ALMA MATER STUDIORUM
UNIVERSITÀ DI BOLOGNA

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

ARTIFICIAL INTELLIGENCE

MASTER THESIS
In:
Emotion Recognition from Facial Expressions

Integrating an Emotion Recognition Model for the Flobi System

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To my parents Ali and Zahra.

Abstract

This thesis investigates if emotional states of users interacting with a virtual robot can be recognized reliably and if specific interaction strategy can change the users' emotional state and affect users' risk decision.

For this investigation, the OpenFace [1] emotion recognition model was intended to be integrated into the Flobi [2] system, to allow the agent to be aware of the current emotional state of the user and to react appropriately. There was an open source ROS [3] bridge available online to integrate OpenFace to the Flobi simulation but it was not consistent with some other projects in Flobi distribution. Then due to technical reasons DeepFace was selected.

In a human-agent interaction, the system is compared to a system without using emotion recognition. Evaluation could happen at different levels: evaluation of emotion recognition model, evaluation of the interaction strategy, and evaluation of effect of interaction on user decision.

The results showed that the happy emotion induction was 58% and fear emotion induction 77% successful.

Risk decision results show that: in happy induction after interaction 16.6% of participants switched to a lower risk decision and 75% of them did not change their decision and the remaining switched to a higher risk decision.

In fear inducted participants 33.3% decreased risk 66.6 % did not change their decision

The emotion recognition model classifies happy emotions as neutral most of the time and has bias to the Neutral emotion. In general the emotion recognition model is not reliable in this application. It can be because of the fact that it has been trained on actors' faces.

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Chapter 1

Introduction

The goal of this thesis is to determine whether users' emotional states when interacting with a virtual robot can be reliably recognized and whether different types of interaction strategies can alter users' emotional states and influence their risk-taking behavior. It looks into the question: Can AI assist people in making decisions?

The thesis consists of four phases including: emotion induction, risk decision making, interaction with robot simulation and again risk decision making. The experiment has been done on 20 participants.

This thesis work consists of five chapters. Chapter one is Introduction and introduces the work which has been done, motivation, goal and the structure of the thesis. Chapter two is Literature Background. Chapter three is Software and Tools which explains all software and tools used for completing the thesis. Chapter four is called Methodology and explains the methodology used for writing the thesis. Chapter five is Results which explains the experimental results.

Chapter 2

Literature background

2.1 Emotion Recognition

Social intelligence skills including communication comprehension, decision-making, and comprehending human behavior are all greatly impacted by emotional factors [4]. Recent years have seen an increase in the number of technology companies whose exclusive concentration has been on creating tools that can recognize emotions from specific input. According to [5], the channels from which we can get affective information are: speech, text, facial expressions, body gestures and movements and physiological states. Other approaches to obtaining emotional data are mentioned in [6]. [5] also has analyzed current technologies to detect human emotions but it has not discussed DeepFace [7]which is used in his thesis. Emotion recognition is applied in the area of Education, Aid for Disabled, Human Computer Interaction and Robotics, Safety Aid and Entertainment [8]

2.1.1 Facial Emotion Recognition

Facial emotion recognition involves recognizing facial expressions that convey emotions such as fear, happiness, and disgust. It is crucial to interactions between people and computers [9]Various applications of automatic emotion recognition based on facial expressions have been presented and applied in several fields, such as safety, health, and human-machine interfaces [4]. In the interface between humans and machines, automated and real-time facial expression is crucial. Humans can recognize emotions quickly and easily, but it is difficult for machines to recognize facial expressions [4]. Some notable uses for facial emotion recognition are: alert system for driving, social Robot emotion recognition system, medical practices, feedback system for e-learning, the interactive TV applications enable the customer, actively give feedback on TV Program, mental state identification, automatic counseling system, face expression synthesis, music as per mood, in research related to psychology, in understanding human behavior, and in interview.

In [5]four technologies used to detect emotions from facial expressions are compared to each other. These technologies are:

- Emotion API (Microsoft Cognitive Services)
- Affectiva
- nViso
- Kairos

Name	API/ SDK	Requires Internet	Information returned	Difficulty of use	Free Software
Emotion API	API/ SDK	Yes	Happiness, sadness, fear, anger, surprise, neutral, disgust, contempt	Low	Yes (Limited)
Affectiva	API/ SDK	Yes	Joy, sadness, disgust, contempt, anger, fear, surprise [1]	Low	Yes, with some restriction
nViso	API/ SDK	No	Happiness, sadness, fear, anger, surprise, disgust and neutral	-	No
Kairos	API/ SDK	Yes	Anger, disgust, fear, joy, sadness, surprise [2]	Low	Yes, only for personal use

Table 1. Comparison of emotion detection technologies from facial expressions [5]

2.2 Influence of Emotion on Decision

Neuroscientific research has revealed that, contrary to what was previously thought, emotional processes, such as emotions and feelings, have a significant influence on consumer behavior (i.e., decision-making). [10]

Emotional processes play a crucial role in influencing decision-making since neuroscientific research has shown that the majority of decision-making is based mostly on emotional and not cognitive processing of information (Alsharif et al., 2021).

Mano in [11] investigated how pleasantness, unpleasantness, and arousal affected risk-taking. He discovered that arousal triggers risk-taking, unpleasantness triggers a need to defend against harm, and pleasantness triggers a desire for gain.

Studies on decision-making in neurological patients who are unable to normally interpret emotional information indicate that people occasionally rely more heavily than usual on their gut feelings or emotions when making decisions. [12]

Authors in [13] investigated how emotion plays a role in making strategic decisions, both good and negative. In contrast to participants in a negative mood, they discovered that participants in a happy mood were more likely to see an uncertain strategic issue as an opportunity and took fewer risks.

Emotions can be measured or recorded using a variety of methods such as pupil dilation (eye tracking), skin conductance (EDA/GSR), brain activity (EEG, fMRI), heart rate (ECG) and facial expressions.

Feelings can be measured with the aid of self-reporting instruments like interviews, surveys, and questionnaires that include rating scales and self-assessment procedures, feelings can be measured.

There is agreement on the two dimensions for assessing emotions: Arousal and Valence. (Alsharif et al., 2021). [10] Valence is a term used to describe either positive or negative reactions, such as pleasure or displeasure. When we talk about arousal, we mean either high or low emotional arousal, such as surprise and calmness, successively [14]. A focus of certain studies on incidental affect and decision-making is how affect affects decision-making in risky situations. Wright and Bower in [15] discovered that participants who were happy thought that positive events were more likely and that negative events were less likely, whereas participants who were depressed thought the opposite (compared to a control condition).

Nygren, Isen, Taylor, and Dulin in [16] discovered that participants in optimistic states tended to overestimate the likelihood of winning compared to the likelihood of losing, although this was not the case for those in a control condition.

Chapter 3

Software and tools

3.1 DeepFace

Serengil [7] states that The Deepface framework provides lightweight face recognition and facial attribute analysis in Python (age, gender, emotion, and race). “It is a hybrid face recognition framework wrapping **state-of-the-art** models: VGG-Face, Google FaceNet, OpenFace, Facebook DeepFace, DeepID, ArcFace, Dlib and SFace”(Serengil, Sefik Ilkin).

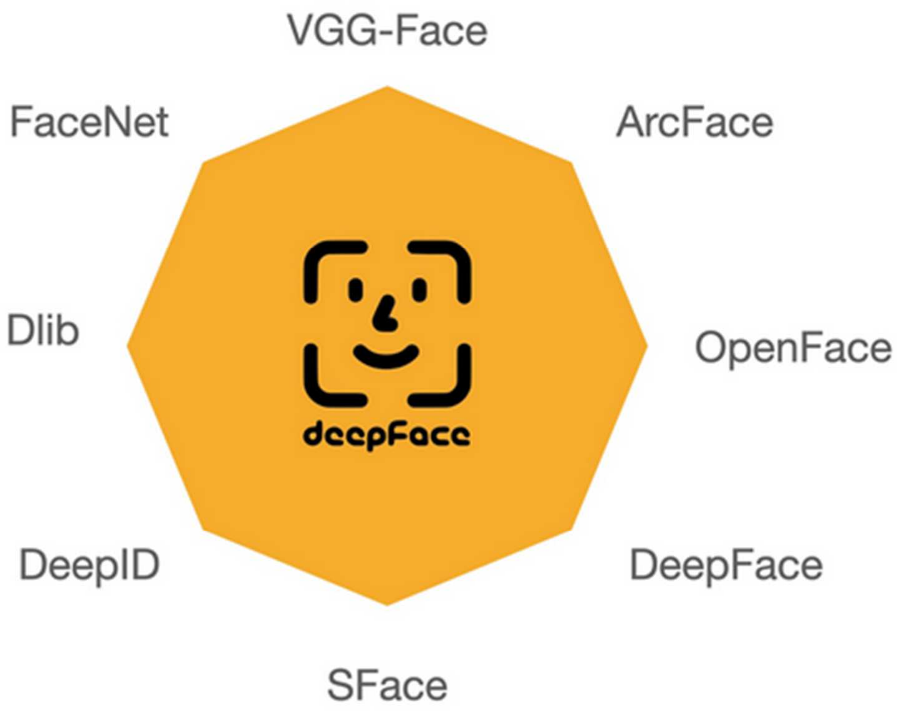

Figure 1. DeepFace models

DeepFace has closed the majority of the remaining gap between machines and the human visual system in the most popular benchmark in unconstrained face recognition, and is now at the brink of human level accuracy [17].

According to [17] the Social Face Classification (SFC) dataset, a large collection of photos from Facebook, is used to train face representation. Then the Labeled Faces in the Wild database (LFW) [18] and the YouTube Faces (YTF) [19] dataset are used to apply the face representation. LFW is the de facto benchmark dataset for face verification in unconstrained environments, and YTF is modeled similarly to the LFW but focuses on video clips.

3.2 Interactive questionnaire for Risk Decision

In this thesis there was an interactive questionnaire designed by one of the members of the project group. The first page was starting with putting the participant number then the second page was the welcoming page which included text to welcome users and Flobi was triggered to repeat those texts to the participant. The whole questionnaire was designed in German language. After the welcoming page, the participant was asked to click the Next button and answer questions about his/her age, gender and education.

3.2.1 Questionnaire Scale to Access Affinity for Technology Interaction

The next questionnaire is Questionnaire Scale to Access Affinity for Technology Interaction. A person's propensity to actively participate in intense technology engagement — or to avoid it — can be determined using the 9-item affinity for technology interaction (ATI) measure. ATI can be considered a vital personal tool for individuals to successfully manage technology [20].

3.2.2 The BFI-10 scale

The next three pages of the questions are the BFI-10 scale [21]. Extraversion, agreeableness, conscientiousness, emotional stability, and openness are the Big Five personality traits measured by the BFI-10, a 10-item questionnaire.

3.2.3 Self-Assessment Manikin (SAM)

The next page is the Self-Assessment Manikin (SAM) of Bradley & Lang [22] is a non-verbal visual evaluation approach that measures the arousal levels (low - high) and feelings (pleasure – displeasure) of respondents in response to varied emotional stimuli.

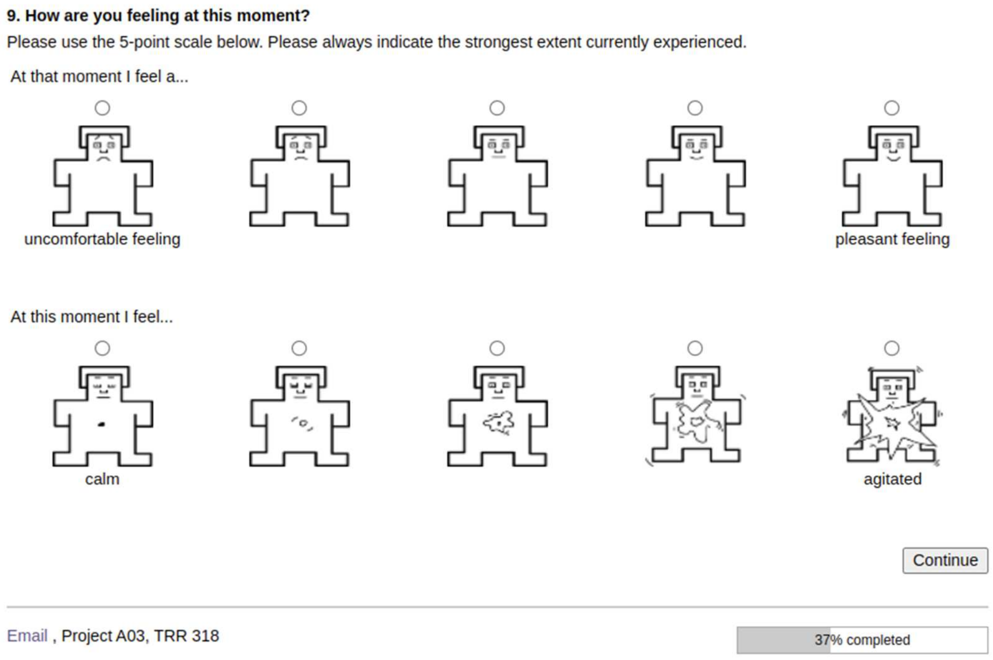

Figure 2: SAM

The next page is the relaxation phase in which Flobi asks the participant to relax for two minutes.

The interactive questionnaire also includes the SAM and BFI-10 scale questions after the emotion induction phase. The emotion induction phase is a page after relation phase in which the Flobi asks the participant to remember a sad or happy moment in his/her life. It also includes the designed game for risk decision making before and after the participant is interacted by Flobi.

3.2.4 The Decision Making Game

The interactive questionnaire includes a game which lets participants select their choice and the choice will be identified as high or low risk choice. The game is based on Risk Aversion and Incentive Effects By CHARLES A. HOLT AND SUSAN K. L [23]. There are 10 Lotteries with each 2 Options. Option B has always a higher Reward with the risk of earning nearly nothing. The Lottery looks like the following:

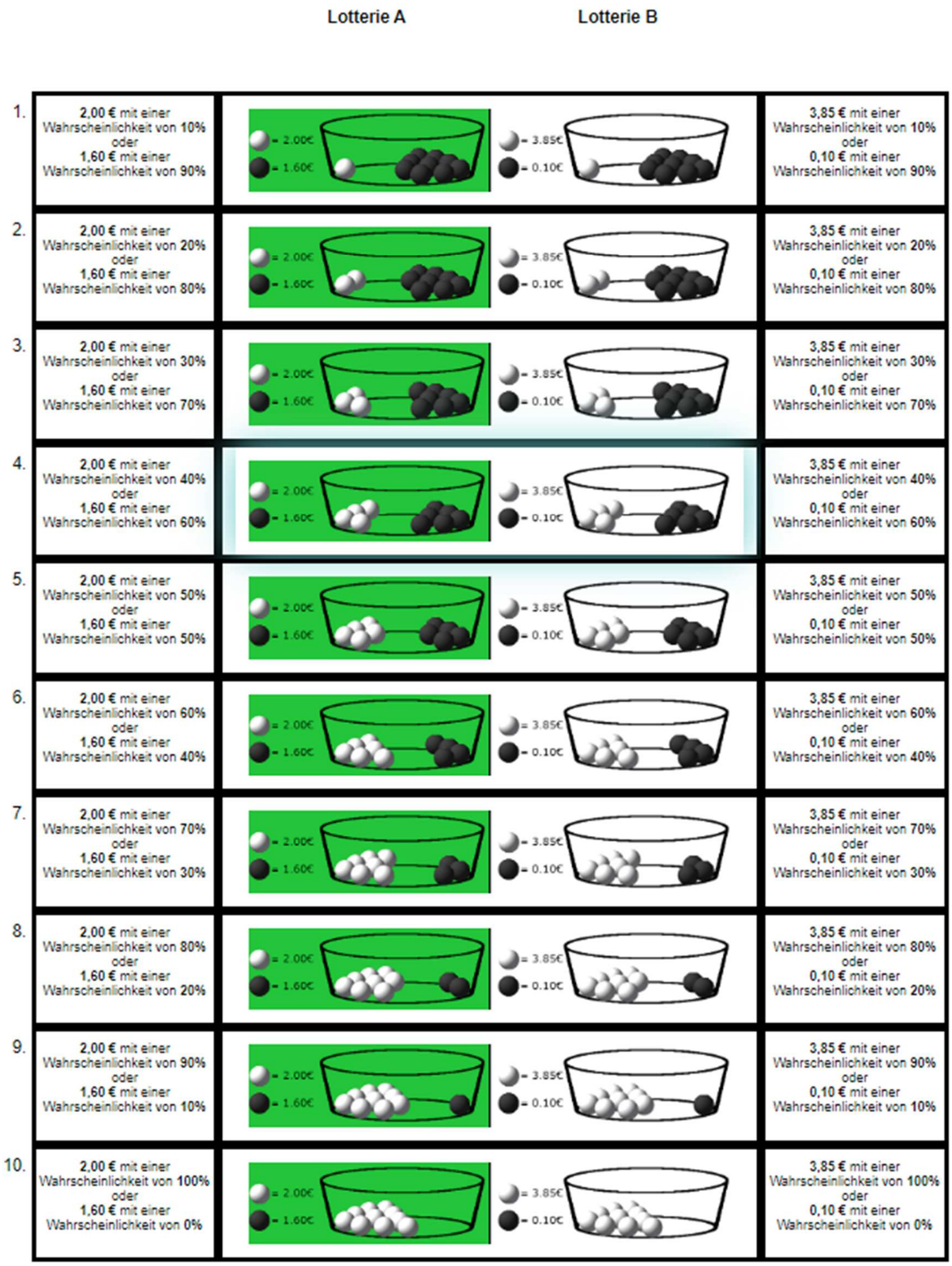

Figure 3. Risk decision making game.

The Participant chooses when they want to switch from the Left to the Right site. An early switch means that the participant is willing to take a higher risk and a late switch takes less risk. Switching at 7 looks like this:

Figure 4. Switch in risk decision making game

They are only allowed to switch one time from left to right. When the Participant has chosen a Lottery (and Flobi suggested to change the lottery depending on the Emotions) one Lottery will be randomly chosen and from that one ball will be chosen.

The Texts on the left and right side of the Lottery are explaining the probabilities. At Game 10 for example the Left side says:

“2.00€ with a probability of 100%

Or

1.60€ with a probability of 0%”

3.3 Flobi, The Bielefeld Anthropomorphic Robot Head

It has been developed in Bielefeld (since 2010) for HRI research. Flobi is an uncanny valley-avoidant robotic head with cartoon-like and baby-like features capable of expressing human-like emotions and to help people feel more comfortable, it was made purposefully simple and cartoonish [2].

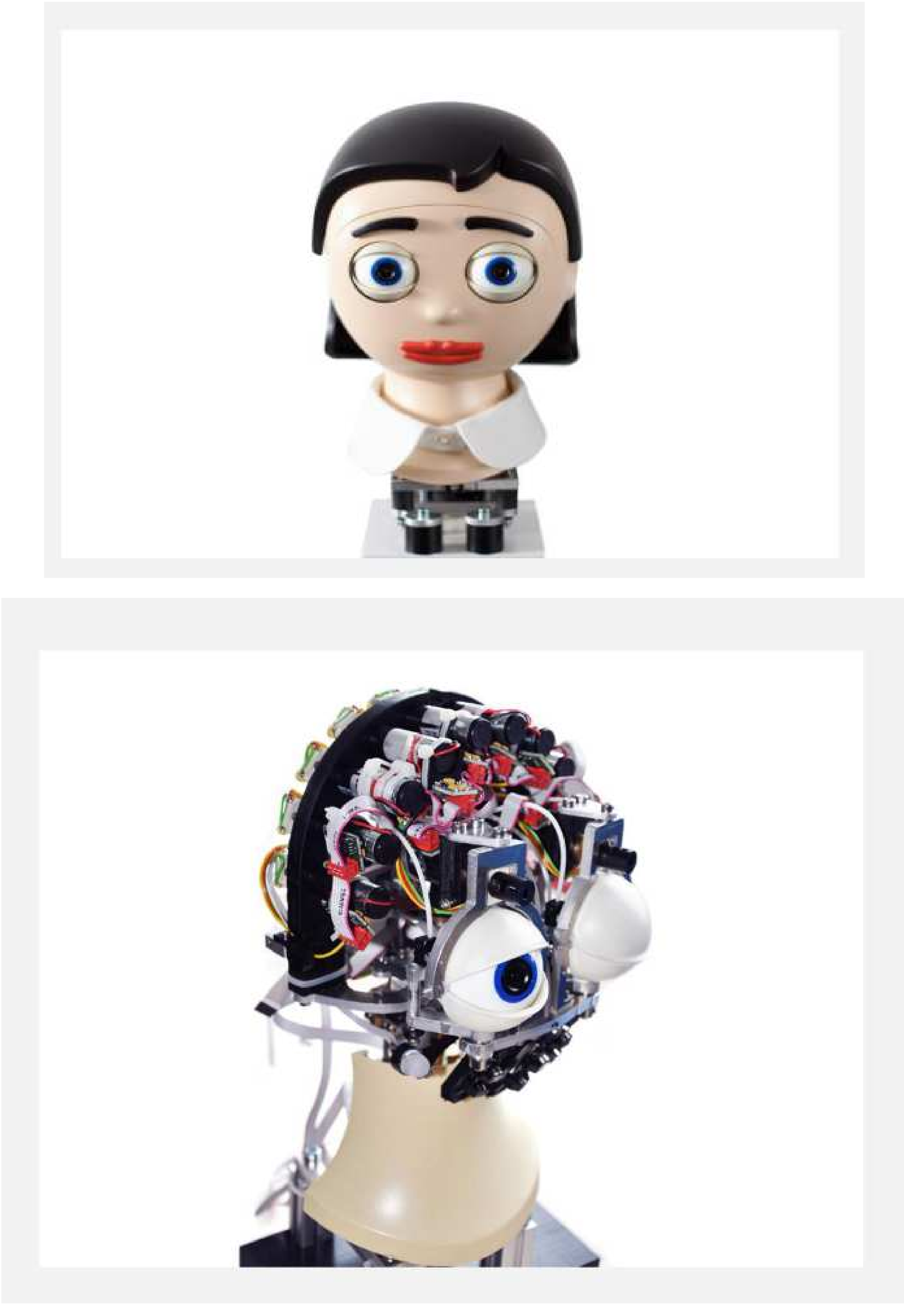

Figure 5. Flobi Robot

Besides the neutral facial expression, five other basic emotions can be represented by Flobi. These emotions are easily recognizable except for fear probably because fear also depends on body posture (Hegel et al, 2010).

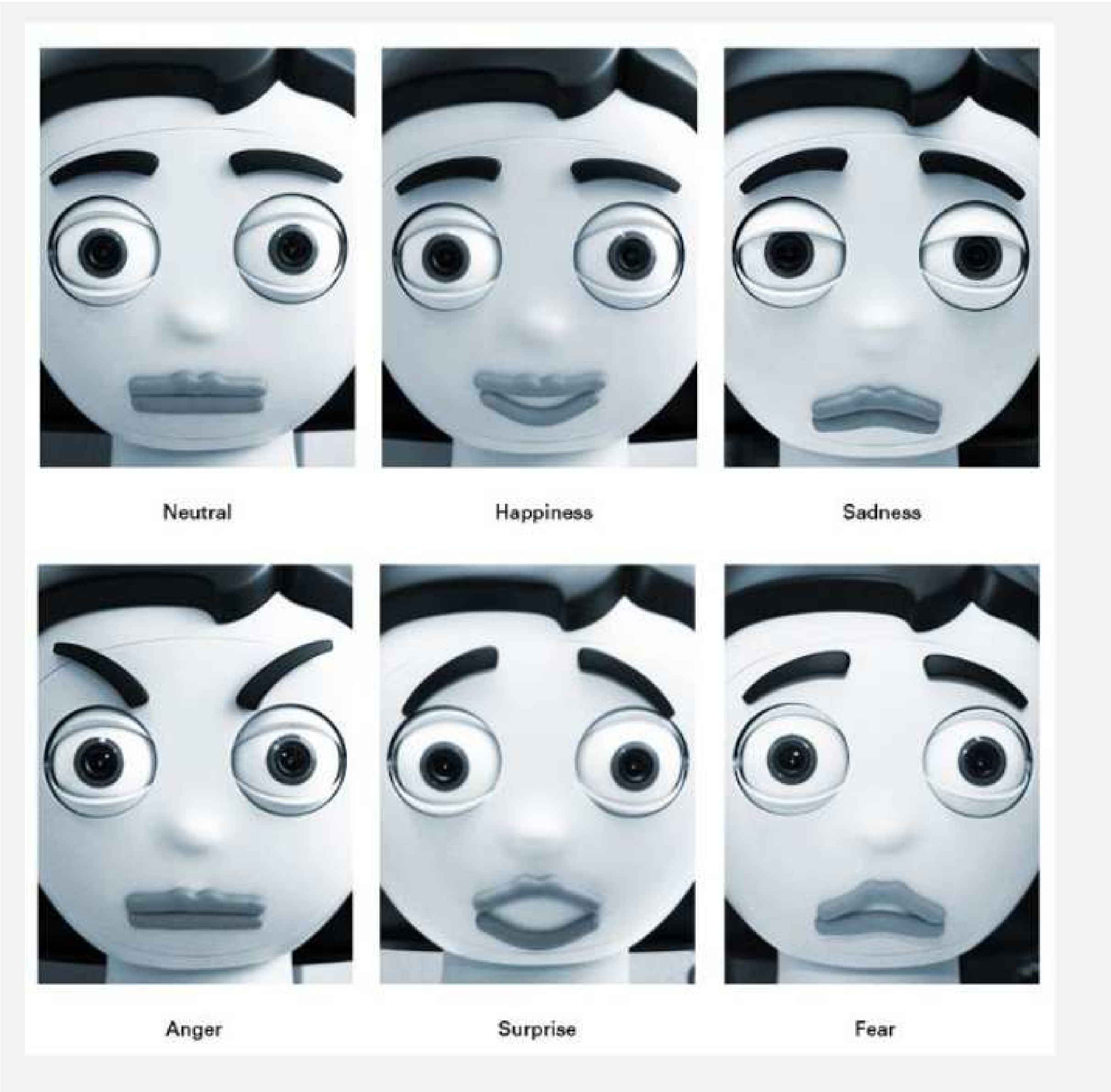

Figure 6. basic emotions with Flobi

3.3.1 Flobi simulation

In this thesis I worked with Flobi simulation not Flobi hardware. There are different distributions for Flobi. The Unity distribution was used in this thesis. The Unity distribution can be installed on Ubuntu 20. The simulation environment looks like as the following:

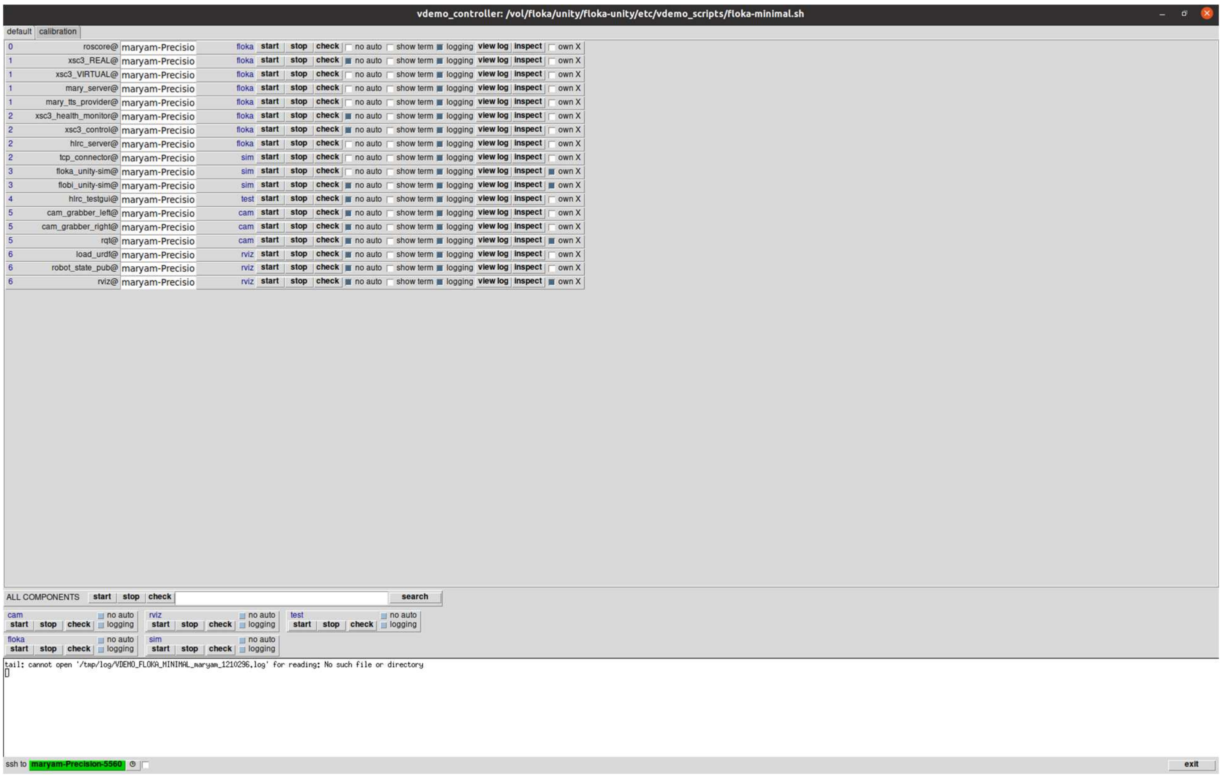

Figure 7. Unity distribution of Flobi

Its different components are shown in the following figure:

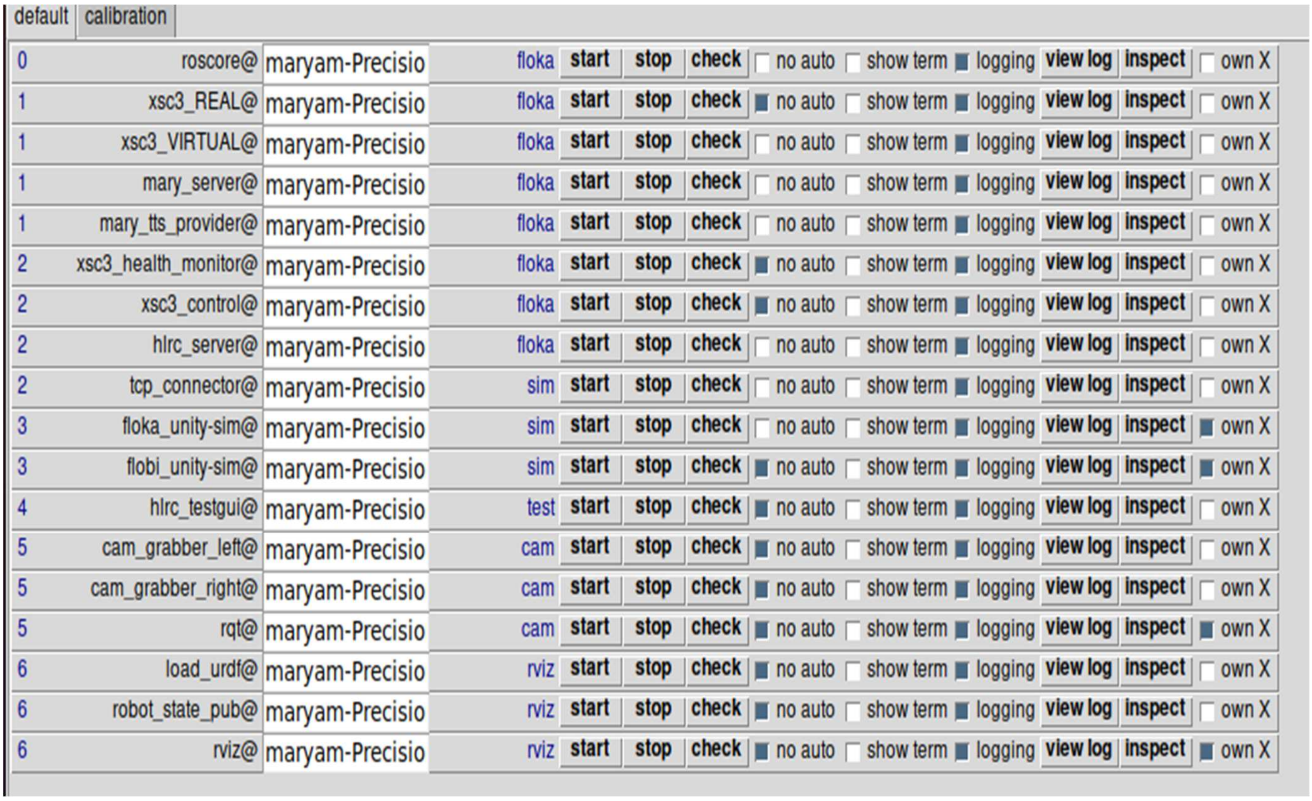

Figure 8. Components of Unity distribution of Flobi

After starting the flobi_unity-sim component you can see the following window:

Figure 9. Flobi head simulation

The installation of the Floka unity distribution needs the RDTK tool and Jenkins [24] installation and building different projects via Jenkins.

3.3.1.1 Jenkins

Jenkins is an open source automation server, which enables developers around the world to reliably build, test, and deploy their software [24].

3.3.1.2 RDTK tool

According to RDTK’s documentation [25], the Research Development Toolkit (RDTK) provides the following techniques and tools for software engineers:

- Continuous Integration (CI) and Deployment (onto diverse target platforms)
- Reproducibility
- Handling of dependencies
- Documentation, cataloging, meta-data and re-use

At the University of Bielefeld's Cluster of Excellence Cognitive Interactive Technology (CITEC), RDTK is used for both internal projects and collaboration with outside parties.

3.3.1.3 ROS

ROS [26], which stands for Robot Operating System. For working with different components of Flobi there is a need for learning ROS and its installation. Since the Unity distribution of Flobi is compatible with Ubuntu 20, I needed to install ROS Noetic. There was a need to learn about the following topics related to ROS:

- creating Catkin workspace with ROS Noetic
- ROS workspace
- ROS package
- ROS nodes
- ROS topics
- ROS messages and publishing message in ROS topic
- ROS computation graph
- ROS Master Node
- ROS publisher and subscriber node in Python
- Running multiple ROS nodes with roslaunch.

Chapter 4

Methodology

4.1 research question and goal

This study addresses three goals: first, evaluating how well the emotion recognition model works? This is done by evaluating performance of DeepFace on real world data. Second, evaluating how well the emotion induction strategy influences the participants' emotion? This is done by comparing user self reported emotion before and after emotion induction. Third, if a certain interaction strategy can help to change the user's behavior in decision making? This is done by evaluating whether Flobi was successful in affecting participant decisions.

This study includes three hypotheses: First, DeepFace recognizes the user's emotion correctly. Second, the interaction will decrease the user‘s emotion. Third, the interaction will also affect the user's decision.

4.2 structure of the study

The study consists of four phases including emotion induction, risk decision making, interaction of Flobi with the participant, and risk decision making again.

In the next subsections, each phase is described in more detail. The thesis has two parts. We have 20 real participants. We know what their emotional state is and we want to see if DeepFace is able to recognize their emotional states. In the second part, this information will be used to evaluate whether an interaction of Flobi can help to decrease the emotion in the participant and whether this new emotional state affects the participant's decision making.

4.2.1 Emotion Induction phase

This can be done using any of five common emotion induction techniques including visual stimuli, music, autobiographical recall, situational procedures, and imagery. This study uses the autobiographical recall method. After the relaxation phase, Flobi will ask the participant to recall a happy or sad situation in his life depending on the inducted emotion.

4.2.2 Risk decision making

Second phase is risk decision making by participants. In my thesis there is an interface which lets participants select their choice and the choice will be identified as high or low risk choice. The detail of the designed game for risk decision is in section 3.2.4 The Decision Making Game. The result of choices are sent to a server to be used in the evaluation step.

4.2.3 Flobi interaction with the participant

Third phase is interaction with Flobi. Flobi interacts with the participant using the interaction strategy. For example if the happy feeling was inducted in induction phase, after performing risk decision by participant, Flobi speaks to the participant and tells him:

You seem very happy right now. Happy people often underestimate risk, thereby taking on more risk than they would under normal circumstances. You can adjust your selection again. The one highlighted in beige is your previous choice. Please click next.

Or
You seem very scared right now. Anxious people often overestimate risk and thereby take less risk than they would under normal circumstances. You can adjust your selection again. The one highlighted in beige is your previous choice. Please click next.

4.2.4 Second risk decision making

Fourth phase is again a risk decision by the user. In this phase the user makes a decision after being interacted by Flobi. Decision is the second round of playing the game.

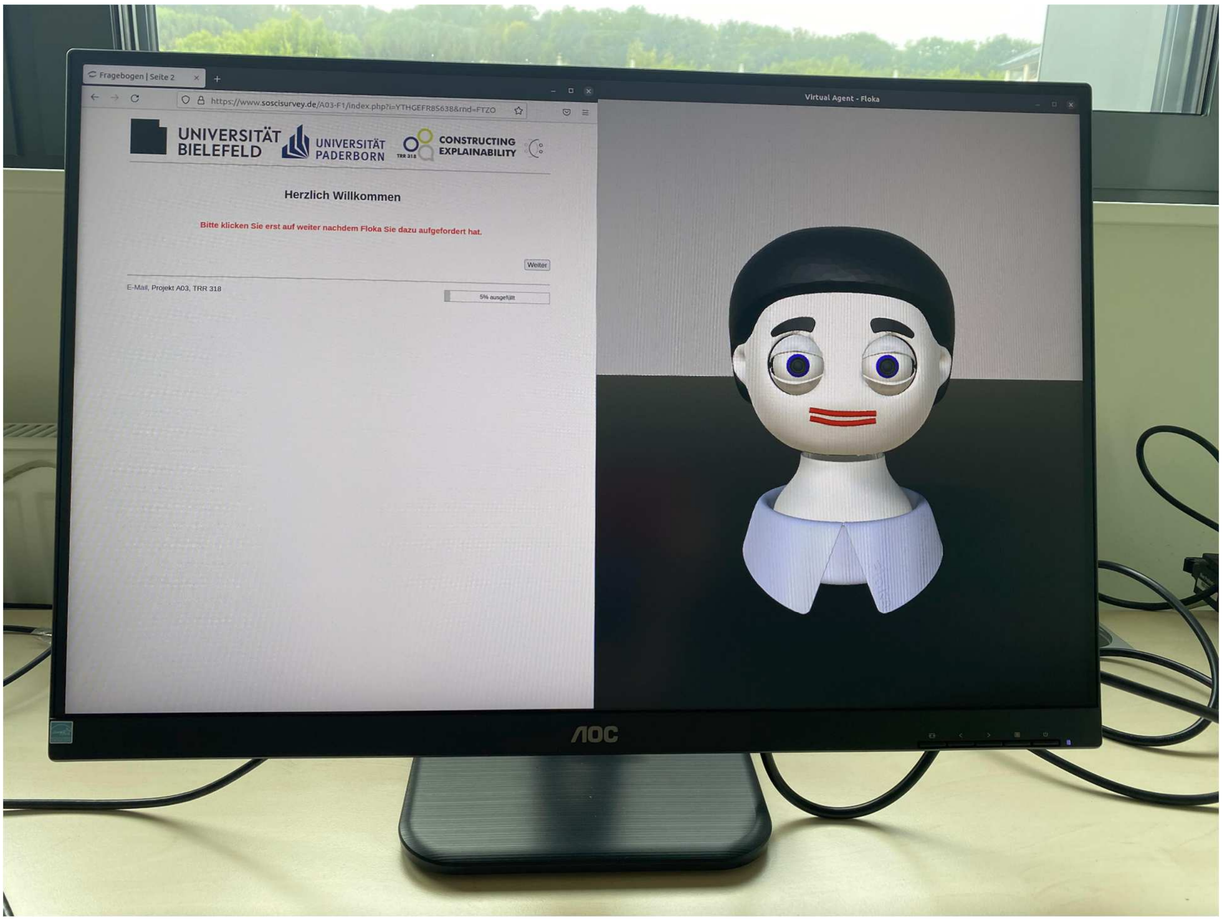

Figure 10. Participant screen

4.3 Study setup

We have a touch screen where participants sit in front of it. There is Flobi simulation on the right side of the screen and Firefox browser on the left side. In Firefox, we open the link for personality and risk decision making tests. The screen has a webcam to record participant faces for emotion recognition.

There are two other screens for me, one is the same as the participant screen to follow what the participant is doing and the other screen to start the GUI and Emotion Recognition script and running roscore and all other setup.

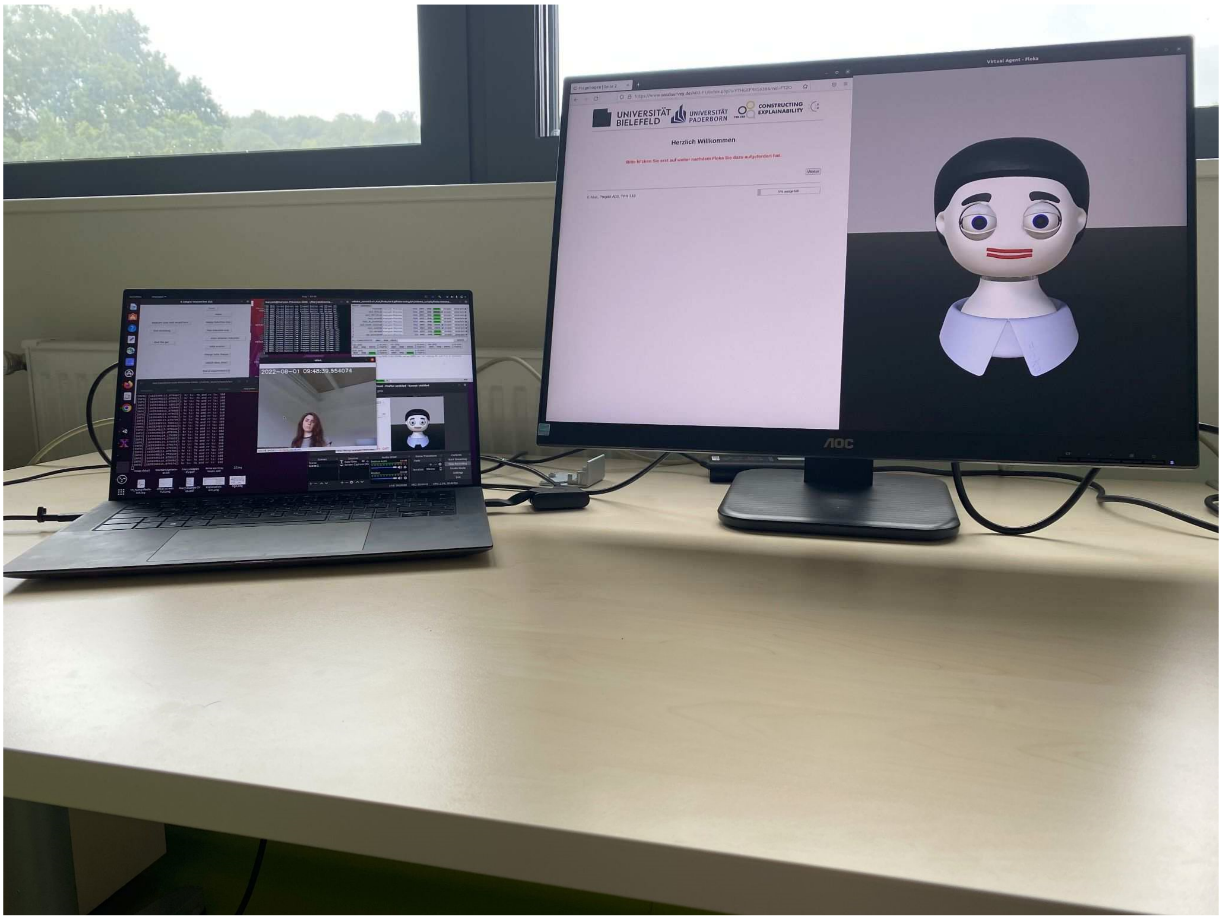

Figure 11. The study setup

On one screen for me, there are different applications and scripts running:

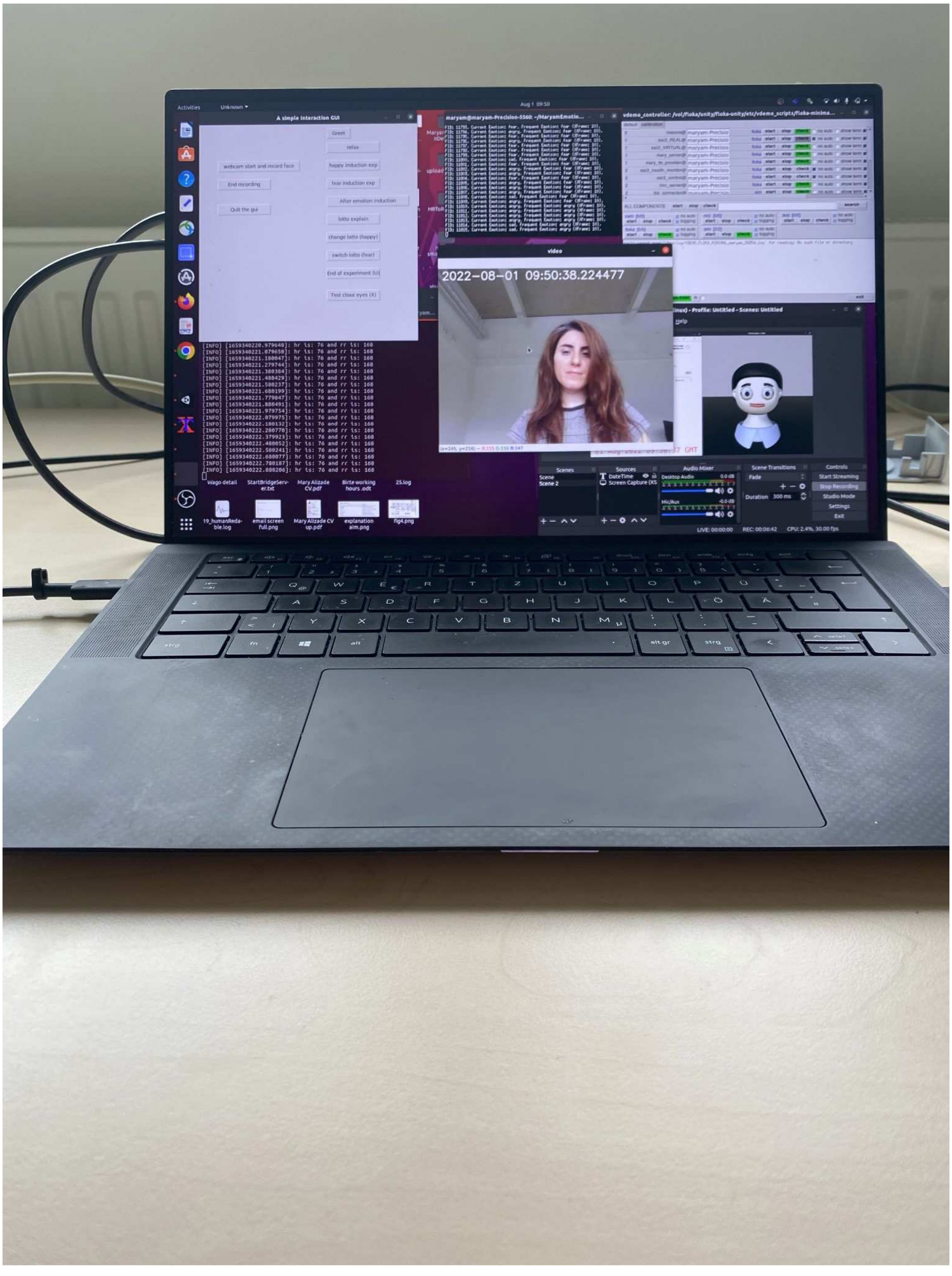
A simple interaction GUI
Greet
relax
webcam start and record face
happy induction exp
End recording
fear induction exp
After emotion induction
Quit the gui
lotto explain
change lotto (happy)
switch lotto (fear)
End of experiment (U)
Test close eyes (X)
video
2022-08-01 09:50:38.224477

Figure 12. The study setup with all scripts and components running

GUI for triggering the Flobi to speak to the participant.

One window for logs of Emotion Recognition Script.

One window playing the recording of the participant's face.

One window for running Flobi simulation components.

OBS studio recording the participant screen.

4.4 Experiment

Before participants entered the room, I was starting the emotion recognition script to record the camera and microphone, and I was preparing the participant screen with Flobi simulation and Firefox window with welcome page.

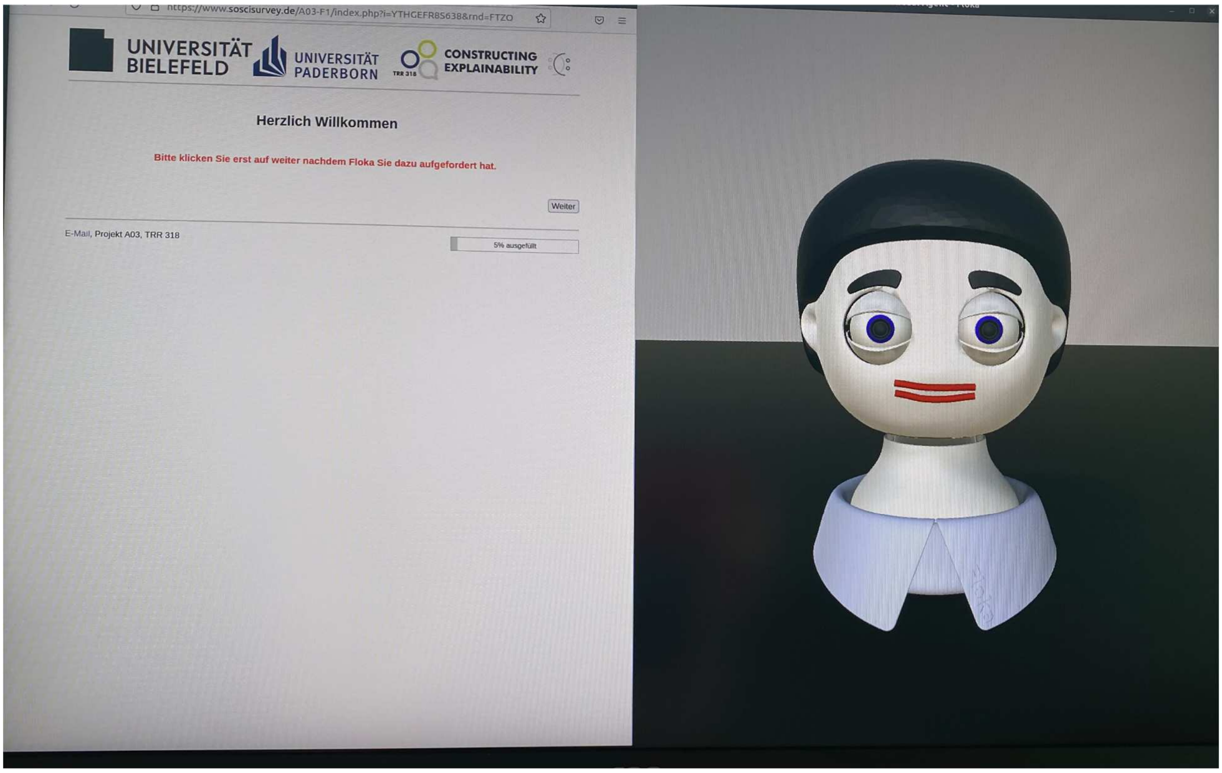

Figure 13. Start of the experiment

When a user entered the study room, first I was introducing myself and the goal of the study and the steps of study and I was asking them to take off their mask. Then I was giving them a study agreement to sign and then I was leaving the study room to my own room and closing the door. After leaving the room, I had two screens in front of me to control the whole study. First, I was triggering Flobi to welcome the participant using the developed GUI.

Then the participant starts to answer some questions including age, gender, education, personality test, and a test to evaluate how interested the participant is in technical stuff for the goal of assessing how successful Flobi is in interaction with different participants. All the answers are sent to a server to later evaluations. These questionnaires and saving the results all are developed by Christian.

Next step is the relaxing phase in which the participant is asked to relax.

After the relaxation phase, the next step of the experiment is the emotion induction step. Flobi asks the participant to write down a situation which makes him happy or feared based on the type of the experiment. There will be different experiments for happy and fear emotions. After emotion induction Flobi asks the user to make a risk decision by playing the designed game. After playing the game, Flobi communicates to the participant and tries to affect the participant's decision. Participant plays the game again and all the games and tests are sent to a server. After the second game, the experiment ends and Flobi thanks the participant and the emotion recognition system gets stopped.

The experiments took 30 minutes and were done on 20 participants. To find participants, I distributed flyers in the university.

Chapter 5

Results

5.1 Emotion recognition evaluation

In this section the result of the self assessment test is compared to the emotions detected by emotion detection script during the self assessment test before and after emotion induction.

The self assessment test has two dimensions: valence and arousal. The self assessment question was as the following:

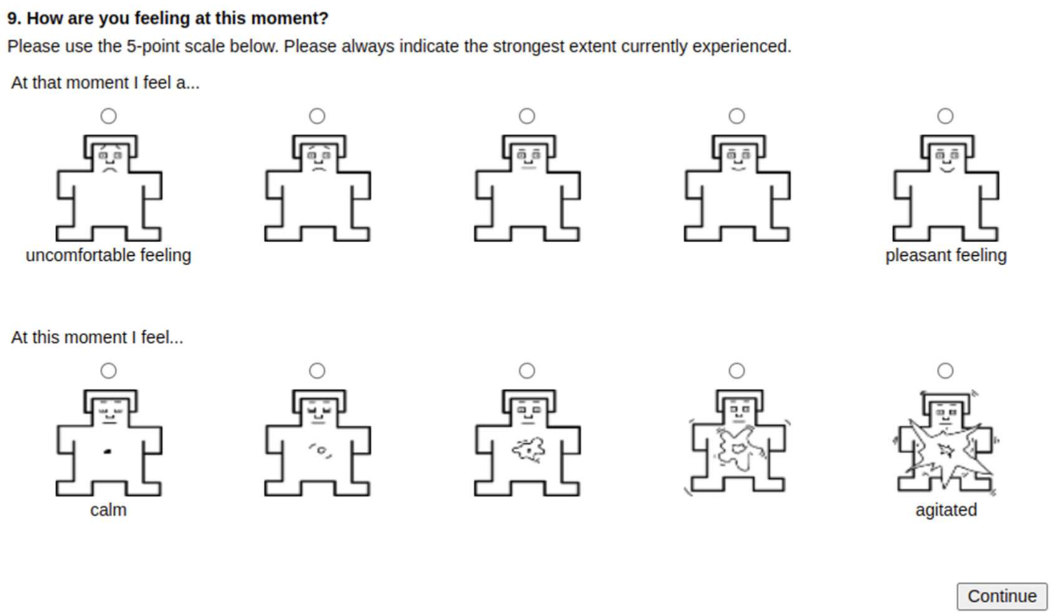

Figure 14. Self Assessment Test

For the evaluation we consider only valence and ignore the arousal.
We assume the following relation between the three emotions and valence scale:

Fear: 1 and 2
Neutral: 3
Happy: 4 and 5

The following plot is a confusion matrix for the reported emotions and detected emotions by the emotion recognition script.

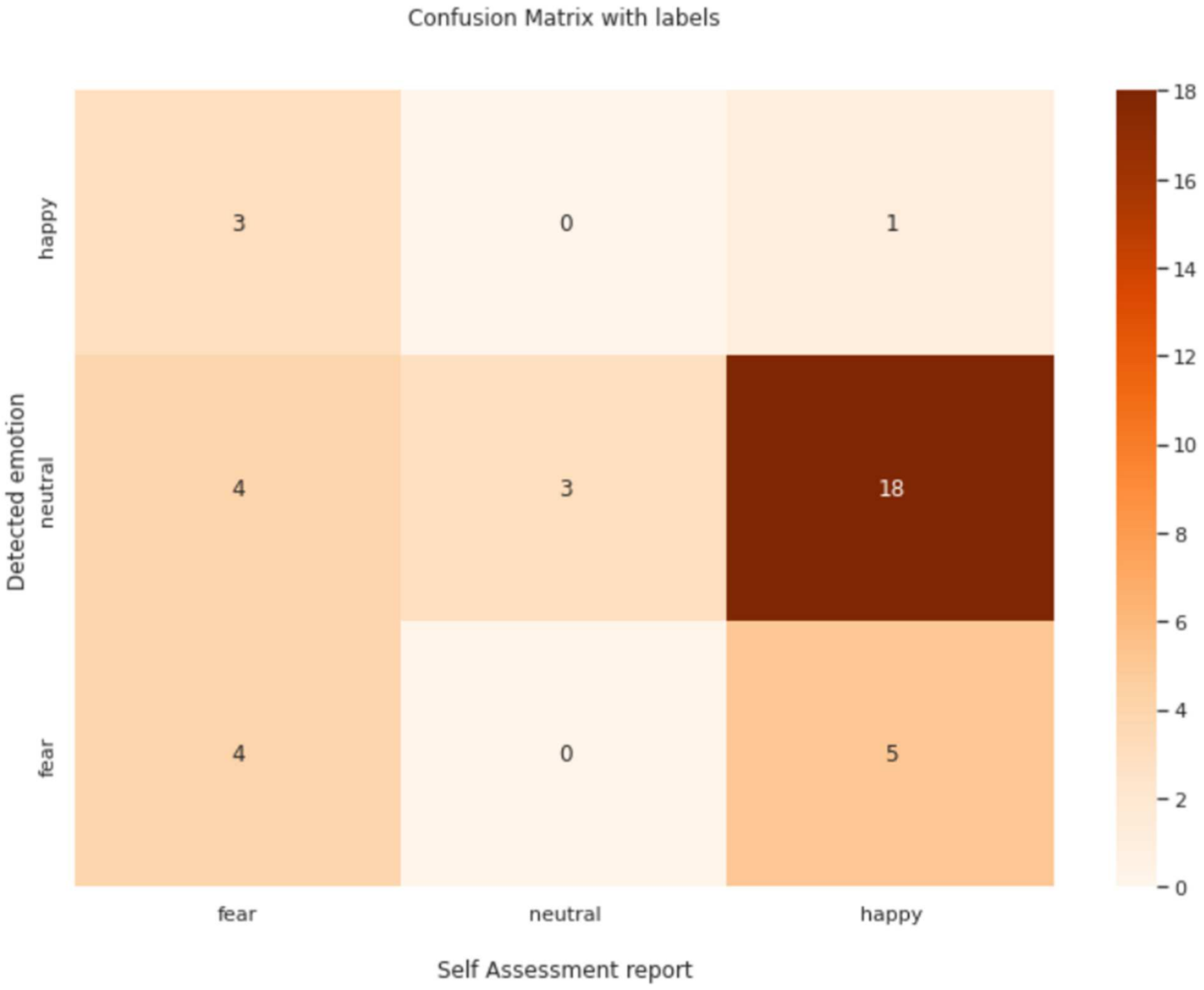

Figure 15. Confusion matrix for emotion recognizer.

As we can see from the confusion matrix, the classifier has bias toward Neutral feeling. In most of the cases happy feelings were detected as Neutral by DeepFace.

When the recognizer detects an expression as happy, we cannot trust it. When the recognizer recognizes the expression as neutral, we can tell it was a happy feeling. If it recognizes an expression as fear, we ca trust it only with 50%.

5.2 Emotion Induction Evaluation

This section checks the effect of inducted emotion on the emotion of participants. There were self assessment questions before and after induction which participants had to answer them.

In the self assessment test both questions have answers from one to five which indicates uncomfortable to pleasant feeling and calm to agitated feeling respectively. The following plot shows the changes of participants' emotion after being inducted by emotion induction strategy.

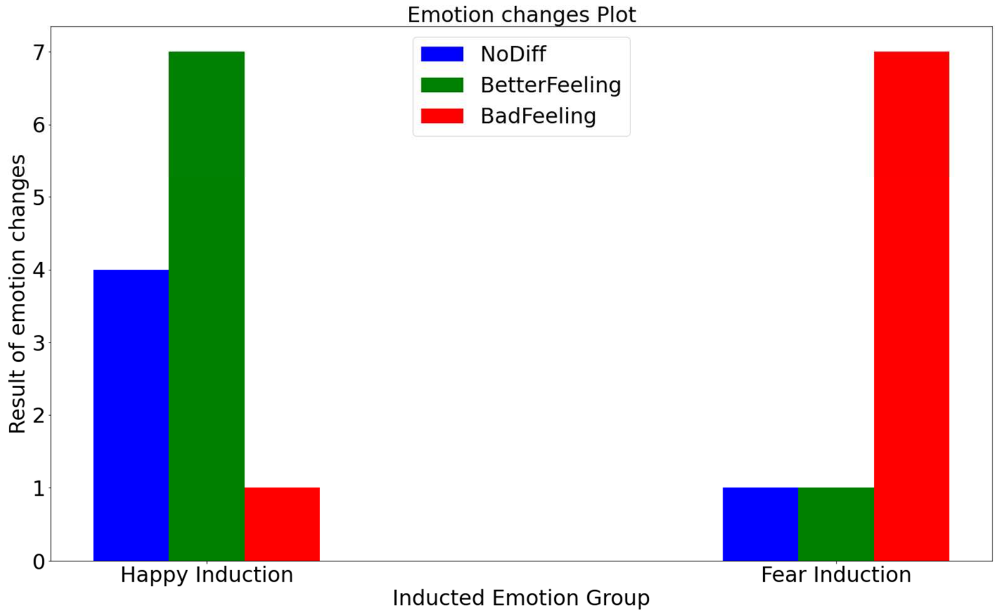

Figure 16. Imotion Induction result plot
NoDiff: emotion is not changed after induction.
BetterFeeling: participants changed to a more calm and pleasant feeling.
BadFeeling: participant changed to a less calm and/or pleasant feeling.

There were two groups of participants based on the type of inducted emotion. As the plot shows, out of 12 participants being inducted by Happy emotion, 7 of them switched to better feeling after induction, 4 of them reported no changes in their feeling and 1 of them reported bad feeling after being inducted by happy emotion.

Out of 9 participants being inducted by Fear feeling, 7 of them reported decreased calm and pleasant feeling after induction, one of them reported changes to better feeling and one reported no changes in feeling.

5.3 Risk decision evaluation

This section evaluates whether Flobi was successful in affecting participants' risk decisions by interaction with them. The following plot shows the result of participants' reaction after being asked by Flobi to change their risk decision.

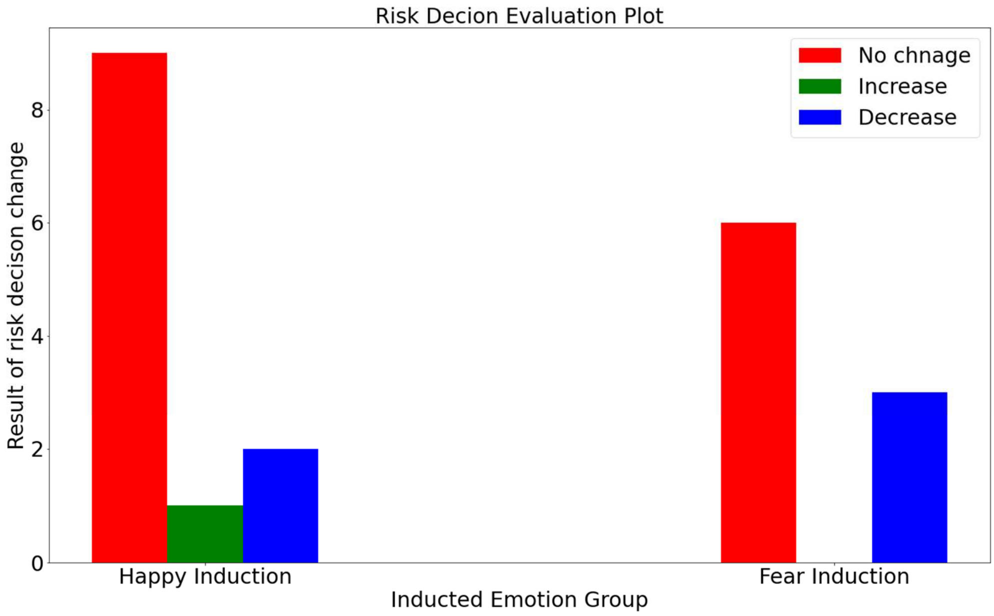

Figure 17. Risk Decision changes result plot
No change means they did not change their decision after being interacted by Flobi.
Increase means they choose a decision with higher risk that the first decision.
Decrease means they switched to a decision with lower risk.

There were two groups of participants based on the type of inducted emotion.

Out of 12 participants' being indicted by happy emotion two of them decreased their risk in their decision, one of them increased and 9 of them did not change their decision.

In the group with fear induction, out of 9 participants three of them switched to a low risk decision and six of them did not change their decision.

Chapter 6

Conclusion

The goal of this thesis was to determine whether users' emotional states when interacting with a virtual robot can be reliably recognized and whether different types of interaction strategies can alter users' emotional states and influence their risk-taking behavior. It looks into the question: Can AI assist people in making decisions?

To address these questions the study was completed in four phases including: emotion induction, risk decision making, interaction with robot simulation and again risk decision making.

To address the question whether users' emotional states when interacting with a virtual robot can be reliably recognized, the performance of the emotion recognition model was analyzed. The result shows that the emotion recognition model had bias toward the neutral feeling and in most of the cases it is not reliable. One reason can be due to the data set that the model is trained on also in future studies we can include more information, for example from other modalities such as Body Gesture, Speech, heart rate, and etc.

To address the question whether different types of interaction strategies can alter users' emotional states, the thesis compares the self assessment test results for each participant before and after inducting emotion. The results showed that the happy induction was successful in 84% and the fear induction was successful in 77.7 percent.

In order to address whether the robot interaction with participants were successful in afecting their risk decision making process, we compared the decisions made by the participant in first and the second decision making game. The robot was suggesting the participants inducted with happy emotion to make a low risk decision and the participants inducted with fear emotion to make a high risk decision. The results show that out of 12 participant inducted with happy emotion, only 2 of them switched to a low risk decision and out of 9 participants with fear induction none of them switched to a high risk decision. Also the results showed that 57.14% of the participant did not change their decision after being inducted by the robot.

This could indicate that people with happy emotion seem to be more likely to adapt their decision as compared to those with fear. Also, fearful people seem to tend to react even more fearful when confronted with a warning or suggestion to reconsider their decision.

The study results indicate that the emotional state of the people affects how people react to AI-based suggestions. More research is necessary to corroborate this first impression. Also, research looking into more detail how different emotions affect users' reactions to AI suggestions would be needed.

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