontology. Ontologies are a formal naming and definition of the types, properties, and interrelationships of the entities that exist for a particular domain of discourse [10]. The terminology defining the domain, containing general properties of concepts, is stored in the terminological box (TBox) of the ontology, whereas knowledge that is specific to individuals belonging to the domain is stored in the assertional box (ABox).

In accordance with the guidelines, the CKB includes:

- The TBox of the ontology (blue cylinder in the Figure), which includes terms from existing upper and domain-specific ontologies as well as *culture-generic knowledge*, i.e., the terminology required to represent the concepts related to *goals*, *actions* and their *parameters*, *norms*, *topics of conversation*, etc., for all the cultures considered in the knowledge base (and ideally for all the cultures of the world).
- The ABox of the ontology (yellow cylinder in the Figure), which stores *culture-specific knowledge*, i.e., assertions required to represent cultural information at national/ethnic level (e.g., the fact that an Indian woman is likely to celebrate the Diwali festival of lights and an English woman is likely to know how to play the bridge card game). *Person-specific knowledge*, i.e., assertions required to represent the unique cultural identity, preferences and environment of the assisted person, are dynamically added to the ABox at runtime.
- Structures and algorithms for *Assessment & Adaptation* (respectively, green cylinder and arrows in the Figure), which implement the $\mathcal{ADORE}$ model allowing for the discovery and update of person-specific knowledge in light of culture-specific knowledge, e.g. relying on "educated guesses" to be confirmed through dialogue or autonomous robot observation.

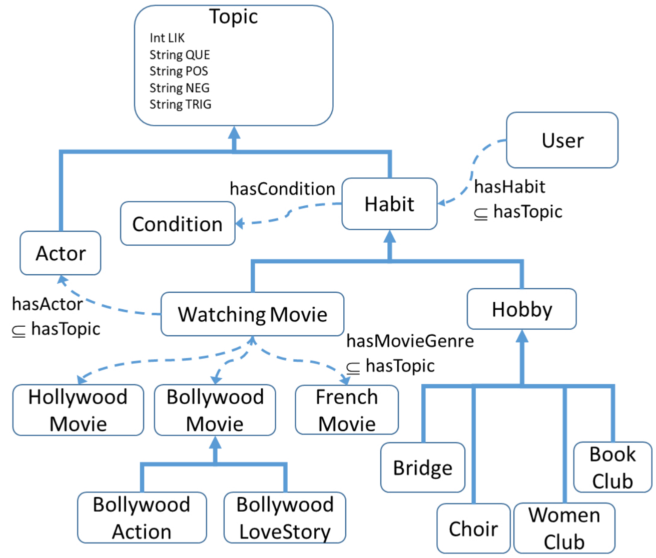

Fig. 3: The portion of the TBox describing the concepts required by the last guideline of Table I.

In the following, we adopt the OWL-2 language [9], with the usual definitions of *Classes*, *object and data properties*, and *Instances*, for the description of the ontology. Notice that the detailed description of the CKB is out of the scope of this article, which rather focuses on the underlying working principle using the last guideline of Table I as a case study.

A. Encoding Guidelines

Figure 3 shows the portion of the TBox (and, in particular, of the area of *Topics of conversation*) which defines the classes required by the last guideline of Table I.

As the Figure shows, in the TBox, specific habits are modelled as subclasses of the class Habit, such as Hobby or WatchingMovie, with object properties such as hasMovieGenre and hasActor relating the habit of watching movies with movie genres and actors. As already stated, all concepts of relevance for all considered cultures are represented in the TBox, regardless of the cultural heritage of the assisted person. As an example, the last two guidelines of Table I describe habits and activities which are likely to be familiar for an Indian and an English person. The role of the Knowledge Engineer is to read the guidelines, identify all the concepts required to describe them, regardless of their relevance for each specific culture, and populate the TBox accordingly. This process might lead to the identification of concepts which, albeit relevant, are not mentioned in

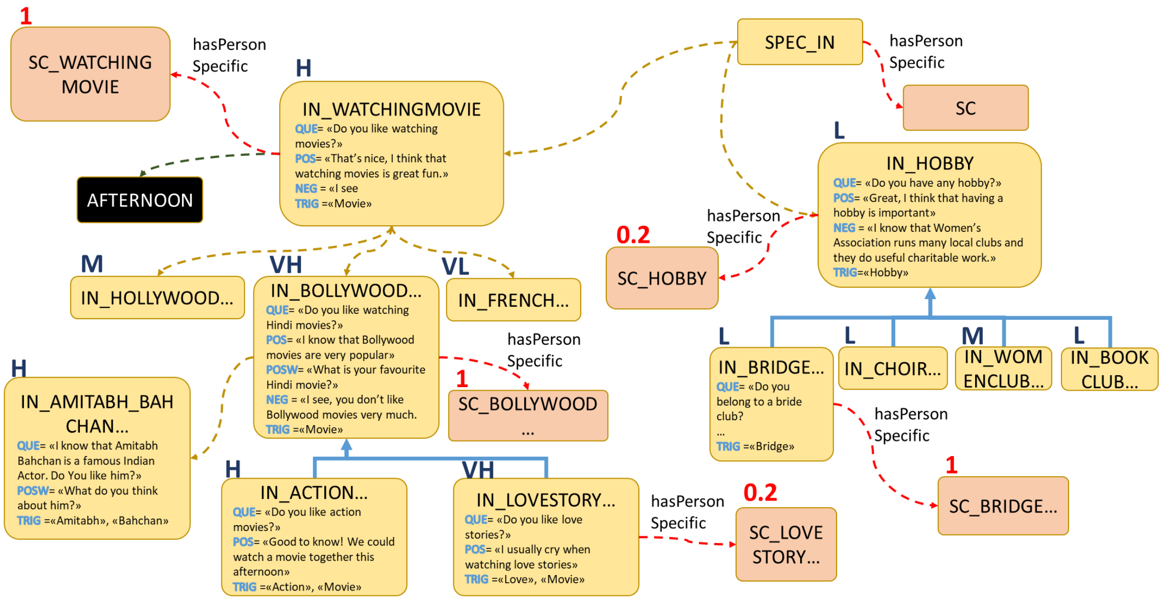

Fig. 4: The portion of the ABox describing the assertions of the last guideline of Table I. Indian culture-specific assertions are denoted with yellow boxes and the IN prefix; person-specific assertions related to a fictional Mrs Sonali Chaterjee are denoted with orange boxes and the SC prefix; concepts which are not culture-specific are denoted with black boxes.

the guidelines. For example, we know nothing about the preferences of Indian persons concerning Hollywood, or French movies, but this information is important to expand the robot's knowledge and avoid stereotypes: in fact, a robot that only knows Bollywood movies and Indian actors is not particularly useful for an Indian user who doesn't like them, and, in turn, it cannot make much use of the information that the user is actually a big fan of Clint Eastwood. As a consequence, filling the TBox is actually an iterative process involving Knowledge Engineers, experts in Transcultural Nursing and Roboticists.

Two classes of the TBox deserve a special attention. The class User represents the person that the robot assists, related to all the other concepts in the TBox by object properties describing ownership, preferences, habits, beliefs, etc. The class Topic (representing any topic that the robot can talk about) is the superclass from which most of the other classes are derived, and it has the following data properties:

- LIK (likeliness). For culture-specific assertions, LIK encodes the likeliness (interpreted as a "conditional probability") that the assertion holds for a person having that specific cultural heritage, and it is directly extracted from the guidelines. For instance, the probability that an Indian person watches Bollywood movies may be Very High, whereas the probability that she plays bridge or belongs to a book club may be Low, while the opposite may be true for an English woman. For person-specific assertions, LIK either encodes the evidence describing the individual attitude of the assisted person, acquired through observations and interactions, or the a-posteriori probability of the assertion to hold, given evidence already acquired about other, related, concepts.
- QUE (question). For culture-specific assertions, QUE encodes the questions that the robot may use to ask the person about her individual attitude, directly extracted from the guidelines. For person-specific assertions, QUE encodes similar questions, that the robot may use to revise previously acquired knowledge, or motivate the user to engage in an activity (e.g., "What about watching a romantic movie now?")
- POS (positive sentence) and NEG (negative sentence). For both culture-specific and person-specific assertions, the data properties POS and NEG encode statements, extracted from the guidelines, that the robot can use to express positive and negative opinions, respectively.
- POSW (positive sentence plus waiting). For both culture-specific and person-specific assertions, POSW has the same meaning of POS, but actually aims at eliciting a long response from the user (e.g., "Why do you like romantic movies?"), which will have no impact upon the cultural knowledge base.
- TRIG (triggering keyword). For both culture-specific and person-specific assertions, TRIG lists a set of keywords which, if heard by the robot while talking with the user, trigger a conversation about the corresponding topic (e.g., if the person mentions the keyword "Movie", or the pair "Action" and "Movie", the robot may start talking about movies or, specifically, action movies).

Figure 4 shows the portion of the ABox encoding Indian culture-specific (yellow boxes with IN prefix and arrows) and person-specific (orange boxes with SC prefix and arrows) assertions. Person-specific assertions describe the habits of an Indian persona named Sonali Chaterjee. In the Figure, boxes denote instances of classes and dotted lines denote

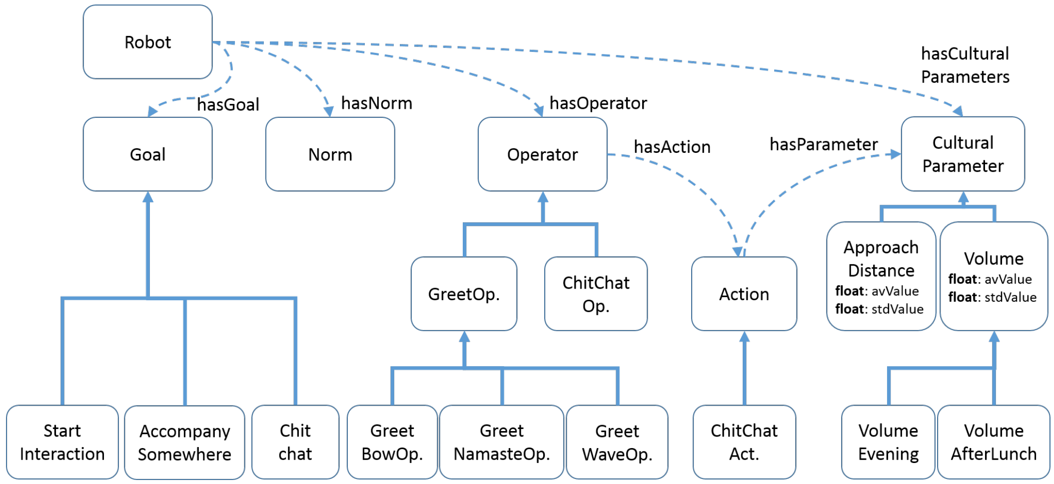

Fig. 5: A portion of the TBox area describing robot actions.

assertions of object properties. Data properties (e.g., QUE) appear within the box of the instance they refer to, while likeliness values (LIK) appear above the top-left corner of the instance they refer to. In accordance with the guidelines, likeliness values are denoted with literals (mapped to numbers for online update as: 0.05 for Very Low, 0.1 for Low, 0.2 for Medium, 0.4 for High, 0.7 for Very High). The reason for this choice is practical: while it is very difficult (if not impossible) to obtain precise a priori probabilities from statistical analyses, it is much easier to infer approximate, qualitative values from the vast (but often inhomogeneous) corpus of information in the literature and on the web.

Culture-specific assertions in Figure 4 can be rearranged in a tree structure, called a *Dialogue Tree*. The Dialogue Tree is used by the Assessment & Adaptation algorithm to drive the verbal interaction between the robot and the user. It is rooted in SPEC_IN and built by iteratively adding:

- all instances that are filler of another instance along a property that is subsumed by hasTopic (i.e., yellow dashed arrows in Figure 4);
- all instances of classes that are subsumed by another concept whose instance is already part of the tree (i.e., blue arrows in Figure 4).

The object property hasPersonSpecific relates culture-generic instances to person-specific instances. As an example, the Figure shows the preferences of Mrs Chaterjee, that may differ from the generic Indian preferences encoded in the culture-specific instances: Mrs Chaterjee definitely likes Bollywood movies (LIK = 1), but, contrary to expectations, she does not like love stories (LIK = H for the culture-specific instance IN_LOVESTORY...; LIK = 0 for the person-specific instance SC_LOVESTORY...). Moreover, the CKB tells us that Mrs Chaterjee loves bridge, even if card games are not very popular among Indian people (LIK = L for the culture-specific instance IN_BRIDGE...; LIK = 1 for the person-specific instance SC_BRIDGE...).

The principles discussed so far apply to all areas of the ontology: exactly like *Topics of conversation*, *Goals*, *Actions* and their *Parameters*, *Norms*, etc., are associated with likeliness values that identify them as more or less preferable for a given culture and/or a given person. As an example, Figure 5 shows a portion of the TBox describing some of the *Goals*, *Actions* and their *Parameters* and *Norms* extracted from the guidelines. All these classes are derived from Topic, which enables corresponding culture-specific and person-specific instances in the ABox to include likeliness values describing the preferences of a cultural group or a person concerning the actual action, parameter, goal... to perform.

B. Implementing $\mathcal{ADORE}$

The algorithm for Assessment & Adaptation aimed at the acquisition of person-specific information informed by culture-specific information relies on the aforementioned Dialogue Tree to verbally interact with the user and on a Bayesian Network, with the same structure of the tree, to dynamically update the person-specific likeliness values upon the acquisition of new evidence. The algorithm implements the $\mathcal{ADORE}$ model as follows:

- $\mathcal{A}$ssess. The robot makes an assumption about the person's preferences in terms of *Goals*, *Actions* and their *Parameters*, *Norms*, *Topics of conversation*, etc., by considering the likeliness of the culture-specific instances (or the likeliness of the corresponding person-specific instances, if already available). For instance, if Mrs Chaterjee mentions "Movie", the Chitchat goal is activated, the robot checks all instances such that TRIG is filled by "Movie" and infers that she might want to talk about Bollywood movies, since the instance IN_BOLLYWOOD... has the highest value, among all alternatives, for the data property LIK.
- $\mathcal{D}$o. The robot's planner oversees the execution of the action Chitchat, which fulfils the current goal, picking as values for the action parameters (e.g., Volume), those with highest likeliness. The robot inquires about its guess by randomly choosing one of the fillers of the data property QUE corresponding to IN_BOLLYWOOD... (possibly adding other sentences moving up and down

the Dialogue Tree), and uses the fillers of the data properties POS and NEG to acknowledge her answer. For instance, the robot may ask Mrs Chaterjee if she likes watching Bollywood movies and if she likes the Indian actor Amitabh Bahchan, while it would ask Mrs Smith, an English woman, if she likes playing bridge.

- $\mathcal{O}$bserve. While chit-chatting, this basically consists in acquiring an answer from the person and processing it[6]. Whenever possible, this also implies observing the visible reactions of the person.
- $\mathcal{R}$evise. Depending on the evidence acquired, the system either creates a new person-specific assertion in the ABox or updates an existing one, by appropriately setting the value of LIK. Specifically, $\text{LIK} = 1$ if the answer is positive, $\text{LIK} = 0$ if it is negative, or it is set to a value in between if the person does not express a clear preference (using expressions such as "Sometimes", "Often", "Not particularly", "For now", etc.), or the robot's autonomous observation cannot be considered conclusive. The updated likeliness is provided to the Bayesian Network, which recomputes the a-posteriori probabilities of all other instances depending on the modelled relations between the nodes. This mechanism captures the intuition that, if the robot discovers that Mrs Chaterjee likes playing bridge, it may be indicative of a more general attitude of Mrs Chaterjee towards card games (even if card games are not very popular in India) and English hobbies in general, and the probability that this reflects on her habits should increase accordingly.
- $\mathcal{E}$valuate. The first column of Table I lists the condition(s) in which each guideline holds. As Figures 4 and 5 show, these conditions, which are not related to likeliness, are represented in the ontology with classes, instances and object properties, that for example specify that IN_WATCHINGMOVIE is a suitable suggestion only in the afternoon, or that the robot's volume should be lower in the evening. A rule-based mechanism identifies the instances that are valid at each given time, to be taken into consideration by the Assessment algorithm.

As the time passes, the robot acquires more and more person-specific knowledge, that makes it attune its behaviour towards the assisted person's preferences and needs.

IV. Implementation Case Study

Figure 1 shows the robot Pepper, equipped with the CKB above described (as well as components for planning, speech synthesis and recognition and execution of sensorimotor behaviours which are not discussed in this article), interacting with an Indian persona named Kabir[7]. Figure 6 reports a transcript of a dialogue between Kabir (white rows) and Pepper (gray rows). The third column reports the components

N.	Sentence	M	CKB
1	Pepper...		
2	Namaste Kabir.	$\mathcal{E}$ $\mathcal{A}$ $\mathcal{D}$	
3	Namaste Pepper.		
4	If you need me, I am here. As an example I can help you to get dressed.	$\mathcal{E}$ $\mathcal{A}$ $\mathcal{D}$	
5	I want to get dressed now.	$\mathcal{O}$	
6	I heard "dress". Let's talk for a while. Choosing the right dresses make you feel comfortable and can improve your mood. Do you sometimes wear traditional Indian dresses?	$\mathcal{A}$ $\mathcal{D}$	TRIG POS QUE
8	Never.	$\mathcal{O}$	
9	I do not like Indian dresses so much. They are too colourful. Do you want to keep talking about this?	$\mathcal{R}$	NEG UP
10	No, it's ok. I want to wear my kimono now.		
11	I heard "kimono". Let's talk together. Do you sometimes wear a Kimono?	$\mathcal{D}$	TRIG POS QUE
12	Always	$\mathcal{O}$	
13	Wearing a kimono is not for every day. But maybe we can make today a special day. If you wish to wear a kimono I would be glad.	$\mathcal{R}$	POS UP
14	Of course.		
15	Do you want to keep talking about this?		
16	No. I want to go out for leaf peeping. It is the season.		
17	I heard "leaf peeping". Let's talk together. Do you like leaf peeping?	$\mathcal{D}$	TRIG QUE
18	I love it.	$\mathcal{O}$	
19	I think a coloured maple leaf is very beautiful. Do you want to keep talking about this?	$\mathcal{R}$	POS UP
20	No. I think it is time to have breakfast now.		
21	I heard "breakfast". Let's talk together. Having a healthy breakfast is very important to start your day. Do you usually have a traditional Japanese breakfast?	$\mathcal{A}$ $\mathcal{D}$	TRIG POS QUE
22	Sometimes.	$\mathcal{O}$	
23	Japanese food is perfect for breakfast. It's very nutritious and healthy. Do you usually have green tea for breakfast?	$\mathcal{R}$ $\mathcal{A}$ $\mathcal{D}$	POS UP QUE
24	Always.	$\mathcal{O}$	
25	Drinking a cup of green tea is the best way to start your day! Do you want to keep talking about this?	$\mathcal{R}$	POS UP
26	No, it's ok. Thank you.		

Fig. 6: Transcript of a dialogue between the Pepper robot and the Indian persona Kabir.

of the $\mathcal{ADORE}$ model which are active at that stage, whereas the fourth column reports the elements in the CKB that are involved: TRIG means that a triggering keyword is detected, POS and NEG mean that the robot pronounces a positive or negative sentence, QUE means that the robot asks a question; UP means that, in light of Kabir's answer, the robot updates the likeliness values associated to the instances in the CKB (i.e., the a-posteriori probabilities in the Bayesian Network).

In Figure 1, corresponding to Lines 6–9 of Figure 6, Kabir has just asserted that he wants to get dressed: culture-specific information related to the Indian cultural group ($\mathcal{A}$,

[6]Using Cloud-based systems for Automatic Speech Recognition (e.g., Nuance, Google ASR) and Natural Language Processing (e.g., DialogFlow).

[7]The transcript is extracted from the video available at: `https://youtu.be/WQJ0d5yXD0A`. A more complex experiment with multiple people belonging to different cultural groups is shown in: `https://youtu.be/RlKtrkmP5us`

Line 6) is used to jump to the right node of the Dialog Tree and start talking about traditional Indian dresses ($\mathcal{D}$, Line 6). Depending on Kabir's answers ($\mathcal{O}$, Line 8), the likeliness/probability associated to other topics in the CKB (e.g., breakfast habits) is updated accordingly ($\mathcal{R}$, Line 9).

As the transcript shows, not all the steps of the $\mathcal{ADORE}$ model are always executed. Line 2 shows a situation in which the robot infers that the right way of greeting Kabir is with Namaste ($\mathcal{E}$ and $\mathcal{A}$) and acts accordingly ($\mathcal{D}$). According to the $\mathcal{ADORE}$ model, the robot might observe Kabir's reaction and use it to revise its assumptions, but this type of observation is ignored for the moment. Similarly, Lines 11–13 shows a situation in which only the $\mathcal{DOR}$ steps are performed: since Kabir started talking about "wearing a kimono", the robot did not have the chance to infer his preferences in terms of clothing before the beginning of the conversation. As previously discussed, the CKB uses person-specific information to continuously revise its knowledge of and suggestions for the user. In the interaction of Figure 6, for example, the robot decides to inquire about Japanese breakfast (Line 21), considering Kabir's responses concerning clothes and hobbies.

V. Conclusions

The article describes the rationale adopted to encode in the knowledge base of a socially assistive robots for the care of older people (in particular, a Pepper robot) guidelines for culturally competent behaviours. The guidelines are composed of: (i) information and rules encoding habits, preferences and expectation of cultural groups, which constitute the basis for the robot interaction with the assisted person, and (ii) the $\mathcal{ADORE}$ model, laying out the methodology that the robot should use at runtime to update its knowledge and adapt its actions, gestures and words to the specific person it assists. The interested reader can find the guidelines developed in the context of the CARESSES project by a multidisciplinary team led by Transcultural Nursing experts in the Research section of the CARESSES website.

We encode the guidelines in an ontology, using specific classes and properties to represent the influence of culture on concepts related to daily life, and we embed the steps defined in the $\mathcal{ADORE}$ model in the working of an algorithm for the acquisition of person-specific knowledge. The algorithm relies on a Dialogue Tree to have a culturally competent verbal interaction with the user and on a Bayesian Network to dynamically update its assessment of the user's preferences and habits, as well as of the most suitable actions, gestures and words to use with him/her. Preliminary experiments (see attached video) have shown that the system can successfully work in real time.

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References

[1] J. Abdi, A. Al-Hindawi, T. Ng, and M. P. Vizcaychipi, "Scoping review on the use of socially assistive robot technology in elderly care," *BMJ open*, vol. 8, no. 2, 2018.

[2] S. Andrist, M. Ziadee, H. Boukaram, B. Mutlu, and M. Sakr, "Effects of culture on the credibility of robot speech: A comparison between english and arabic," in *HRI 2015*, 2015, pp. 157–164.

[3] S. Bedaf, G. J. Gelderblom, D. S. Syrdal, H. Lehmann, H. Michel, D. Hewson, F. Amirabdollahian, K. Dautenhahn, and L. de Witte, "Which activities threaten independent living of elderly when becoming problematic: inspiration for meaningful service robot functionality," *Disability and Rehabilitation: Assistive Technology*, vol. 9, no. 6, pp. 445–452, 2014.

[4] R. Bemelmans, G. J. Gelderblom, P. Jonker, and L. De Witte, "Socially assistive robots in elderly care: A systematic review into effects and effectiveness," *Journal of the American Medical Directors Association*, vol. 13, no. 2, pp. 114–120, 2012.

[5] R. Bevilacqua, E. Felici, F. Marcellini, S. Glende, S. Klemcke, I. Conrad, R. Esposito, F. Cavallo, and P. Dario, "Robot-era project: Preliminary results on the system usability," in *International Conference of Design, User Experience, and Usability*. Springer, 2015, pp. 553–561.

[6] J. Broekens, M. Heerink, H. Rosendal *et al.*, "Assistive social robots in elderly care: a review," *Gerontechnology*, vol. 8, no. 2, pp. 94–103, 2009.

[7] B. Bruno, N. Y. Chong, H. Kamide, S. Kanoria, J. Lee, Y. Lim, A. Kumar Pandey, C. Papadopoulos, I. Papadopoulos, F. Pecora *et al.*, "Paving the way for culturally competent robots: a position paper," in *26th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN)*, 2017.

[8] B. Graf, U. Reiser, M. Hägele, K. Mauz, and P. Klein, "Robotic home assistant Care-O-bot® 3-product vision and innovation platform," in *Advanced Robotics and its Social Impacts (ARSO), 2009 IEEE Workshop on*. IEEE, 2009, pp. 139–144.

[9] W. O. W. Group *et al.*, "OWL 2 web ontology language document overview," 2009.

[10] N. Guarino *et al.*, "Formal ontology and information systems," in *Proceedings of FOIS*, 1998, pp. 81–97.

[11] G. Hofstede, G. J. Hofstede, and M. Minkov, *Cultures and organizations: Software of the mind, third edition*. McGraw-Hill Professional, 2010.

[12] R. Kachouie, S. Sedighadeli, R. Khosla, and M.-T. Chu, "Socially assistive robots in elderly care: a mixed-method systematic literature review," *International Journal of Human-Computer Interaction*, vol. 30, no. 5, pp. 369–393, 2014.

[13] S. Katz, T. D. Downs, H. R. Cash, and R. C. Grotz, "Progress in development of the index of adl," *The gerontologist*, vol. 10, no. 1_Part_1, pp. 20–30, 1970.

[14] M. P. Lawton and E. M. Brody, "Assessment of older people: self-maintaining and instrumental activities of daily living," *The gerontologist*, vol. 9, no. 3_Part_1, pp. 179–186, 1969.

[15] I. Papadopoulos, *Transcultural health and social care: development of culturally competent practitioners*. Elsevier Health Sciences, 2006.

[16] J. Pineau, M. Montemerlo, M. Pollack, N. Roy, and S. Thrun, "Towards robotic assistants in nursing homes: Challenges and results," *Robotics and autonomous systems*, vol. 42, no. 3-4, pp. 271–281, 2003.

[17] S. Sabanovic, C. C. Bennett, W.-L. Chang, and L. Huber, "PARO robot affects diverse interaction modalities in group sensory therapy for older adults with dementia," in *Rehabilitation Robotics (ICORR), 2013 IEEE International Conference on*. IEEE, 2013, pp. 1–6.

[18] D. Sancarlo, G. D'Onofrio, J. Oscar, F. Ricciardi, D. Casey, K. Murphy, F. Giuliani, and A. Greco, "Mario project: A multicenter survey about companion robot acceptability in caregivers of patients with dementia," in *Italian Forum of Ambient Assisted Living*. Springer, 2016, pp. 311–336.

[19] L. Wang, P.-L. P. Rau, V. Evers, B. K. Robinson, and P. Hinds, "When in rome: the role of culture & context in adherence to robot recommendations," in *HRI 2010*, 2010, pp. 359–366.

[20] Y.-H. Wu, V. Cristancho-Lacroix, C. Fassert, V. Faucounau, J. de Rotrou, and A.-S. Rigaud, "The attitudes and perceptions of older adults with mild cognitive impairment toward an assistive robot," *Journal of Applied Gerontology*, vol. 35, no. 1, pp. 3–17, 2016.