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# Impact of Varying Collision Avoidance Strategies on Human Stress Level in Human-Robot Interaction

**Master Thesis**

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by

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„*Das ist die Widmung / This is the dedication (optional)*“

# Acknowledgement

Das ist die Danksagung / This is the acknowledgement (optional)

# Abstract

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# Inhaltsverzeichnis

# Nomenclature

**Greek symbols**

**Abbreviations and Acronyms**

| | |
|---|---|
| EDA | Electrodermal Activity |
| GSR | Galvanic Skin Respons |
| HR | Heart Rate |

**Usage of generative AI models**

| | |
|---|---|
| $\ddagger_{\text{MO}}$ | Media optimization: Correction, optimization, or restructuring of entire passages |

**Explanations for the usage of generative AI models and its notation:**
The bottommost level at which the identification is presented regarding the possible uses of generative AI models are subchapters of the 2nd order (e.g., 1.1.1, which may also appear without numbering), as otherwise, the identification would disrupt the reading flow due to frequent occurrences. Algorithms used for implementing generative AI models are mentioned at least in the text or provided as pseudo-code to facilitate appropriate identification.

# 1 Introduction

‡MO

## 1.1 Motivation

‡MO Industry 4.0, also known as the Fourth Industrial Revolution, has brought about significant transformations within the industry, particularly in the manufacturing sector. This revolution has been characterized by the introduction of intelligent technologies such as the Internet of Things (IoT), cloud connectivity, big data, and human-robot collaboration, among others. These advancements have led to notable improvements and innovations, with the core principle and driving force of innovation in Industry 4.0 being the enhancement of efficiency and productivity. Human-robot collaboration, a key component of Industry 4.0, has played a huge role in this advancement by bringing humans closer together and facilitating more efficient and cooperative workflows.

Looking towards the future of the emerging Industry 5.0, the focus shifts towards a more human-centric approach. Industry 5.0 aims to strike a balance between technological advancements and human needs and interests, placing a strong emphasis on sustainable and resilient industrial practices. The goal is to merge the technological efficiency of Industry 4.0 with a greater emphasis on enhancing human well-being and personalizing the production process. Industry 5.0 brings back the human workforce to the factory, where humans and machines are paired to increase process efficiency by utilizing human brainpower and creativity through the integration of workflows with intelligent system (Nahavandi 2019). This shows a significant shift from purely efficiency-driven operations to those that also prioritize human factors and environmental sustainability.

Traditionally, industrial robots like manipulator arms, autonomous mobile robots, and gantry models have been kept separate from human workers primarily due to concerns regarding safety. These robots are typically characterized by their large size, substantial weight, and high speed, attributes that pose potential hazards when in close proximity to humans. Consequently, their design is predominantly focused on fulfilling specific tasks such as drilling, welding, or loading and unloading where their size and speed are necessary for efficiency but also necessitate isolation from human workers to ensure safety. This traditional approach prioritized the physical separation of robots and humans in industrial settings. However, advancements in Industry 4.0 have significantly increased the use of

collaborative robots (cobots) , bringing them closer together to jointly accomplish tasks. This evolutionary progression has witnessed the transformation of robots from being secluded behind safety barriers to now operating side-by-side with their human counterparts, effectively capitalizing on their unique capabilities which combine human adaptability and decision-making skills with the precision and consistency offered by robots.
While technological advancements aim to optimize production, the comfort and well-being of human workers have not always been prioritized. This thesis aims to delve into the human aspect of human-robot interaction, considering how proximity to robots might affect the operator's physiological state. It aims to investigate how continuous interaction with robots impacts the stress levels experienced by humans and emphasizes the importance of monitoring and accurately assessing stress levels in human-robot collaborative environments. Sauppé und Mutlu (2015) have previously indicated that co-bots have the ability to influence the mental states of human workers, as they are often perceived as social entities. The close proximity of humans to robots in the workplace can lead to heightened levels of mental stress, particularly if the movements of the robot appear to be potentially harmful (Lasota und Shah 2015). For instance, if a co-robot swiftly moves towards a worker or follows an unpredictable path, it may induce feelings of anxiety or fear due to the perceived risk of sustaining an injury. This, in turn, can negatively impact both productivity and the efficacy of human-robot collaboration. Furthermore, it can impede the complete utilization of the advanced capabilities offered by collaborative robots. Identifying and addressing these stress factors is key to optimizing the human-robot collaboration for enhanced productivity and make the working environment effective, efficient and safe.

## 1.2 Aim of the Thesis

[‡MO] The aim of this thesis is to evaluate the impact of varying collision avoidance strategies on human stress levels in the context of human-robot interaction. Our objective was to conduct a study to collect and analyze data to understand the different stress levels in relation to varying robot collision avoidance strategies. This is done taking different collaboration levels and robot control strategies into account. We then used this data to create a predictive model that can identify and address sources of stress during human robot collaboration.
Specifically, the objectives of the thesis are:

- **Assessment of Human Stress Levels**: Develop a holistic approach for evaluating stress levels in human-robot interactions, combining both objective physiological measures and subjective experiences. Objectively, the study will employ various physiological indicators such as Galvanic Skin Respons (GSR), Electrodermal Activity (EDA), Heart Rate (HR), and body posture analysis. These indicators will provide quantifiable data on the body's physiological response to robot interactions. Subjectively, the study aims to incorporate personal feedback from participants, gathered through questionnaires. This will offer insights into their personal feelings and perceptions regarding their interactions with robots. By blending these objective and subjective methods, the study aims to provide a comprehensive understanding of stress in human-robot interactions.

- **Development of Data Acquisition and Synchronization System:** Designing an acquisition system that successfully takes data from several sensors at different frequencies and synchronizes it. Devices such as the Empatica E4 wristband are utilized for gathering data on GSR, EDA, and other parameters, as well as a motion capture system to record human posture and movement. A vital aspect would be to synchronize these many data streams, ensuring accurate and consistent assessment of human physiological states across different robot interaction scenarios.

- **Data Collection and Evaluation**: Designing and conducting a subject study to collect data on participants' physiological responses while doing different assembly tasks under different robot-human interaction scenarios. These scenarios included three distinct levels of robot collision avoidance strategies: No Collision Avoidance, Dynamic Collision Avoidance, and Predictive Collision Avoidance as well as three different collaboration levels: Different Workspace with the cobot, Shared Workspace, and Shared Workspace with Direct Collaboration. The aim is to gather comprehensive data to analyze the impact of these varying robot control strategies on human stress levels.

- **Stress Prediction Model**: Developing a model for predicting and classifying stress levels during human robot collaboration. This model trained on the dataset of human physiological responses collected from the subject study.Various preprocessing techniques and feature engineering techniques are used to prepare the data for the model. Various machine learning models such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and others, are evaluated to determine the best model for predicting stress levels.

## 1.3 Related Work

Still not sure if to add realted work related to various stress detection strategies here or add it in the therotical foundations citing how people have used this for stress detection.Will a one page of related work suffice here or does it have to be detailed also looking at if any robot human collaboration experiments/studies have been done before.

## 1.4 Structure of the thesis

Chapter 1 presents the motivation behind the study and the aims of the thesis. In Chapter 2, we delve into the fundamental concepts of stress and examine the relationship between stress and key physiological signals such as EDA, HR and GSR etc. Chapter 3 describes the data collection process of the subject study that was conducted to collect data on participants' physiological responses. Chapter 4 describes the data analysis process of the subject study to analyze the collected data and the different pre-processing techniques and feature selection used to build the model. Chapter 5 describes the results of the subject study and the different machine learning models that were evaluated to determine the best model for predicting stress levels. Chapter 6 concludes the thesis and outlines the future work and research directions.

# 2
# Theoretical foundation

## 2.1 Stress Framework/Biosignals

### 2.1.1 Photoplethysmogram-PPG

### 2.1.2 Electrodermal Activity-EDA

### 2.1.3 Motion Capture

# 3 Data Collection-Subject Study

A collaborative assembly task involving wooden pieces was designed in the robot laboratory of the Institute of Control Theory and Systems Engineering at the Technical University of Dortmund. This setup aimed to accurately replicate the types of tasks commonly seen in industrial settings where collaboration between humans and cobots is frequently observed. The Universal Robot UR10 was selected as the cobot to be used in the study. A call for participants invite was sent out, and 20 male students who all had a technical background volunteered to participate in the study. 17 of the students did not have any previous experience working with a robot in any way, whereas the remaining had some previous experience with robots. All of them were between the ages of 21-28. Before the experiment began, all participants were given a comprehensive overview of the study's objectives and procedures, along with a consent form. Only those participants who agreed to the terms and signed the consent form were permitted to proceed with the experiment. To ensure the ethical integrity of the study, a prior request for ethical approval was submitted to the appropriate ethics council (to be added) and permission was obtained to conduct the subject study.

## 3.1 Design of Tasks

Since we wanted to replicate an industrial assembly task, assembly of various mock items using wooden children's toys was selected. The effect of stress on different factors was to be investigated.
These included three distinct levels of different collaboration levels:

- **Different Workspace**: Human and cobot have no overlapping space. The cobot works in the background.The human already has all items required for the assembly task in front of him.
- **Shared Workspace**: Where the human and cobot share the same work area.The cobot brings the each item required for the assembly tasks to the human and places it on the table in front of the human.
- **Shared Workspace with Direct Collaboration**: Where the human and cobot share the same work area as well, The cobot brings the item required for the assembly tasks to the human and directly hands over the items to the human.

| Collision Avoidance Strategy | Different Workspace (A) | Shared Workspace (B) | Shared Workspace with Direct Collaboration (C) |
|---|---|---|---|
| **No Collision Avoidance (X)** | AX | BX | CX |
| **Dynamic Collision Avoidance (Y)** | Not Available | BY | CY |
| **Predictive Collision Avoidance (Z)** | Not Available | BZ | CZ |

Tabelle 3.1: Task names for different Collision Avoidance Strategies and Workspace Scenarios

As well as three robot collision avoidance strategies:

- **No Collision Avoidance**: No collision avoidance measures are in place, and the robot stops at a collision.
- **Dynamic Collision Avoidance**: The robot identifies the human as a dynamic obstacle and adjusts its trajectory to avoid collisions.
- **Predictive Collision Avoidance**: This strategy uses predictions to predict the human's future position and adjusts its trajectory to avoid collisions.

The table 3.1 shows the various combinations of factors and the naming conventions of the tasks, yielding a total of seven experimental scenarios since collision avoidance is not applicable when different workspaces are involved. For example task BZ employed a predictive collision avoidance strategy whilst the task was done in a shared workspace. So a within-subject experimental design was employed where each participant was tested on all seven different scenarios. By having the same participants perform each task, we minimized the impact of differing skill sets, experiences, and cognitive abilities, which could otherwise skew the results.

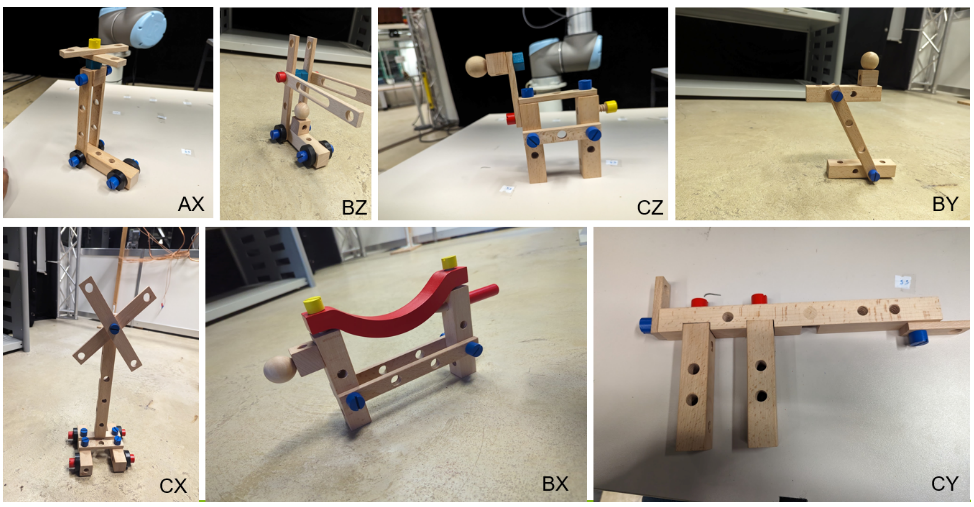


Abbildung 3.1: 7 different assembly tasks

To avoid any potential learning effects and ensure that each task measures the intended variables accurately, we had to design 7 different assembly tasks. Each task involved assembling a unique item, carefully chosen of similar complexity and required effort. This similarity in task difficulty was crucial to avoid the introduction of other variables such as familiarity with the task which could affect the results. Figure 3.1 shows the final assemblies completed in each of the seven tasks. Each task had approximately 4-6 different parts which was supposed to be screwed together to complete the tasks. By standardizing the complexity across tasks, we aimed to isolate the impact of the collision avoidance strategies and collaboration levels. We also had to consider the order in which the task was administered for each participant, ensuring that learning or fatigue did not affect the outcomes in any way. Each participant experienced the tasks in a unique order, balancing out any potential biases introduced by the order of task presentation.

## 3.2 Apparatus and Experimental Setup

The experiment was set up in a specially designated area of our laboratory. At the center of this arrangement was the collaborative workspace, featuring a table and chairs for the human participant (Area B in Fig 3.2), positioned directly opposite the robot's dedicated workspace. Adjacent to this, on the right side of the collaborative workspace, a table was placed to hold the various items needed for the assembly tasks(Area A Fig3.2). The robot would pick the necessary items from this table for each specific task and deliver them to the human participant. In front of the human participant, a mobile device was also placed. This device was key to the experiment, as it presented the participant with concise, step-by-step instructions for each assembly task. These instructions were visually displayed, offering clear and easy-to-follow guidance. The participant would start the assembly task as soon as the first item is delivered to the human participant. The robot would then proceed to the next item, and so on until all items are delivered to the human participant. Figure 3.2 shows the experimental setup.

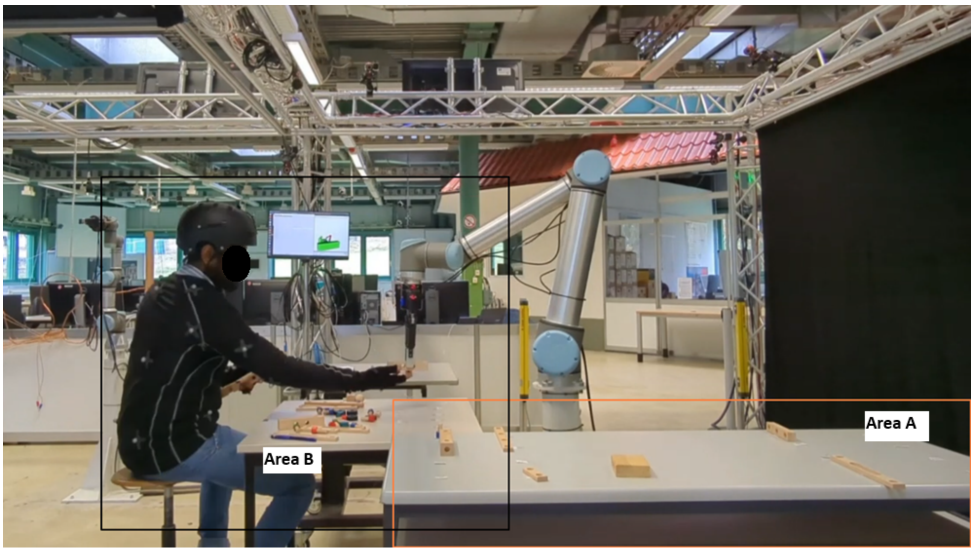


Abbildung 3.2: The experimental setup

The entire experimental area had an advanced OptiTrack motion capture system, outfitted with 12 high-precision cameras seen in Fig 3.3. These OptiTrack cameras, known for their exceptional accuracy and low latency are used to capture every detail of the human participant's movements. This setup was necessary in providing a detailed and continuous record of the participant's interactions with the robotic system, also aiding the collision avoidance trajectory planning for the robot. The use of the OptiTrack system enabled us to gather precise data on human motion and behavior, crucial for analyzing the efficacy and safety of human-robot interaction in assembly tasks. The participants were equipped with the motion capture suit which had 25 distinct marker points which were used to capture the human's head and upper body. To prioritize participant safety, especially given the proximity to robotic operations, a helmet was provided to each participant.

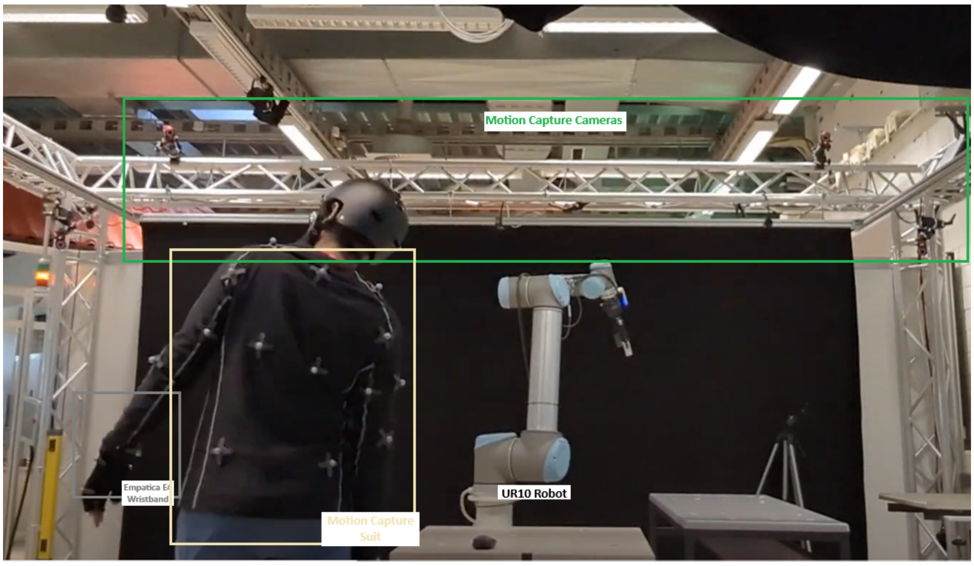


Abbildung 3.3: Apparatus used

For capturing the physiological signal of the participants, the Empatica E4 wristband was equipped in the participant's non-dominant hand. The participant's physiological signals such as GSR, EDA, HR and temperature, among others are captured by the Empatica E4 wristband, which transmits data wirelessly via Bluetooth to a Windows PC. This PC runs the E4 streaming server, facilitating the real-time transfer of this data. The various motion capture cameras recording the participant's movements are synced together and are connected to the windows PC as well running the motion capture software,Motive.

The physiological data from the Empatica E4 and the motion data from the motion capture system are then streamed to a Linux PC running the Robot Operating System (ROS) specifically ROS1 Melodic. The motion capture data is published to /tf topic. Whereas the Empatica E4 node is available as a ROS2 node running inside a docker container interfacing with the ROS1 using a ROS bridge. Then a data synchronization script is used to create a ROS node that subscribes to the multiple topics from various sources, synchronizes the incoming data, and publishes a compiled message to the aggregated data topic. This synchronized data topic is then recorded to a rosbag. A general schematic of this is shown in Fig 3.4.

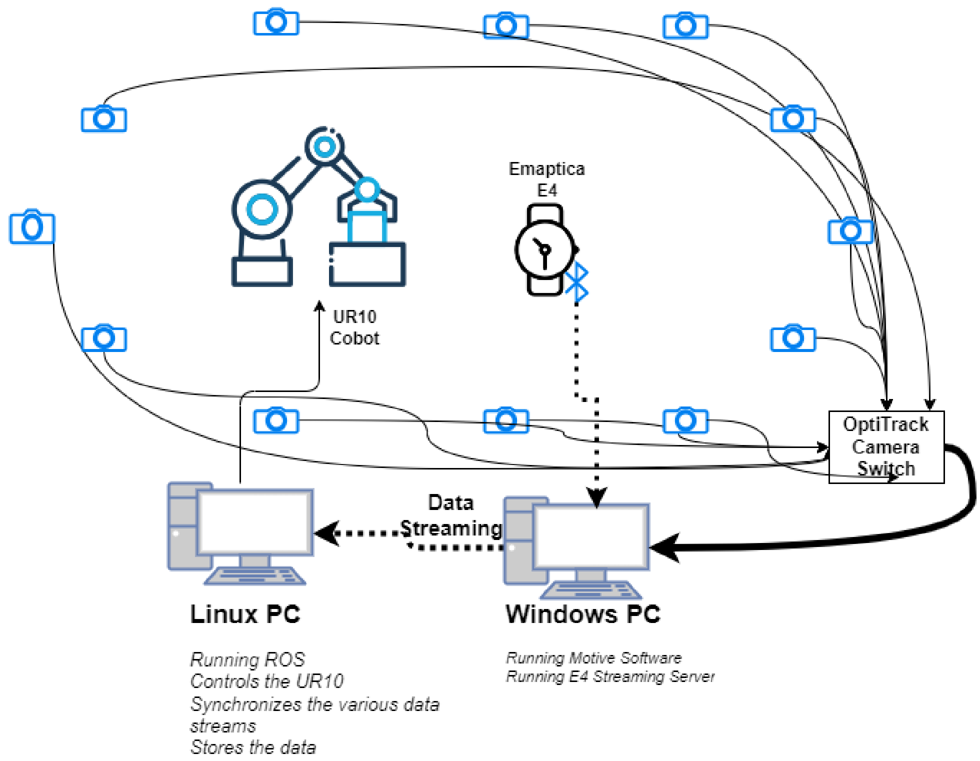


Abbildung 3.4: Schematic of the experiment setup

## 3.3 Procedure/Protocol

The experiment commenced with an initial briefing where participants were given a detailed explanation of the experimental procedures. Following this orientation, the Empatica E4 wristband and the motion capture (MoCap) system were set up, which took approximately 10 minutes. Participants then completed an initial questionnaire that included a consent form, general information, and questions about their prior experience with collaborative robots (cobots).

Once the preliminary documentation was complete, we established a baseline of physiological signals for each participant, which involved recording data for 2 minutes without any interaction with the cobot. This step ensured that we had a standard reference point for each participant's physiological state prior to beginning the tasks.

The main experimental procedure involved a sequence of seven distinct tasks. Each task began with a brief introduction, lasting around 2 minutes, to familiarize the participant with the specific requirements and objectives of the upcoming task. After the introduction, participants performed the task (Task i), during which both physiological and motion data were recorded. Each task lasted for about 5 minutes in average

Upon completion of each task, participants were asked to fill out a post-task questionnaire. This included the NASA Task Load Index (NASA-TLX) to assess cognitive workload and the Self-Assessment Manikin (SAM) to measure emotional response. These instruments were crucial for evaluating the impact of the task on the participant from both a cognitive and emotional perspective.

The process of task performance and subsequent evaluation was repeated for each of the

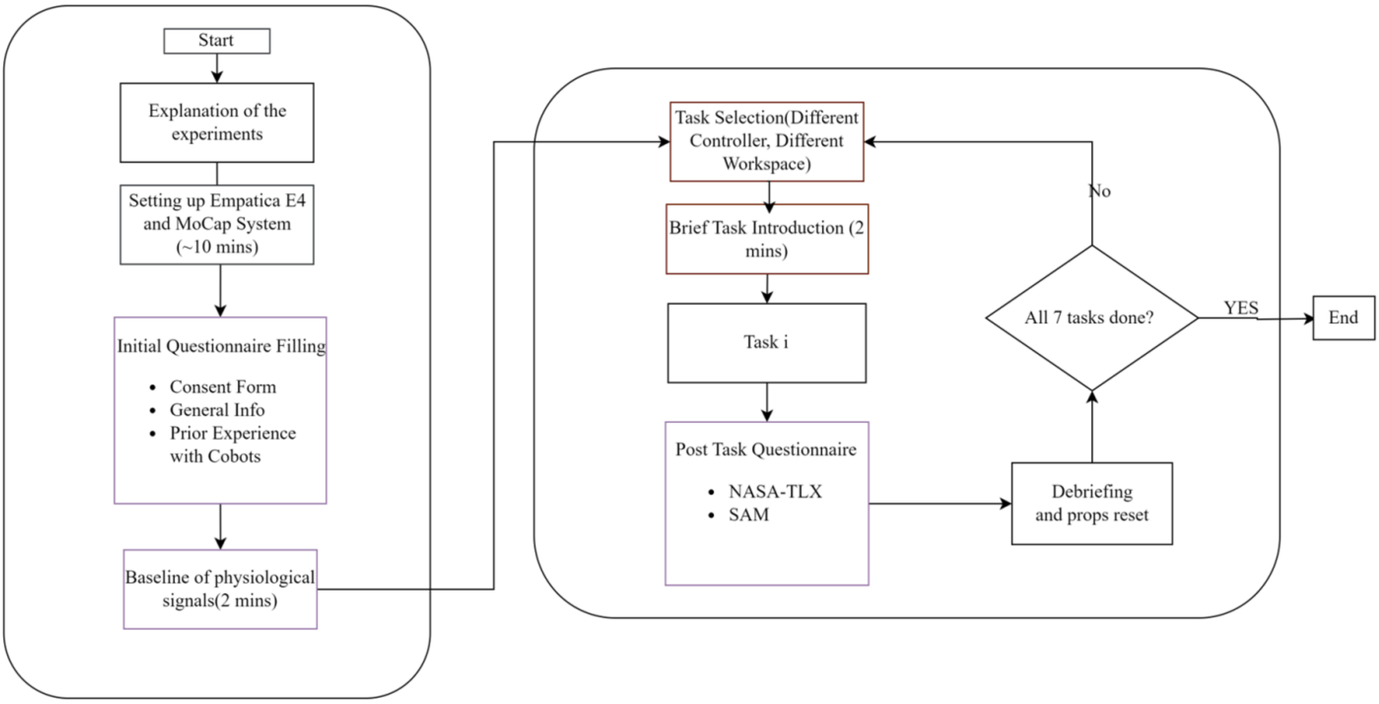


Abbildung 3.5: Schematic of the experiment protocol

seven tasks. After a participant had completed all tasks, we conducted a debriefing session. During this session, the participant could provide feedback and discuss their experiences. The procedure was carefully designed to ensure a controlled environment that would allow for the capture of reliable data regarding human-cobot interaction, taking into account both the performance and wellbeing of the participants.

# 4

# Stress Detection Methodology

## 4.1 Pre-Processing

## 4.2 Feature Extraction

## 4.3 Classification /Stress Detection/

Latex

- *http://miktex.org/*
  Windows Latex Distribution
- *https://tug.org/mactex/*
  Os X Latex Distribution
- *http://texstudio.sourceforge.net/*
  TeXstudio Development environment (recommended)
- *http://www.texniccenter.org/*
  TeXnicCenter Development environment
- *http://de.wikipedia.org/wiki/Hilfe:TeX*
  Collection of mathematical commands
- *http://www.ctan.org/*
  Documentation of all packages
- *http://en.wikibooks.org/wiki/LaTeX/*
  HILFE
- *http://www.texify.com/*
  Try Latex Code by Copy/Paste (Formulas)

Graphics

- *http://www.inkscape.org/*
  Vector graphics

- *http://www.imagemagick.org/*
  converted from *.* to eps

Matlab

- *http://www.mathworks.com/matlabcentral/fileexchange/22022-matlab2tikz*
  exported figure to tikz
- *http://www.mathworks.com/matlabcentral/fileexchange/21286-matlabfrag*
  exported figure to eps + tags
- *http://www.mathworks.com/matlabcentral/fileexchange/23604-fixlines*
  replaces " Matlab " lines with " reasonable " lines
- *http://www.mathworks.com/matlabcentral/fileexchange/23629-exportfig*
  exported figure to eps, pdf, etc. (with fixlines, without tagging)

# 5

# Result

# 6
# Discussion and Conclusion

# Literatur

**Lasota, P. A. und J. A. Shah (2015):** „Analyzing the Effects of Human-Aware Motion Planning on Close-Proximity Human–Robot Collaboration“. In: *Human Factors* 57.1. PMID: 25790568, S. 21–33.

**Nahavandi, S. (2019):** „Industry 5.0—A Human-Centric Solution“. In: *Sustainability* 11.16. URL: `https://www.mdpi.com/2071-1050/11/16/4371`.

**Sauppé, A. und B. Mutlu (2015):** „The Social Impact of a Robot Co-Worker in Industrial Settings“. In: URL: `https://doi.org/10.1145/2702123.2702181`.

# 7 Appendix

Das ist der Anhang (siehe Abschnitt ??) / This is the appendix (see section ??)

## 7.1 Usage of generative AI - Affidavit

☐ not at all

☒ for correcting, optimizing, or restructuring the entire work (This eliminates the need for explicit marking of individual passages or sections, as this type of usage refers to the entire written work. Explicit marking in the text is not necessary, as this serves as the global indication.)

☐ Code optimization: Optimization or restructuring of software function

☐ Code generation: Creating entire software functions from a detailed functional description.

☐ Substance generation in code: Generating entire software source code

☐ Media optimization: Correction, optimization, or restructuring of entire passages

☐ Media generation: Creating entire passages from given content.

☐ Substance generation in media: Generating entire sections

☐ More, namely:

I assure that I have provided all usages completely. Missing or incorrect information may be considered an attempt to deceive.

place, date

Jane Doe