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Personalized Clothing Recommendation by a Social Robot

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***Abstract*—Social robots can assist individuals with performing a number of different daily tasks. One such task, which has not been extensively explored, is suggesting appropriate clothing to an individual. This paper presents a novel, autonomous, clothing recommendation system that employs social robots. The proposed system can autonomously recommend options, from a user's wardrobe, that are personalized to an activity at hand. The novelty of the system lies in its ability to learn from the individual users' preferences over time. The learning-based personalization feature allows the system to assist new users as well as adapt to users whose preferences change over time. Human-robot interaction studies were conducted to assess both the performance of the overall system as well as its potential long-term adaptability.**

I. Introduction

Social robots can provide assistance with daily activities, such as exercising [1], weight-loss through diet advice [2], meal assistance and monitoring [3], [4], and leisure activities such as playing games [5]-[7]. Studies have shown that these types of interactions can improve enjoyability of the tasks [8], increase motivation to perform them [9], and provide companionship and social stimulation [10]. In order for such robots to effectively interact with users on a long-term basis, they need to be engaging and not simply just convey information [11]. They should display emotions and evolve their behavior over time to better suit who they are interacting with [12]. A major challenge when developing social robots is to be able to effectively encompass a wide variety of preferences, behaviors, and social/cultural values, in order to provide person-centered interactions.

Despite studies showing the beneficial use of social robots to aid with daily living activities, assistance for getting dressed has not yet been explored thoroughly. The act of getting dressed is something individuals do daily, often taking for granted the impact it has on their well-being. Clothing that a person chooses to wear offers protection against harsh weather conditions and hazardous surfaces [13]. Additionally, clothing choices have been shown to have a significant influence on first impressions [14], self-esteem [15], and social identity [16]. Although seemingly trivial, there are many factors that need to be considered when choosing an outfit: weather conditions, activities that will be undertaken, and one's sense of identity and self-expression.

In this paper, we present the development of an autonomous clothing recommendation system for socially assistive robots, which provides clothing suggestions that are personalized to the activity and user. We have integrated the system with the small humanoid robot, Leia, to interact with and guide the user through the decision. Leia obtains information regarding the weather, the user's preferences regarding comfort and dress code, and information about their activity plans such as whether they will be outside, and if the activity is athletic in nature. The proposed system incorporates a novel, adaptive, long-term learning strategy to provide personalized clothing choices.

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II. Related Work

A. Clothing Recommendation Software

Existing clothing recommendation software can be categorized into three areas: 1) extracting feature information (e.g., patterns, fabrics) from pictures of clothing [17], [18], 2) recommending clothing based on the occasion it is being worn for (e.g., a wedding, school, or a job interview) [19]-[22], and 3) recommending new clothing items to consumers [23]-[25].

In [17], a latent support vector machine (SVM) based model was used to extract feature information in the form of a histogram of oriented gradients, local binary pattern, color moment, color histogram, and skin descriptor, from pictures of clothing items. A linear SVM was used to learn scores for each clothing item based on the features for given occasions; then, optimal upper-body and lower-body clothing item pairs from the user's wardrobe were determined for the occasion based on the similarity of their scores. In [22], a Bayesian network was used to represent the probabilistic relations between contextual information, such as season and temperature, with clothing features like color and sleeve-length. The clothing item with the highest posterior probability was chosen. In [25], user data (ratings, clicks, time spent viewing an item), and clothing textual (sleeve, collar, button type) and visual (histograms of oriented gradients, HSV color histograms) data was mined from an online shopping website and stored in a database. A *k*-nearest-neighbors ranking algorithm was used to find similar clothing items and users with similar preferences.

A commonality between commercial applications for smartphones, e.g., [19], [20], is their emphasis on fashion, style, sharing outfits with friends, and purchasing new clothing. Other clothing-related smartphone applications have focused on providing instructions for physically dressing. For example, in [26], an app was developed to guide children with autism spectrum disorder through the steps of getting dressed, using video demonstrations.

The limitations of the majority of the existing software systems is that they do not: 1) incorporate feedback from a user regarding the recommended clothing option in order to provide alternative choices if the user is not satisfied with the choice, and 2) adapt/personalize over time to a user, and therefore, can recommend the same outfit for a given set of conditions and wardrobe options.

B. Social Robot Embodiment

Utilizing robots to engage people in daily activities can be effective at both incentivizing them to partake in the activity while improving their overall experience. A handful of researchers have explored the importance of robotic embodiment on interactions. For example, a meta-analysis was performed in [27] on a corpus of 33 experimental works comparing interaction between robots and virtual agents in various activities. It was found that in 79% of the studies, physical robots were found to elicit more favorable responses from users. The robot was found to be more arousing, persuasive, positively perceived, and also resulted in higher activity performance. In [28], a study was conducted comparing the use of a humanoid Nao robot with a virtual Nao robot during an interaction where a quiz game was played with children. Results showed that engagement as defined by focus of attention was higher with the robot.

The effect of embodiment has also been analyzed for daily activities, in which the activity will be recurring over long periods of time. In [29], a study with an exercise coach was conducted over a two-week period, in which half the participants interacted with the humanoid Bandit robot, and half with a virtual Bandit. Participants enjoyed the physical robot more, preferred to exercise with it, and found stronger motivation to exercise using the robot.

C. Clothing Assistance Robots

Robotic clothing assistance has mainly focused on helping to physically dress a person [30]-[32]. For example, in [30] and [31], the Baxter robot was used to place clothing items on users. In particular, in [32], a real-time pose estimation technique that utilizes randomized decision trees was used to track the person's current pose and body measurements. From the estimated poses, the robot's motions were determined using inverse kinematics motion planning.

D. Person-Centered Social Robots

Adapting a robot's behavior to a specific user via personalization has been considered for a variety of human-robot interaction (HRI) scenarios [33]-[39]. For example, in [33], the social robot, Bandit II, played a music-guessing game with participants from a seniors' care facility, changing the level of difficulty of the game, in order to maintain user interest and improve performance. A supervised learning algorithm was trained through a calibration phase, where each participant played the game once at each difficulty level. Once the algorithm was trained, the participants played the game again with the robot, starting on their most comfortable difficulty level. Success rates in the game and response reaction time where used to adjust the level of difficulty of the game. In [34], the robot, Brian 2.0, facilitated one-on-one memory card games with users. User stress levels during the game were measured using a heart-rate sensor, and used to adapt the robot's assistive behaviors using a MAXQ hierarchical reinforcement learning method.

In the aforementioned approaches, on-line learning was used during the interactions to adapt a robot's behavior to a user. However, these personalization strategies were focused on a single interaction, and did not consider future or multiple interactions with the same user. In our proposed system, we present a long-term personalization strategy, in which preferences of each specific user is used to create a user preference model.

Other robotic systems have incorporated techniques to allow for user adaption over time [36]-[39]. For example, in [36], a study was conducted with the snack-delivery robot, Snackbot, in order to analyze the effects of incorporating user personal information (e.g., snack consumption patterns, time since they last used the service) in the robot's behavior. Participants were delivered snacks by the robot during a 4-month timeframe. For one group of participants, the developers manually updated the behaviors of the robot to include information about their previous interactions. For the other group, the robot's default behaviors were used. Questionnaire results showed that the first group was more engaged and cooperative towards the Snackbot, and felt a higher degree of rapport for the robot.

In [39], users had short conversations with the PaPeRo robot, in which their personal preferences were incorporated. User preference models, represented by linear classification models, were learned for each user. In order to train the preference models, each user participated in a 40-minute session, where he/she was asked to define preferred robot behaviors for each stage of the conversation.

Our work proposes the first autonomous clothing assistance system for social robots. The main contributions of the proposed system are that the social robot can 1) autonomously learn users' preferences during interactions in order to suggest clothing items, and 2) learn preference models that can be adapted to specific users over long-term interactions.

III. Robotic Clothing Recommendation System

The proposed autonomous robotic clothing recommendation system consists of four main modules: 1) user storage, 2) information retrieval, 3) clothing recommendation, and 4) robot behavior, Fig. 1. The social robot, Leia, and a 10.1 inch touchscreen tablet are used to interact with a user. Leia is a small humanoid Nao robot which uses both gestures/body language, and the color changing LEDs around its eyes to display its assistive behaviors. The robot and tablet communicate wirelessly with a central server which contains the main system modules and uses the Robot Operating System (ROS).

Each user has a unique profile. When ready to interact with the system, the user selects his/her profile on the tablet, using the developed Graphical User Interface (GUI). The robot initiates the interaction by greeting the user and gathering information regarding daily activity plans, weather and dress code requirements. This information is gathered using the Information Retrieval module. Once all the contextual information is gathered by the Information Retrieval module, it is sent to the Clothing Recommendation module, which determines the recommended outfit. The robot verbally suggests the outfit, which is also visually displayed on the tablet. The Clothing Recommendation module makes this recommendation by utilizing the contextual information along with the user's wardrobe and personalized recommendation model, which are stored in the User Storage module. If the user does not agree with the recommendation made by the robot, the system provides alternative choices. During the interaction, the robot's behaviors are determined by the Robot Interaction module.

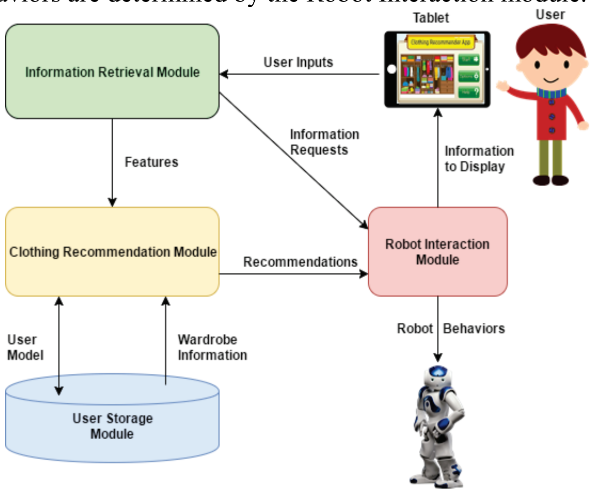

Figure 1. Clothing recommendation system architecture.

A. User Storage Module

The User Storage module is where each user's personal wardrobe information, and their personalized recommendation models, are stored. The clothing items in the wardrobe are categorized as belonging to one of four possible categories: upper-body, lower-body, shoes, and outerwear. Within each category, clothing items are grouped into a set of types belonging to that category, defined herein as labels. Example labels for the upper-body category would be t-shirt, sweater, and tank top. Each clothing category has a set of defining features represented by weather conditions, comfort levels, dress code, and suitability for athletics. The set of features describes the context in which the clothing is being worn. Different labels are intended to be suitable for various combinations of features.

Each new user, to the recommendation system, can create a unique profile, which generates a default recommendation model for him/her. Once the profile is created, items in his/her wardrobe can be input into the system using the GUI based on the aforementioned categories and labels, and pictures may be included for each item. The wardrobe can be updated or changed by a user at any time.

B. Information Retrieval Module

The Information Retrieval module obtains the necessary features during the interaction. All information is gathered from the user through the GUI except for the local weather information, which is obtained in real-time via the OpenWeather online service [40]. The GUI uses a custom-developed Android application, used to also communicate the inputs from the user to the system modules. Once a clothing recommendation is provided to the user, the Information Retrieval module is used to obtain user feedback about the outfit. The user can choose to replace either the entire outfit, or select individual clothing categories to replace.

GUI Design Overview

In designing an intuitive and effective human-robot interface to facilitate interaction, a touchscreen was chosen, due to speed of use, easiness of hand-eye coordination, and direct manipulation [41]. Through the touchscreen, the robot presents context-specific information such as the proposed outfit and it provides control elements in the form of buttons for the user to select.

In terms of the GUI design, three main design principles were considered: linear navigation, large and simple graphical elements, and customization. Users with less computer literacy often become disoriented within the navigations of complex programs, so a simple and linear navigation is beneficial [42]. Larger fonts and button sizes have also been shown to significantly improve reaction time and button-press accuracy [43]. Lastly, we also included the ability to customize graphical settings, based on design guidelines [44]. For our GUI, users can change the font type, size, color, and background based on their preferences.

When the user first starts the interaction, a welcome screen is presented (Fig. 2a), with the option of starting the interaction, getting help regarding the application, or changing the application settings (Fig. 2b). Once the interaction begins, the user first selects their profile (Fig. 2c), and is given the option to input the contextual information regarding his/her daily activity plans, comfort preference, and dress code requirements through either choosing a preset activity option, which captures this information, or to individually specify each of these information inputs (Fig. 2d). Some examples of these preset activities are watching television and going for a jog outside. If the user chooses to specify the individual inputs, four screens are shown on which the user can select the desired comfort level, dress code requirements, whether the activity is outdoors or indoors, and whether the activity is athletic (Fig. 2e-h). The user is then presented with a recommended outfit choice (Fig. 2i), which he/she can give feedback on through the GUI, by either accepting or rejecting the outfit. If the user rejects the outfit, he/she can choose to replace the entire outfit, or select individual items to replace (Fig. 2j).

C. Clothing Recommendation Module

Once the contextual features are obtained from the Information Retrieval module, they are used in conjunction with a user's wardrobe and recommendation model to rank clothing options via the Recommendation Algorithm. Personalization of the user recommendation model occurs each time a clothing recommendation is accepted by the user during an interaction, which is defined as his/her preferences herein.

Recommendation Algorithm

A multinomial logistic regression (MLR) approach was developed to provide the recommended clothing options. The requirements for this approach were twofold: 1) it must be able to provide a ranking of its outputs (rather than a single output choice), and 2) it should incorporate on-line learning. An MLR model is learned for each of the four clothing categories. Given an input set of features (e.g., contextual information) represented in vector $\boldsymbol{x}$, and a vector of weights for each label $\boldsymbol{w_k}$, the discrete probability distribution vector $\boldsymbol{y}$ is determined across all labels for a category. Each element of the vector $\boldsymbol{y}$, represents the probability of each label $\boldsymbol{k}$. In the binary logistic regression problem, the probability of one of two classes being the correct class is represented by the sigmoid function:

$$\mathrm{P}(k=1|\boldsymbol{x}) = \frac{1}{1+e^{(-w\cdot x)}} \;, \tag{1}$$

where the parameter weights w are trained using a training set of features-label pairs.

In order to expand this into the multi-class problem, a binary one-versus-rest classification model is trained for each clothing label k, resulting in a vector of weights for each label, $\boldsymbol{w_k}$. To determine the probability distribution across all classes $\boldsymbol{y}$, the inner product of the weights and input features is defined as a vector $\boldsymbol{z}$. The magnitude of each element z_k in $\boldsymbol{z}$ is proportional to the likelihood of label k fitting a set of features, and is determined by considering a linear combination of the n weights in $\boldsymbol{w_k}$, and the input features, $\boldsymbol{x}$, plus a bias weight, w_0:

$$z_k(\boldsymbol{x}, \boldsymbol{w_k}) = x_1 w_1 + x_2 w_2 \ldots + x_n w_n + w_0. \tag{2}$$

To represent our finite set of real-valued numbers $\boldsymbol{z}$ as the probability distribution, $\boldsymbol{y}$, across all M labels, the softmax function is applied, where each element of $\boldsymbol{y}$ is as follows:

$$y_k = \frac{e^{z_k}}{\sum_{m=1}^{M} e^{z_m}}. \tag{3}$$

A ranking of which labels best match the features is obtained from this distribution of all possible clothing labels for that category through sorting the vector $\boldsymbol{y}$.

User Preferences

Prior to the first interaction with a user, default recommendation models for the clothing categories are stored in the User Storage module. Then, these default models are updated online based on a user's acceptance or rejection of a given clothing recommendation. This is achieved by using stochastic gradient descent (SGD). The existing weights for a specific label k being accepted or rejected by the user, $\boldsymbol{w}_{k,old}$, are updated to new weights through the following SGD update step (i is the i^{th} weight):

$$w_{k,new}^{(i)} = w_{k,old}^{(i)} + \alpha\left[(c - y_k)x^{(i)}\right] - \lambda\left(w_{k,old}^{(i)}\right)^2, \tag{4}$$

where c is a binary value representing a user's acceptance (1) or rejection (0) of a clothing item belonging to label k for the specific input set of features $\boldsymbol{x}$. The variables α and λ are the learning rate and weight decay, respectively. Over time, the weights of a recommendation model are adapted to an individual user's clothing preferences.

D. Robot Behavior Module

The robot behavior module uses a finite-state machine (FSM) to determine the robot's appropriate behavior in each state. Leia's distinct behaviors involve a combination of changing eye color, gestures, body language, speech, and vocal intonation. Emotions are incorporated into certain responses by the robot, such as either expressing happiness or sadness depending on whether the user is satisfied with the recommendation or not, as displaying emotions is shown to increase both engagement and social acceptance [45]. Figure 3 shows the architecture of the FSM. The FSM is linked to the GUI through network socket communication, and state transition triggers occur based on user inputs via the tablet touchscreen. For example, the FSM will begin in the waiting state; once the user presses the start button and selects their profile, this is the trigger which transitions the FSM into the Introduction state of the interaction. Examples of robot behaviors corresponding to the FSM during the overall interaction are presented in Table I and Fig. 4.

Figure 2. Example screens displayed in the GUI during the interaction.

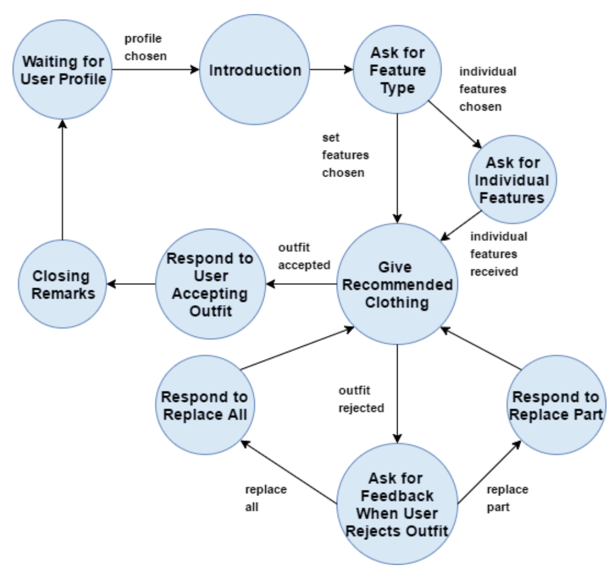

Figure 3. FSM for determining robot behaviors. Arrows without explicitly stated triggers represent automatic transitions.

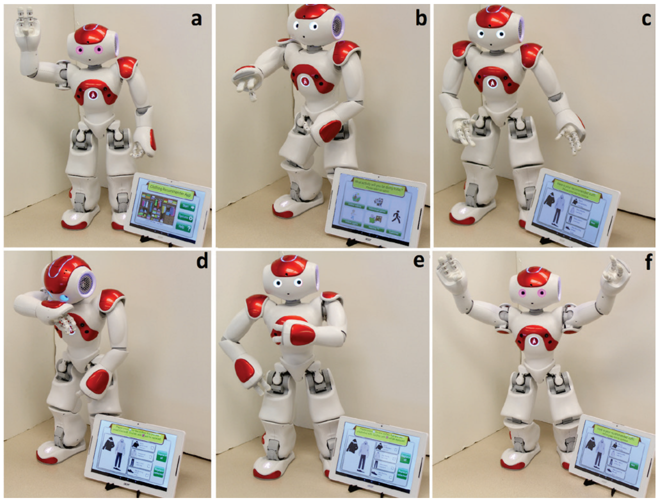

Figure 4. Examples of robot behaviors.

TABLE I. EXAMPLES OF ROBOT BEHAVIORS

Robot Behaviors	Speech	Eye Color	Gestures/Body Language
Introduction (Fig. 4a)	*"Hi John, I am Leia, your personal wardrobe assistant. I hope you're doing well today. I am going to help you pick out an outfit to wear."*	Pink (Happy)	Waving, pointing to self
Ask for Feature Type (Fig. 4b)	*"You have the option of either choosing a preset activity option, or selecting your own custom settings. Please select your option choice on the touchscreen."*	Clear (Neutral)	Ponting to the user, gesturing towards the tablet
Give Recommended Clothing (Fig. 4c)	*"Your clothing recommendation for the day is your orange T-shirt, your navy jeans, your white sneakers, and your black raincoat."*	Clear (Neutral)	Looking downwards to think, gesturing towards the tablet
Ask for Feedback when User Rejects Outfit (Fig. 4d)	*"That's too bad. Let's fix that then! Let me know if you want to replace the whole outfit, or just part of the outfit."*	Blue (Sad)	Putting head into arm and shaking from side to side, putting hands together, pointing towards tablet
Respond to Replace Part of the Outfit (Fig. 4e)	*"Okay, let me come up with new recommendations for the items you chose to replace."*	Clear (Neutral)	Pointing to self
Respond to Replace All of the Outfit	*"You chose to replace the whole outfit. Let me come up with a new recommended outfit for you."*	Clear (Neutral)	Pointing to self
Respond to User Accepting Outfit (Fig. 4f)	*"Great, I'm so glad you like it."*	Pink (Happy)	Raising arms into the air
Closing Remarks	*"I'm glad I could be of assistance. I hope you have a great rest of the day! Bye for now, see you soon."*	Clear (Neutral)	Bowing, Waving

IV. EXPERIMENTS

Two different studies were conducted to evaluate the performance of the robot clothing recommendation system: 1) a user study to obtain feedback from potential users on their experience with the system, and 2) system performance studies. Prior to the studies, the default MLR models for each of the clothing categories were trained using data obtained from an online survey, in which participants rated a set of features for each clothing label in each category. A training set of 383 examples was gathered. The population group for the survey was young adults (ages 18-35).

A. User Experience

A study was conducted with ten participants (age: μ = 23.3 and σ = 1.34), who were university students. Eight participants were male and two were female. They interacted with Leia on two separate occasions (two different days) to obtain clothing recommendations. After the final interaction, the participants were requested to complete a questionnaire based on their experiences. The questionnaire included both five-point Likert items (5- strongly agree, 3- neutral, and 1- strongly disagree) and open-ended questions. Likert item questions were chosen to consider use of the system, its specific features and overall satisfaction using a combination of positively and negatively worded statements. The open-ended questions were used to gain a deeper insight into the Likert-item responses. These questions were structured into three different categories: 1) the clothing recommendations and corresponding features, 2) the social robot's behaviors, and 3) overall experience. Examples of questions are: "*Is there any additional features that should be included in the clothing recommendations*", "*What specific behaviors of Leia were helpful*" and "*How did you feel about the overall flow of the interaction with Leia?"*

Results and Discussions

The descriptive statistics for the Likert items are presented in Table II. The results showed that the participants found the overall system easy to use and engaging (Statements 1 and 7), the GUI intuitive (Statement 13), and the length of the interaction and the number of questions Leia asked suitable for the activity (Statements 2 and 3). They found the clothing recommendations appropriate and would trust the robot to provide them with such recommendations (Statements 5 and 6), however, they were neutral on whether the recommendations would be useful to them (Statement 4). Furthermore, the gestures and speech were clear and appropriate (Statements 9-12).

For the open-ended questions, participants ranked their favorite aspects of the system as the robot's gestures/body language, the simplicity of the GUI, and the visualization of the recommended outfit. They also mentioned that the flow of the interaction was both very good and intuitive. Two participants mentioned the descriptions that the robot provides could be shortened.

In addition to the existing system, participants suggested potentially including fashion-oriented preferences such as choosing a desired color scheme for the recommended clothing, as well as suggesting the inclusion of accessories into an outfit such as a hat or belt.

B. System Performance Studies

The system performance tests included verifying that the clothing recommendations were appropriate based on the input information, and that they can be personalized to a user. In order to verify whether the recommended clothing items were appropriate, a coder was used to evaluate the recommended outfits provided by the robot as good, acceptable or not suitable. Good recommendations provided the most appropriate clothing item matches based on all the input contextual information. Acceptable recommendations were ones in which the clothing items were all suitable with respect to the contextual information, however, better label matches were available for some of the recommendations. Wrong recommendations did not match the contextual information. Ninety percent of the recommendations were categorized as good, and ten percent were categorized as acceptable. No recommendations were categorized as not suitable. For the acceptable outfits, the inputs given were usually conflicting, such as requesting an outfit that was formal, but also suitable for athletic activities. Therefore, the system would try to choose an outfit which was closest to matching both these features, and in doing so would not necessary find the best label match for one of the features.

Two of the participants (randomly chosen) from the user experience study were invited to participate in a longer-term study to investigate the personalization feature of the robot clothing recommendation system. The two participants, #1 and #5, used the clothing recommendation system 21 and 27 times, respectively, on a regular basis. Participant #1 used the system to obtain clothing recommendations for school, while Participant #5 used the system to obtain clothing recommendations for going to the fitness center in his condominium. The objective was to investigate how the clothing recommendations were personalized to the users over time for the same activities.

Results

Figure 5 presents the probabilities for specific clothing labels becoming optimal over the number of interactions, for each participant, for upper-body and lower-body clothing items. Namely, how the recommended clothing items change based on a user's preferred choices. Participant #1 was initially recommended casual clothing to wear to school, e.g., jeans and a long-sleeved (LS) shirt. However, the participant rejected this choice and decided on an outfit that is less casual: trousers and a button-downed (BD) shirt. As can be seen in the figure, the probabilities for these two clothing items start to increase with the number of interactions. After rejecting the jeans once, the trousers label has a higher probability as the top ranked recommendation for the second interaction, as these two labels were very close initially. For the upper-body, on the other hand, it takes three rejections of replacing the long-sleeved shirt with the button-down shirt for the initial recommendation to change.

Similarly, Participant #5 was initially recommended an athletic top and athletic shorts for working out. However, during the interactions, the recommendation model adapts to the participant's preference for a tank top and athletic pants. After numerous interactions, the label probabilities converge for both participants.

TABLE II. LIKERT QUESTIONNAIRE RESPONSES

	Frequency of Likert Responses					
Statement	**1**	**2**	**3**	**4**	**5**	**Median**
1. The system was easy to use.	0	0	0	4	6	5
2. The interaction took too long.	2	4	3	1	0	2
3. Leia asked me too many questions.	5	5	0	0	0	1.5
4. Clothing recommendations would be useful to me.	0	2	5	2	1	3
5. The recommendations were appropriate for the context.	0	0	0	6	4	4
6. I would trust Leia to provide me outfit recommendations.	0	0	1	6	3	4
7. I felt engaged with Leia during the interaction.	0	1	1	7	1	4
8. The interaction with Leia is more enjoyable than just using a touchscreen.	0	2	1	5	2	4
9. Leia's gestures and movements were appropriate.	0	0	4	1	5	4.5
10. Leia's gestures and movements contributed positively to the interaction.	0	1	1	3	5	4.5
11. Leia's speech was appropriate.	0	0	2	3	5	4.5
12. Leia's speech was clear and understandable.	0	1	1	1	7	5
13. The graphical user interface was intuitive to use.	0	0	0	2	8	5
14. The graphical user interface enabled effective and clear communication with the robot.	0	0	1	1	8	5

V. CONCLUSIONS

In this paper, a novel autonomous robotic clothing recommendation system is presented. The system provides clothing recommendations from a user's own wardrobe, incorporating information about the weather, the user's daily activity plans, and dress code. A personalization strategy was incorporated to allow the recommendations to adapt to each individual user. Experiments showed that the system was easy to use, intuitive and enjoyable, while being able to provide appropriate recommendations and adapt to user preferences through interactions.

REFERENCES

[1] J. Fasola and M.J. Mataric, "A socially assistive robot exercise coach for the elderly," in *JHRI*, vol. 2, 2013, pp. 3-32.
[2] C.D. Kidd and C. Breazeal, "A robotic weight loss coach," in *Proc. of the Nat. Conf. on Artificial Intelligence*, vol. 22, 2007, p. 1985-1986.
[3] D. McColl and G. Nejat, "Meal-Time with a Socially Assistive Robot and Older Adults at a Long-term Care Facility," in *Journal of Human-Robot Interaction*, vol. 2, 2013, pp. 152-171.

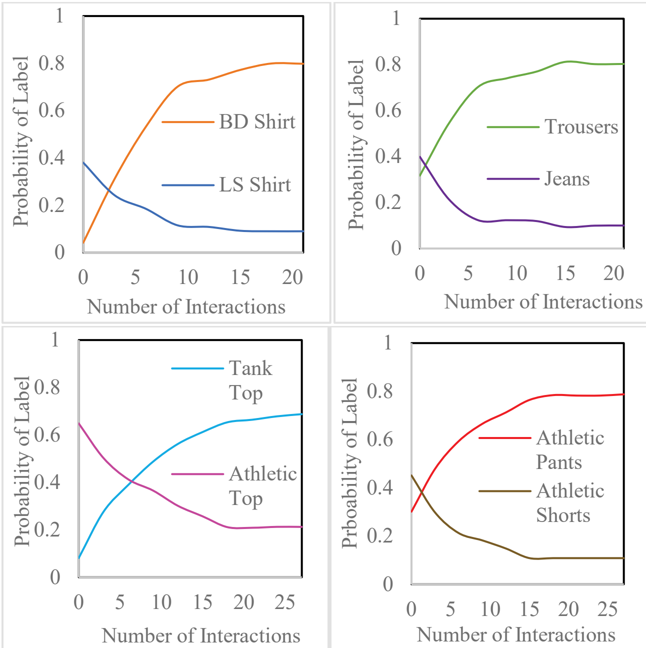

Figure 5. Clothing label probabilities for the long-term personalization study for Participant #1 (top) and Participant #5 (bottom).

[4] D. McColl, W. G. Louie, G. Nejat, "Brian 2.1: A Socially Assistive Robot for the Elderly and Cognitively Impaired," in *IEEE Robot. Autom. Mag.*, Vol. 20, 2013, pp.74-83.

[5] C.A. Pop, "Can the social robot Probo help children with autism to identify situation-based emotions? A series of single case experiments," in *INT J HUM ROBOT*, vol. 10, 2013, 1350025.

[6] W.Y. Louie et al., "Acceptance and attitudes toward a human-like socially assistive robot by older adults," in *Assist Technol.*, vol. 26, 2014, pp. 140-150.

[7] W.Y. Louie et al., "Did Anyone Say BINGO: A Socially Assistive Robot to Promote Stimulating Recreational Activities at Long-Term Care Facilities," in *ASME J. Med. Devices*," vol. 8, 2013, 030944.

[8] M.J. Mataric et al., "Socially assistive robotics for post-stroke rehabilitation," in *J Neuroeng Rehabil*, vol. 4, no.5, 2007, pp. 1-9.

[9] J. Fasola and M.J. Mataric, "Using socially assistive human–robot interaction to motivate physical exercise for older adults," in *Proc. of the IEEE*, vol. 100, no. 8, pp. 2512-2526.

[10] K. Dautenhahn, "Socially intelligent robots: dimensions of human–robot interaction," in *PHILOS TRANS R SOC B-BIOL SCI*, vol. 362, 2007, pp. 679-704.

[11] I. Leite et al., "Social robots for long-term interaction: a survey," in *Int J Soc Robot.*, vol. 5, 2013, pp.291-308.

[12] R. Gockley et al., "Designing robots for long-term social interaction," in *Proc.of the IEEE/RSJ Int. Conf. on Intelligent Robots and Systems*, 2005, pp. 1338-1343.

[13] R.A. Scott., *Textiles for Protection*, Amsterdam, NL: Elsevier Publishing Co., 2005.

[14] N. Howlett et al., "The influence of clothing on first impressions: Rapid and positive responses to minor changes in male attire," in *J. of Fashion Marketing & Management: An Int. J*, vol. 17, 2013, pp.38-48.

[15] C.M. Daters, "Importance of clothing and self-esteem among adolescents," in *Cloth. & Textiles Res. J.*, vol. 8, 1990, pp. 45-50.

[16] D. Craney, "*Fashion and its social agendas: Class, gender, and identity in clothing*," Chicago, IL: University of Chicago Press, 2012.

[17] S. Liu et al., "Hi, magic closet, tell me what to wear!" in *Proc. of the ACM Int. Conf. on Multimedia*, 2012, pp. 619-628.

[18] X. Chao et al., "A framework for robust feature selection for real-time fashion style recommendation," in *Proc. of the Int. Workshop on Interactive Multimedia for Consumer Electronics*, 2009, pp. 35-42.

[19] "Cluise: Wardrobe Assistant," Available: http://cluise.com [Accessed September 25, 2016]

[20] "ClosetSpace: Professionally styled outfits, personalized for you," Available: http://closetspace.com [Accessed September 25, 2016].

[21] E. Shen et al., "What am I gonna wear?: scenario-oriented recommendation," in *Proc. of the Int. Conf. on Intelligent User Interfaces*, 2009, pp. 365-368.

[22] L. Yu-Chun et al., " Personalized clothing-recommendation system based on a modified Bayesian network," in *Proc. of IEEE/IPSJ Int. Symp. on Applications and the Internet*, 2012, pp. 414-417.

[23] H.T. Nguyen et al., "Learning to rank for personalised fashion recommender systems via implicit feedback," in *Mining Intelligence and Knowledge Exploration*, New York, New York: Springer International Publishing, 2014.

[24] Y. Kalantidis et al., "Getting the look: clothing recognition and segmentation for automatic product suggestions in everyday photos," in *Proc. of the ACM Int. Conf. on Multimedia Retrieval*, 2013, pp. 105-112.

[25] E.V. de Melo et al., "November. Content-based filtering enhanced by human visual attention applied to clothing recommendation," in *Proc. of IEEE Int. Conf. on Tools with Artificial Intelligence*, 2015, pp. 644-651.

[26] "iDo Getting Dressed," Available: https://itunes.apple.com/ca/app/ido-getting-dressed/id931890910?mt=8 [Accessed February 7, 2017].

[27] J. Li, "The benefit of being physically present: A survey of experimental works comparing copresent robots, telepresent robots and virtual agents," in *Int J Hum Comput Stud.*, 2015, pp. 23-37.

[28] R. Looije et al., "Help, I need some body the effect of embodiment on playful learning," in *Proc. of IEEE Int. Symp. on Robot and Human Interactive Communication,* 2012, pp. 386-397.

[29] J. Fasola and M. Mataric, "Comparing physical and virtual embodiment in a socially assistive robot exercise coach for the elderly," *Tech. Report*, 2011.

[30] S.D. Klee et al., "Personalized assistance for dressing users," in *Int. Conf. on Social Robotics*, 2015, pp. 359-369.

[31] Y. Gao et al., "User modelling for personalised dressing assistance by humanoid robots," in *Proc. of IEEE/RSJ Int. Conf. on Intelligent Robots and Systems,* 2015, pp. 1840-1845.

[32] T. Tamei et al., "Reinforcement learning of clothing assistance with a dual-arm robot," in *Proc. of IEEE-RAS Int. Conf. on Humanoid Robots,* 2011, pp. 733-738.

[33] A. Tapus et al., "The use of socially assistive robots in the design of intelligent cognitive therapies for people with dementia," in *Proc. of IEEE Int. Conf. on Rehabilitation Robotics,* 2009, pp. 924-929.

[34] J. Chan and G. Nejat, "Social intelligence for a robot engaging people in cognitive training activities," in *INT J ADV ROBOT SYST*, vol. 9, 2012, pp. 1-13.

[35] A. Jain et al., "Learning trajectory preferences for manipulators via iterative improvement," in *Adv Neural Inf Process Syst*, 2013, pp. 575–583.

[36] M.K. Lee, "Personalization in HRI: A longitudinal field experiment," in *Proc. of ACM/IEEE Int. Conf. on Human-Robot Interaction,* 2012, pp. 319-326.

[37] A. Tapus et al., "Hands-off therapist robot behavior adaptation to user personality for post-stroke rehabilitation therapy," in *Proc. of IEEE Int. Conf.on Robotics and Automation,* 2007, pp. 1537-1553.

[38] M. Mason and M.C. Lopes, "Robot self-initiative and personalization by learning through repeated interactions," in *Proc.of ACM/IEEE Int. Conf. on Human-Robot Interaction*, 2011, pp. 433-440,

[39] T. Matsubara et al., "Adaptive choreography for user's preferences on personal robots," in *Proc. of IEEE Int. Symp. on Robot and Human Interactive Communication, 2012*, pp. 1032-1038.

[40] "OpenWeatherMap," Available: http://openweathermap.org/api [Accessed February 7, 2017].

[41] M.R. Bhalla, A.V. Bhalla, "Comparative study of various touchscreen technologies," in *Int. j. comput. appl. appl. sci.*, 2010, pp. 12-18.

[42] A. Cake and Y. Oeffner, "Method and apparatus for improving accuracy of touch screen input devices," U.S. Patent Application 10/830,788, April 23, 2004.

[43] Hsiao et. al, "Usability evaluation of the touch screen user interface design," in *Proc. of Int. Conf. on Human Interface & the Management of Information,* 2013, pp. 48-54.

[44] A. Darejeh and D. Singh, "A Review on User Interface Design Principles to Increase Software Usability For Users With Less Computer Literacy," in *J. of Computer Science,* 2013, pp. 1443-1450.

[45] C. Breazeal, "Emotion and sociable humanoid robots," in *Int J Hum Comput Stud.,* 2003, pp.119-155.