# Improving Health and Safety Promotion with a Robotic Tool: A Case Study for Face Mask Detection

Sergio D. Sierra M.
sergio.sierramarin@bristol.ac.uk
Bristol Robotics Laboratory
FARSCOPE CDT
University of Bristol
University of the West of England
Bristol, UK

Maria Insuasty
maria.insuasty@urosario.edu.co
Dpt. of Biomedical Engineering
Universidad del Rosario
Escuela Colombiana de Ingenería
Julio Garavito
Bogotá, Colombia

Daniel E. Garcia. A.
daniel.garcia-a@mail.escuelaing.edu.co
Dpt. of Biomedical Engineering
Universidad del Rosario
Escuela Colombiana de Ingenería
Julio Garavito
Bogotá, Colombia

Marcela Munera
marcela.muneraramirez@bristol.ac.uk
Bristol Robotics Laboratory
University of Bristol
Bristol, Colombia

Carlos A. Cifuentes
carlos.cifuentes@uwe.ac.uk
Bristol Robotics Laboratory
University of the West of England
Bristol, Colombia

## ABSTRACT

Social robots have been shown to effectively promote healthy behaviour in humans. In the context of the pandemic, these robots have been used to encourage the use of face masks and other biosafety measures. However, human perception in these scenarios is yet to be assessed. This study evaluates the effectiveness of using a social robot, specifically the NAO robot, to promote face-mask usage in public spaces with a hybrid experiment. The methodology involves an in-person study, as well as an online survey. The results show that the robot was able to detect correct face-mask usage with 95% accuracy, and 87.5% of participants had a positive experience interacting with the robot. Statistical results also suggest that the users perceiving a human-robot interaction scenario through a pre-recorded video can perceive differently the robot's trust, safety, and intelligence, among others. These findings suggest that social robots can be a valuable tool for promoting health and safety measures, not only during the pandemic but in other collaborative environments as well.

## CCS CONCEPTS

• **Human-centered computing** → *Empirical studies in HCI*; *User studies*; • **Applied computing** → Sociology.

## KEYWORDS

Social Robots, Human-Robot Interaction, Face Mask Detection


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## 1 INTRODUCTION

Back in 2020, the health emergency caused by the SARS-CoV-2 spread rapidly around the world [1]. Given the transmission rate of the virus, the number of infections and deaths in the last years represented a worldwide concern [1]. Consequently, different governments and other institutions focused their efforts on the development of strategies to reduce or mitigate the effects of the pandemic [2, 3]. For example, physical distancing, constant hand washing, monitoring of temperature, regular disinfection, and using the face-masks were some of the adopted prevention measurements [3–5]. In this scenario abiding by safety protocols was paramount [2, 4, 6]. For that reason, multidisciplinary teams in the area of health and engineering worked intensively to generate solutions focused on using robotics and artificial intelligence as support tools for managing and controlling compliance with such protocols [7–10].

These solutions had a positive impact on the control of the pandemic. However, the literature suggests that monitoring the use of face masks in closed spaces - such as industrial scenarios, laboratories, and health institutions- is still of great relevance [11–13]. In this sense, empowering social robots with machine-learning techniques for face-mask detection might tackle health and safety promotion issues in multiple industrial scenarios [11]. Such models are often based on deep learning to allow computer systems to autonomously identify when a person is wearing a mask correctly [12, 13].

According to the above, this study describes the preliminary assessment of a social robot empowered with a face-mask detection algorithm. The robot behaviours were designed to gently enforce the use of face-mask as a general health and safety approach. This work seeks to explore the effectiveness of a social robot to promote health and safety features, such as the use of face masks. The main contribution of this paper is to present evidence demonstrating the benefits of using social robots to enforce safety norms, such as the wearing of masks, in contexts such as pandemics and industrial scenarios.

The following research question is targeted:

R1: *What is the potential of social robots to enforce and promote health and safety features in environments requiring the wearing of face masks?*

# 2 METHODOLOGY

This section describes the robotic system that was used for health and safety promotion, for a face mask usage scenario. The algorithm for face mask detection is briefly defined, and the experimental protocol is outlined.

## 2.1 Human-Robot Interface

To monitor and promote the use of face masks, the proposed system (see Figure 1) is composed of (1) a social robot that interacts with the users, (2) two cameras to record the environment of the study, and (3) a computer to process data and trigger the robot's behaviours.

*2.1.1 Main Modules.* The NAO social robot was implemented for this study (NAO V6, Softbank Robotics, USA), a fully programmable robot, capable of interacting naturally with all types of audiences.

Due to the low resolution of the robot's camera, an external camera was used. The LifeCam Studio webcam (LifeCam Studio, Microsoft, Redmond, WA, USA) was used because its Full HD 1080p sensor offers good sharpness and high image quality. For this specific case, two cameras were implemented, one to capture the face of the subject approaching the system and a second one to record the entire studio environment.

The system's main PC consists of an Omen laptop (HP, Palo Alto, CA, USA) integrated with an 8-core Intel Core i7-7700HQ (2.80 GHz) and a RAM memory of 16 GB. The device runs the Robotic Operating System (ROS, Kinetic version) under a Linux distribution (Ubuntu 16.04-Xenial). This device is responsible for interfacing all the modules of the system.

*2.1.2 Algorithm for face mask detection.* This study entails a pre-trained Deep Neural Network to detect whether a person is wearing a face mask or not. The used model is available at https://github.com/sergiosierram/mask_detection.

*2.1.3 Robot's Behaviours.* As presented in Figure 1, the robot exhibited two main behaviours to interact with users. In both cases -wearing and not wearing face-mask- when the robot identifies a person, it provides verbal and visual feedback, depending on the result of the face mask detection. In case of correct face-mask usage, all robot's LEDs are turned on with green colour and the robot text-to-speech engine is used to say "*Hello, you can pass*". In case of incorrect or no usage of face-mask, all robot's LEDs are turned on with red colour and the robot says "*Hello, your access is not granted, please use the face-mask*". These behaviours were accompanied by movements of the robot's arm to emphasize the instruction and make it appear more natural.

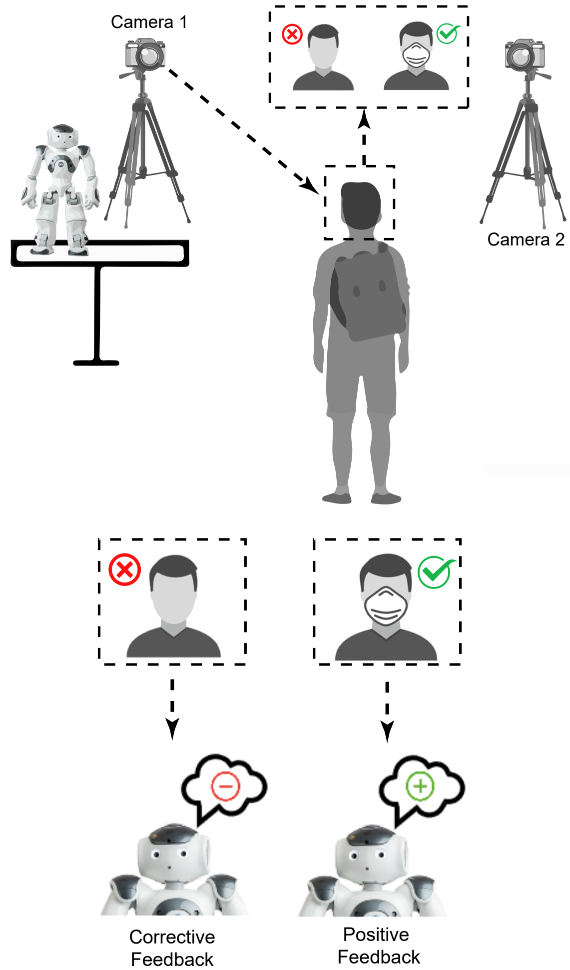


**Figure 1: Illustration of the social robotic system for health and safety promotion. a) Experimental setup for in-person interaction. b) Types of feedback.**

## 2.2 Experimental Protocol

This study comprises two-fold experimentation. First, the system was deployed for in-person interaction with the real robot. Second, a video of actors interacting with the robot was delivered through an online survey. Both studies were assessed using UTAUT and Godspeed questionnaires (5-point Likert scale questions).

During the first study, two types of videos were also recorded. First, recordings of the participant's full body to identify their movements and environment. Second, recordings of the participant's face to identify reactions towards the robot's behaviours. These videos were processed by two coders, who extracted: (i) the existence of a reaction from the user towards the robot, (ii) the type of the reaction (verbal, movement, another), (iii) the type of participant's attitude towards the feedback (positive, neutral, negative), (iv) the accuracy of the feedback, (v) whether the participant followed the robot's

**Table 1: Godspeed comparison $p$-values between in-person and online interaction, using the Mann-Whitney-Wilcoxon test.**

| Category | In-Person | Online | In-Person vs. Online |
|---|---|---|---|
| Anthropomorphism | 3.5 ± 1.15 | 3.4 ± 1 | 0.08 |
| Animacy | 3.6 ± 1.2 | 3.3 ± 1.2 | <0.01 |
| Likeability | 4.4 ± 0.9 | 4.23 ± 0.82 | <0.01 |
| Perceived Intelligence | 4 ± 4 | 3.6 ± 1.1 | <0.01 |
| Perceived Safety | 4.1 ± 1 | 4.2 ± 0.8 | 0.75 |

**Table 2: UTAUT comparison $p$-values between in-person and online interaction, using the Mann-Whitney-Wilcoxon test.**

| Category | In-Person | Online | In-Person vs. Online |
|---|---|---|---|
| Usability | 4 ±1 | 4.3 ± 0.8 | 0.01 |
| Utility | 4.4 ±0.8 | 4.2 ± 0.8 | 0.01 |
| Safety | 5± 1 | 4.4 ± 0.7 | <0.01 |
| Trust | 4± 1 | 4.2 ± 0.8 | <0.01 |
| Sociability | 3 ± 1 | 2.9 ± 1.3 | 0.04 |
| Social Presence | 4 ±1 | 3.3 ± 1.2 | <0.01 |

instruction, and (vi) whether the participant waited for the robot to finish the feedback before leaving.

The first experiment was performed at the Escuela Colombiana de Ingeniería Julio Garavito, Bogotá, Colombia, involving 50 subjects. In this case, 67.39% of them were males, and 32.6% were females. The participants were mainly undergraduate and graduate students (91.5%). Professors also participated in the study (8.51%). The second study was conducted online, involving 227 subjects In this case, 70% of them were males and 30% were females.

## 2.3 Data Analysis

Qualitative data were collected from the video recordings of the interaction with the robot, as well as from the surveys completed by the participants. The answers from the surveys were grouped using the categories described in the Godspeed and the UTAUT questionnaires. For the Godspeed survey, five categories were used: anthropomorphism, animacy, likeability, perceived intelligence and perceived safety. For the UTAUT survey, six categories were used: usability, utility, safety, trust, sociability and social presence. Thereafter, the scores were reported using mean and standard deviation, and finally, the results from both studies were compared using the Mann-Whitney-Wilcoxon test.

## 2.4 Ethics Statement

The Research Ethics Committee of the Escuela Colombiana de Ingeniería Julio Garavito approved this experimental protocol. All participants provided their signed consent to participate in the study after being informed about the experiment's scope and purpose.

# 3 RESULTS

The analysis of the in-person encounters gave the following outputs: 69.95% of the participants reacted to the feedback provided by the robot, and 61.11% of those reactions were facial gestures such as smiles. Also, 33.33% of the participants exhibited movements, and 5.55% showed verbal reactions.

The participants' attitudes were mainly positive, with an 87.5% incidence. The remaining 12.5% of the reactions were neutral, with zero negative reactions. Regarding the robot's performance, it provided correct feedback in 95.45% of the cases. In the remaining 4.54%, the algorithm failed to detect a person or gave incorrect feedback. Regarding the actions of the participants after receiving feedback, 97.5% of the people followed the robot's instructions. Finally, 71.43% of the participants waited for the robot to finish the correction. These results may be due to the participant's interest in the system's operation or towards the robot and its functionalities.

The second study gathered a larger sample of participants to compare Godspeed (See Table 1) and UTAUT (See Table 2) results between users who watched videos against the users of the first study. These tables also reported the mean and standard deviation for the participants' responses. The Godspeed questionnaire showed the existence of significant differences for *animacy*, *likeability*, and *perceived intelligence*. The UTAUT questionnaire showed significant differences for all the categories. These outcomes were expected as the perception is affected when online recordings are used.

# 4 DISCUSSION

Regarding the in-person interactions, participants and spectators demonstrated curiosity about the system's operation and the robot. They found it pleasant and engaging in most of the interaction types. The users manifested this with gestures of approval in the form of smiles and movements towards the robot and the research team (e.g., thumbs up was the most frequent). For example, when the robot detected a non-correct use of the face mask and gave the corresponding feedback, the participants showed a more positive reaction than the reaction to the robot's dialogue when the robot provided positive feedback. This might be explained by the fact that the users enjoy being corrected by the robot in a friendly way. However, this should be explored in further mid-term studies to remove the novelty effect.

Using accessories such as caps interfered with the system's ability to detect the mask properly. This system's malfunctioning generated neutral reactions in the users with movements associated with impatience while waiting for the robot's feedback. This behaviour may affect the perception of safety and intelligence, influencing the user's confidence in the system. These results are evident in the surveys conducted, where statistical analysis found significant differences between the perceived intelligence category of Godspeed and the safety category of the UTAUT.

For most of the interaction encounters, the first reaction of the participants towards the robot was to smile when the robot performed the recognition or when the robot started speaking. When the robot corrected participants accompanied by more people, it was possible to identify a preliminary tendency to look first at the social group before attending to the robot's correction. This behaviour could be explained by the user's willingness to see the reaction of others to the robot's correction.

One of the participants sought to identify the capabilities of the face mask detection system, initially with a non-use of the mask, then correctly using the mask and finally the participant placed his hand on his face to wait if the robot made the correct correction. However, the robot did not recognise the participant in the last trial. Therefore, it was possible to identify an interest of the participant regarding the capabilities of the detection system and the robot. In another case, one of the participants was incorrectly wearing the mask. However, the robot provided feedback as if the participant was wearing his mask correctly. Despite this, upon receiving feedback from the robot, the participant put his mask on properly and continued on his way.

The proposed experimental protocol addresses two scenarios: (I) directly interacting with a robot (in person) and (ii) observing someone else interacting with a robot (online). These situations allow comparing the effects of the robot and the interaction from different points of view and thus allowing a broader understanding of socially assistive robots for rules enforcement. Finally, this study exhibits a limitation related to the feedback accuracy with the actors. In particular, the videos shown to the online participants exhibited a robot with perfect feedback accuracy, which might lead to differences in perceived usability, intelligence, and safety, among others.

## 5 CONCLUSION

This work presented the implementation of a face mask detection algorithm in a socially robotic system to provide positive and negative feedback according to interaction with users. The robot dialogues were simple and easily understandable and thus ensure a natural and intuitive interaction. A hybrid experiment involved in-person interaction and online surveys to assess the proposed system. The system recorded the attitudes, reactions, and heeding to the robot's feedback for those participants interacting with the robot in person. Also, their usability and acceptance perception was evaluated and compared against a larger sample of online participants who watched a video recording of the proposed scenario.

According to the results, the participants involved in the in-person interaction exhibited a mostly positive attitude towards the robot's feedback. Such an attitude facilitates interaction with the robot and encourages the user to follow the robot's instructions. In comparison with the perceptions of the online participants, the recorded videos resembled a typical interaction with the robot for a face mask feedback task. The videos showed actors using a face mask, correctly and incorrectly, while the robot gave proper feedback. The participants watched multiple variations of this scenario. Statistical analysis found significant differences in participants' perception of animacy, likeability, intelligence, safety and trust.

In this sense, first, these preliminary results suggest that users might prefer in-person interactions with social robots in monitoring or feedback tasks. Second, users tend to exhibit positive attitudes towards the robot and its feedback strategies for in-person interaction. This application has the potential to go beyond face mask usage monitoring, as the robot could be used for monitoring other health and safety issues in clinical scenarios, as well as work/industry settings. Future works should compare the robot feedback against instructions given by other persons or with plainly written signs.

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