Can a Humanoid Robot be part of the Organizational Workforce? A User Study Leveraging Sentiment Analysis

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***Abstract*— Hiring robots for the workplaces is a challenging task as robots have to cater to customer demands, follow organizational protocols and behave with social etiquette. In this study, we propose to have a humanoid social robot, Nadine, as a customer service agent in an open social work environment. The objective of this study is to analyze the effects of humanoid robots on customers in a work environment, and see if it can handle social scenarios. We propose to evaluate these objectives through two modes, namely: survey questionnaire and customer feedback. The survey questionnaires are analyzed based on the datapoints provided in the questionnaire. We propose a novel approach to analyze customer feedback data using sentic computing. Specifically, we employ aspect extraction and sentiment analysis to analyze the data. From our framework, we detect sentiment associated to the aspects that mainly concerned the customers during their interaction. This allows us to understand customers expectations and current limitations of robots as employees.**

I. INTRODUCTION

The field of robotics has improved drastically in the last decade. From robots that were initially meant to reduce manual labour or automate menial tasks, current robots focus on social aspects such as teachers [1] and companions for the elderly [2]. The appearance of robots has also evolved over this period. In recent years, robots which are more human-like and are autonomous when interacting with humans are preferred over conventional robots. Due to this, the field of social robotics has gained momentum. In contrast to early task-based robots, design of humanoid social robots involves developing cognition that considers context, work environment and social interaction clues.

With the development of Artificial Intelligence and robotics, there is a universal question “Can a humanoid social robot be a part of a company’s workforce?”. Does it have all the skills and etiquette to function in an open work environment with different tasks successfully?

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Human-robot interaction (HRI) studies are usually conducted in controlled settings or pre-defined tasks. Such kind of interaction would not allow us to understand if a robot can adapt to and perform any role in an organization. To answer these questions in this paper, we have conducted an initial study with Nadine [3], a humanoid social robot as a customer service agent in an insurance company. The setup was entirely open for the public, and the customer could ask any questions. As a service agent, Nadine is required to be able to answer customer queries and maintain a courteous, professional behavior during her interaction. The objective of this study is to evaluate customer’s willingness to interact with a humanoid staff.

Nadine’s success as an insurance agent is based on the quality of customer-agent interaction. To evaluate such HRI, we employed a two-fold architecture based on survey questionnaires and customer feedback, respectively. The survey questionnaire was prepared in such a way that the customer can rate the interaction with the robot agent in terms of functionality, behavior, usefulness and many more features. Also, the customer can provide feedback about his/her interaction. Even though surveys can be quantified easily, the same is not applicable for feedback. Usually, customer feedback has to be manually read by someone to determine the limitations and scope of improvements in a robot.

In this paper, we have borrowed sentic concepts, specifically, aspect-based sentiment analysis and applied it to the collected customer feedback. In contrast to sentiment analysis, that detects sentiment of overall text, aspect-based analyzes each text to identify various aspects and determine the corresponding sentiment for each one. The proposed framework examines each aspect, customer talks about. This will also help us to quantify customer feedback data and aspects that customers notice in a work environment. Also, limitations and future extensions to humanoid robots in the work environment can be identified.

The rest of the paper is organized as follows: Section II describes related work for HRI in the context of aspect-based sentiment analysis; Section III explains the experimental setup of Nadine at the insurance company; Section IV describes the details of our data collection methods; Section V provides details of our framework to analyze user comments based on aspect-based sentiment analysis; Section VI presents experimental results of the analysis of survey and user comments; finally, Section VII provides concluding remarks.

II. Literature Review

A. Robots at work places

Robots have become an integral part of society. In recent times, several researchers and organizations are considering to make robots a part of their workforce. Initial studies of the robot at workplaces were restricted to simple tasks such as greeting at information booth[1], performing the predefined skill of archery [4] and bartender with communication skills [5], museum guide [6]. Robovie [7] was used as a language tutor for a small group of people in elementary school. In all these tasks, the HRI complexity was low, and mistakes made by a robot in such scenarios are inconsequential.

Robots have been considered for a more open work environment with serious consequences as well. For instance, healthcare [8], restaurant waiters [9], space research [10] and rescue functionalities [11] have also been considered. Ljungblad et al. [8] introduced a simple utility robot in a hospital environment for transporting goods between departments for 13 days and studied effects of it using interviews, questionnaires and observations. Juan Fasola et al. [12] used a socially assistive robot to motivate physical exercise for older adults. The results of the survey questions regarding participant perceptions and feelings toward the robot were very encouraging; the participants rated the robot highly in terms of intelligence and helpfulness attributed a moderately high level of importance to the exercise sessions, and reported their mood throughout the sessions to be normal-to-moderately pleased.

In a restaurant setting, [13] employed robots that could move, take orders and even talk to customers in a limited fashion. However, these robots were limited in nature as they could not carry heavier items like soup, pour water to customers or properly communicate. The success of robots in each of these applications is measured differently due to the variation of tasks involved in them. In most of the applications considered for robots at workplaces, the tasks involved are simple and social interactions with the human is considerably less. The appearance of the robots are not human-like always depending upon the task they are involved. In contrast, we choose to use a realistic looking humanoid social robot, Nadine for our experiments. Also, we set her up as an insurance agent to interact with customers in open social scenarios and perform tasks defined for an agent in the organization.

B. Customer satisfaction analysis using aspect-based sentiment analysis

Hu et al. [14] analyzed customer reviews using an aspect extraction method. The authors restricted themselves to explicit aspects and set of rules based on statistical observations. Scaffidi et al. [15] presented a method that uses a language model to identify product features. They assumed that product features are more frequent in product reviews than in a general natural language text.

[1]https://en.wikipedia.org/wiki/Actroid

Zhang et al. [16] introduced an expert system, Weakness Finder, which can help manufacturers find their product weakness from Chinese reviews by using aspect-based sentiment analysis. For explicit features, they incorporated a morpheme-based method and HowNet based similarity measure for grouping them. While a collocation selection method for each aspect was employed for grouping implicit features. For each of the extracted aspects, they utilized a sentence-based sentiment analysis method to determine the polarity. All these methods were applied to product reviews to quantify about product's features and usage. In contrast, we apply sentic computing [17] to understand customer demands and expectations of humanoid robot agent in a work place.

For any new technology, gauging customer satisfaction is very important as it can provide essential insights on usefulness and customer demand. For these reasons, customers are usually asked to rate their experience via simple questionnaires and provide feedback. However, customers tend to skip these surveys as it is usually voluntary. The analysis of such feedback comments is also tedious as it requires someone to read all reviews and highlight the primary customer demands manually. Such manual analysis could be time-consuming and subject to human bias. In contrast, we propose a NLP based framework relying on aspect-based sentiment analysis to analyze customer feedback. The analysis gives an insight to customer's experience with Nadine as an agent and points out areas (aspects) of improvement.

III. Experimental Setup

For our experiments, we have used Nadine, a realistic humanoid social robot with natural skin, hair and appearance. Figure 1 shows Nadine's architecture [3] that consists of three layers, namely, perception, processing and interaction. Nadine receives audio and visual stimuli from microphone, 3D cameras and web cameras to perceive user characteristics and her environment, which are then sent to the processing layer. The processing layer is the core module of Nadine that receives all results from the perception layer about environment and user to act upon them. This layer includes various sub-modules such as dialogue processing (chatbot), affective system (emotions, personality, mood), Nadine's memory of previous encounters with users.

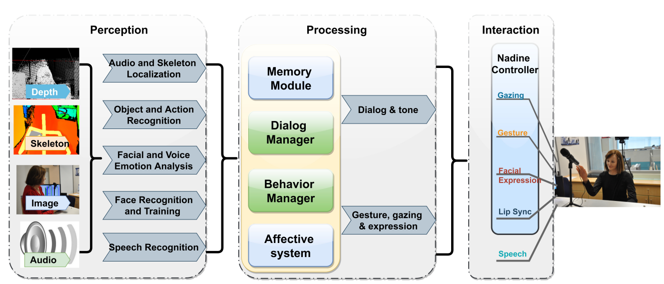

Fig. 1. Nadine Robot's Architecture

Fig. 2. Nadine setup in insurance company

What is your gender?
How old are you?
Does the staff posses the required skills and knowledge about the company's products and services.
Was the staff friendly and behaving in a courteous manner when dealing with you.
Is the staff professional and has a pleasing and presentable appearance.
Was the staff willing to listen and respond to your needs on time.
How would you rate the ease of access and the usefulness of our online e-care with the help of the staff?

TABLE I
CUSTOMER SURVEY QUESTIONS

Responses are sent to interaction layer so that they can be executed and visibly shown by Nadine such as head movement to maintain eye gaze, gestures and facial expressions, dialogue and tone (to show different emotions, personality).

Nadine was set up in an insurance company to work as a customer service agent alongside other human employees. She was required to handle customer queries and behave like a courteous service agent. For customer queries, the company had provided several FAQs from their customer interactions. A separate chatbot [18] was trained based on these FAQs and integrated into Nadine, that allowed her to handle customer queries. The main objective of the study was to see if customers were willing to interact with the robot service agent and is Nadine able to handle such workplace scenarios? The customers voluntarily fill in a survey form to rate their experience with Nadine and provide feedback comments.

IV. DATA COLLECTION FOR SURVEY

To analyze Nadine's performance as a customer service agent, we needed to collect feedback from customers. The data collected was used for analyzing customer-agent(robot) interaction and effectiveness of the robot in the workplace. For this purpose, we employed two modes of data collection, namely, Survey Questionnaire and customer feedback. In this section, we outline the details of both these modalities.

A. Survey Questionnaire

We created a questionnaire on Survey Monkey with seven questions. Throughout the questionnaire, Nadine was addressed as staff rather than as a robot. The survey was voluntary for the customers to fill in and was set up in a tablet. We collected 14 customer survey responses on Nadine's performance as a customer service agent. The questions are tabulated in Table I

B. Customer feedback

We also asked all customers to give unrestricted feedback on Nadine's performance as a customer service agent at the insurance company so that they can express their opinion on Nadine outside the survey questionnaire. Total of 75 users gave their valuable feedback on Nadine. These comments were analyzed using sentic computing framework explained in Section V and the analysis in Section VI.

V. PROPOSED NLP FRAMEWORK FOR ANALYSIS OF CUSTOMER FEEDBACK

This section discusses the proposed framework for the aspect extraction and sentiment analysis on customer comments. We use sentic computing to analyze user comments. Sentic computing aims to bridge the gap between statistical NLP and many other disciplines that are necessary for understanding human languages, such as linguistics, commonsense reasoning, and affective computing. The sentic computing framework is designed to receive as input a natural language concept represented according to an M-dimensional space, and predict the corresponding sentic levels for the four affective dimensions.

We first analyze the comments based on aspects and then parse the sentence through SenticNet for polarity detection (Figure 3). The framework depicts the sentiment analysis of each aspect customers talk about. As customers talk only about the single aspect in their feedback so, the sentence polarity is the same as the aspect polarity. We explain how aspect extraction and SenticNet works in subsection V-A and V-B, respectively.

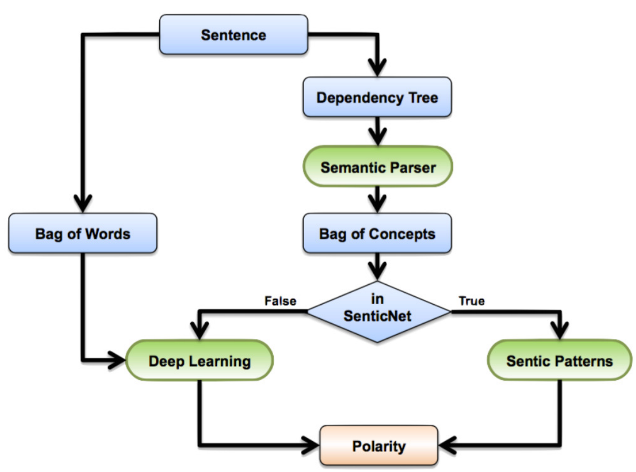

Fig. 3. Flowchart of the sentence-level polarity detection framework. Text is first decomposed into concepts. If these are found in SenticNet, sentic patterns are applied. If none of the concepts is available in SenticNet, the ELM classifier is employed. [17]

A. Aspect Extraction

Aspect-based opinion mining [19] focuses on the relations between aspects and document polarity. An aspect, also known as an opinion target, is a concept in which the opinion is expressed in the given document. The framework [20] incorporates a 7-layer deep convolutional neural network (CNN) which tags each word in opinionated sentences as either aspect or non-aspect word. The model also includes a set of linguistic patterns for the same purpose and combined them with the CNN. This ensemble model is used to extract the aspect from the customers' comments. The procedure for aspect model is as follows:

1) form a window around the word to tag
2) apply CNN on that window
3) apply maxpool on that window
4) obtain logits
5) apply CRF for sequence tagging

The trained model can be found here[2]

B. SenticNet

SenticNet is the knowledge base which the sentic computing framework leverages on for concept-level sentiment analysis. SenticNet is a publicly available semantic resource for concept-level sentiment analysis that exploits an ensemble of graph mining and multi-dimensional scaling to bridge the conceptual and affective gap between word-level natural language data and the concept-level opinions and sentiments conveyed by them [21]. SenticNet provides the semantics and sentics associated with 100,000 commonsense concepts, instantiated by either single words or multi-word expressions.

Figure 3 shows how a sentence is processed. The input text is first decomposed into concepts. If these are found in SenticNet [22], sentic patterns are applied. If none of the concepts is available in SenticNet, the ELM classifier is employed.

VI. Experimental Results and Discussions

In this section, we explain the results of our proposed survey questionnaire and aspect-based sentiment analysis on customer feedback. We also discuss the limitations and possible future directions based on the analysis of the customer-agent interaction data.

A. Analysis of Questionnaire

The first two questions of the survey were meant to understand the customer demographics in the insurance company. This helped us to understand the group of customers that robots like Nadine would attract in a work environment. From our questionnaire, we observed that females were more interested in talking to Nadine. People in the age group of $36-45$ had interacted the most with her. In general, we can observe that the younger generation was more comfortable and willing to interact with the robot. The results of both questions can be seen in figures 4 and 5.

[2]https://github.com/SenticNet/aspect-extraction

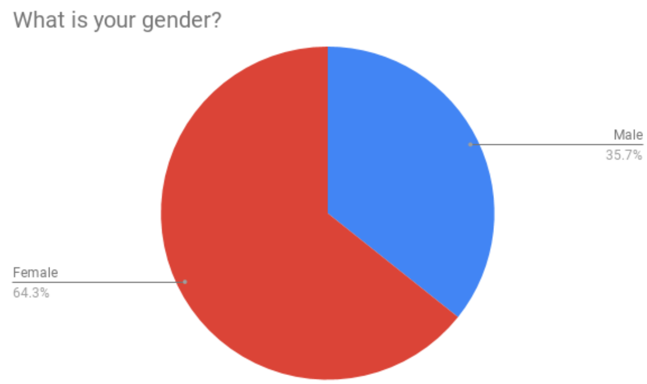

Fig. 4. Customer response to question 1

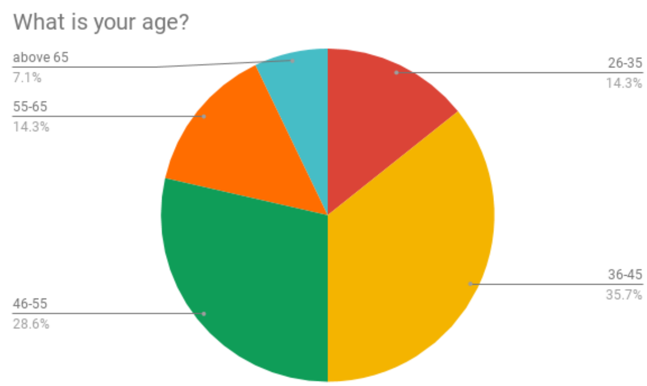

Fig. 5. Customer response to question 2

It was observed that 39% of the customers recorded that Nadine had the required skills and knowledge about the insurance company's products and services. In this initial study, Nadine was required only to answer customer queries and behave with the apt etiquette for the customer service agent. The skill set and questions provided for Nadine were limited. Due to security reasons and privacy concerns, Nadine was not able to access sensitive and personal data such as customer policy information. Due to the open nature of dialogue, the customers believed that she could access this type of data and help them with all possible queries, which Nadine was not trained for. This could be the reason why only 32% of the customers believed that Nadine was professional. People whose queries she could not handle thought she was not professional. Also, Nadine has a very realistic human-like appearance, which raised customer's expectations of the robot's professional ability and insurance-related functionality to be high. Thus it also shows there needs to be a trade off between the tasks trained for robots and its appearance. Nadine had an additional capability to help customers use the online platform of the insurance company. The motive was to familiarize the customers with the new online platform, which customers can use at their homes to get all routine policy-related information.

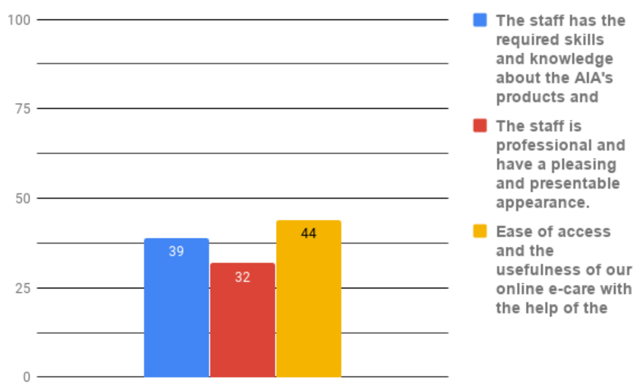

Fig. 6. Customer response to questions 3, 5, 7

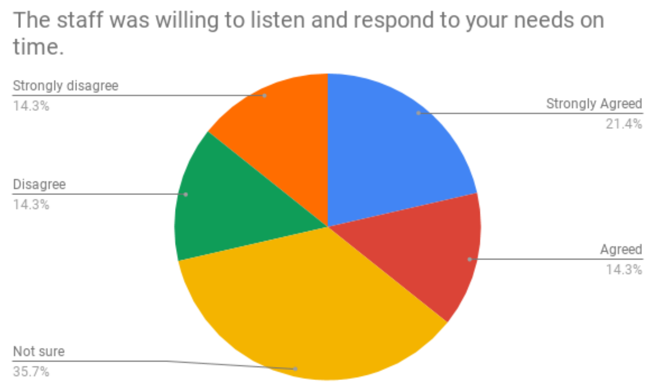

Fig. 8. Customer response to question 6

This would help to avoid unnecessary travel to the service centre. Nadine could guide them step by step to register their account and change their address on online platform. Mostly customers rated Nadine moderate on the help of the online platform. The results of questions 3, 5, 7 are shown in Figure 6.

For the question on Nadine's courteous nature and friendliness, customers mostly agreed or were neutral. For a customer service agent, it is necessary to be pleasant, courteous, always smiling and show emotions. As a social robot, Nadine has been programmed to simulate a range of emotions and had been set up according to the needs of an agent in the insurance company. Similarly, the customers mostly agreed or were neutral, when asked on Nadine's willingness to listen and respond on time. As a robot, Nadine is always welcoming and willing to listen, but responses could be delayed. For instance, when a customer's question is not in her database, she searches online for the most appropriate answer, which will delay her responses. Also, sometimes, she may not reply when the customer did not speak into the microphone correctly as she did not receive any input. The results of questions 4 and 6 can be seen in figures 7 and 8, respectively.

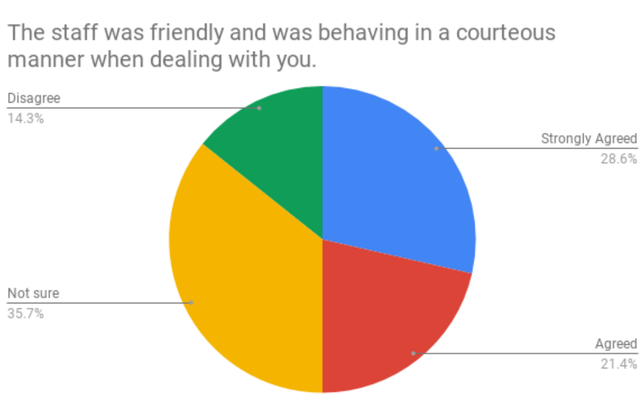

Fig. 7. Customer response to question 4

B. Sentic Computing Framework results of Customer Feedback

The results show the aspects and sentiments associated with the aspects of the user comments. The results discussed here will help the future generation of humanoid robots to enhance HRI. The aspects in Figure 11 shows the main characteristics that the customer looked for in the robot. The size of the aspects are proportional to the frequency of it being used in the text. It can be observed that functionality, appearance and performance were three main aspects that any customer commented on.

The sentiments can be either Positive, Negative and Neutral. The overall sentiment observed in customer feedback can be seen in Figure 9. 50% of the customers were Positive towards Nadine as an employee, 37.1% Negative and 10% as Neutral sentiments. SenticNet could not find sentiments in 2.9% of the feedback since they were written in informal language (microtext) [23] which our current version is not able to handle. The aspect-based sentiment can be seen in 10.

Due to the non-availability of sensitive customer data, Nadine cannot perform all tasks or functionalities that a customer agent can perform. We also need to add a security layer to be able to handle sensitive data. In an open social interaction, there are no restrictions on questions a customer can ask.

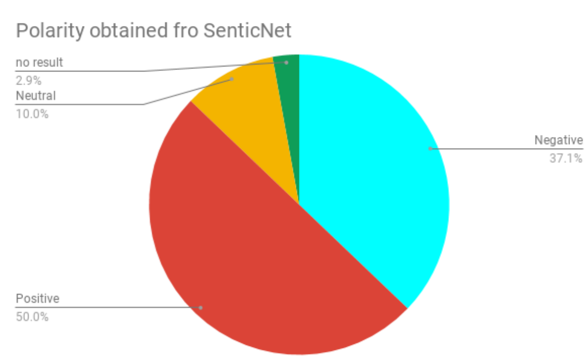

Fig. 9. Polarity detection

It is challenging to train a robot for open-ended questions. Thus, if Nadine is not trained for any question, she would have to go online and depend on her network speed for her answers. This will affect her response time and performance. It includes retraining model to answer more effectively and quick. The appearance of the robot plays a vital role in the way customers perceive the robot. Due to the uncanny valley [24], the expectation of realism from a human-like robot is high. The customers would believe Nadine could handle all types of situations and interactions like other human agents. Due to this, the results were mostly positive but with some negative comments focusing on manicure and other minute details. Few comments are related to the hardware used (such as the speaker, microphone), the language of communication and appearance (requires manicure) that can be easily changed to give a better customer interaction experience. We observe that most majority of sentiments are positive. The positive sentiments are mainly for the appearance, while negative sentiments focus around functionality, performance and response time. The negative sentiments are the result of the robot being very human-like, which increases the expectation of customers. We are also working on adding microtext normalization [25] to handle informal texts and common sense reasoning for an effective dialogue system. Future work revolves mostly around the negative aspects customers gave feedback about.

To summarize, our results show that the customers had an overall positive experience with Nadine as their service agent. Both user survey and aspect-based sentiment analysis of customer feedback show that Nadine's social behavior was acceptable and pleasing. The functionality and performance of Nadine was limited due to some of the reasons as mentioned above but can be improved as a part of our future work, e.g., by integrating commonsense reasoning [26], [27], [28] and recent dialogue systems technologies [29], [30].

VII. Conclusion

We have conducted user studies on a social robot at the workplace. Based on the customer feedback and survey questionnaire, we have identified customer expectations and demands of such a robot employee.

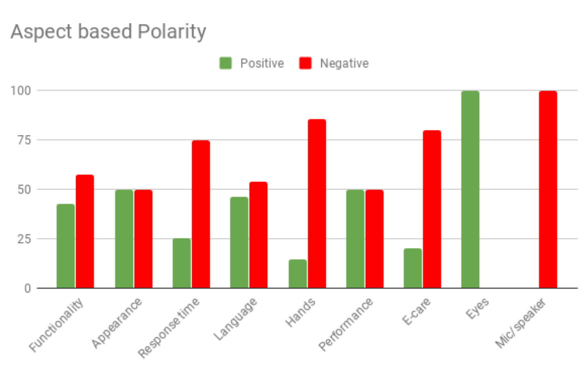

Fig. 10. Aspect-based Polarity

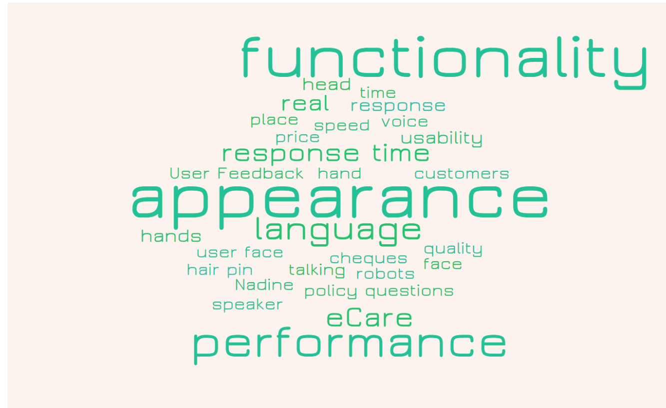

Fig. 11. Aspect Cloud from Customer's comments

We analyzed customer feedback using aspect-based sentiment analysis to identify aspects and sentiments associated with them. From our experiments, we observed that the general customer sentiment was positive towards Nadine. Functionality, appearance and performance were 3 main aspects of customer feedback. From our analysis, we also observed that Nadine performs well in a work environment and is capable of maintaining proper social etiquette that is pleasing to the customers.

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