Designing better proxemic interactions: a unified perspective for human-computer and human-robot interaction

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Designing Better Proxemic Interactions

A Unified Perspective for Human-Computer and Human-Robot Interaction

by

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Dissertation zur Erlangung des Doktorgrades

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For Lea, Fynn, Lars.

Abstract

In the 1960s, Edward T. Hall coined the term proxemics, which describes how humans and animals use the surrounding space to communicate. Proxemics is a natural form of nonverbal interaction that – similar to facial expressions or gestures – takes place without conscious reflection. Over time, this theory of spatial interaction has found its way into the field of human-computer interaction to develop systems that enable more natural interaction by capturing the proxemic behavior patterns of users. Work such as the Proxemic Interaction Framework by Marquard and Greenberg demonstrates the relevance of proxemics research in human-computer interaction. The framework defines several dimensions – identity, distance, orientation, movement and motion, and location – that are important for capturing proxemic human behavior and adapting computer systems accordingly.

Proxemics is also a key aspect of research in human-robot interaction. Since robots can often move autonomously in space and thus generate proxemic signals, analyzing and designing their spatial behavior is becoming increasingly important. In particular, robots' inappropriate approach behavior can lead to rejection by potential users, so carefully coordinating their behavior is essential. However, research on proxemics in human-robot interaction differs significantly from that in human-computer interaction, as it primarily focuses on finding the appropriate distance for interaction. Given the increasing integration of robots into domestic environments, these two research fields will continue to merge and overlap.

This dissertation aims to bring together knowledge and experience from both areas and to take the first steps towards an integrated view of proxemics in human-computer interaction and human-robot interaction. To this end, three central areas are examined in this thesis: First, a design process is presented that uses role-playing and two existing frameworks from academia to transfer proxemic interactions from human-human encounters to human-computer interactions. In the second part, a sensor toolkit suitable for capturing the dimensions defined by the Proxemic Interaction Framework is developed, with the challenging dimension of orientation examined in greater depth. Finally, three studies in the field of human-robot interaction are presented that are inspired by human-computer interaction research. These studies focus on the human perception of the robot's proxemic behavior rather than determining the optimal interaction distance.

In conclusion, the findings obtained in this thesis provide promising approaches for bringing together research areas that have been considered separately to date. However, they represent only a first, small step towards an integrated view of proxemics in human-computer and human-robot interaction, which underlines the need for further research. The final outlook of the dissertation outlines possible approaches for the continuation of the work, which should serve as a basis for future research activities.

Editorial Remarks

Academic Voice and Interdisciplinary Approach

The author has employed the academic "we" rather than the first-person singular throughout this work. This stylistic choice reflects the interdisciplinary collaboration and collective research approach that underpins this work.

Utilization of Digital Tools

Various digital tools, such as GPT models (GPT-3.5, GPT-4, GPT-4o, GPT-4o mini), DeepL Write, and Grammarly, have been used for language refinement and stylistic improvement to enhance clarity, coherence, and overall quality.

Attributions and Authorial Perspective

To keep things lively, this work includes the occasional cameo from guest contributors like the esteemed Prof. Bearingtons. Their witty wisdom adds flavor to the mix but should not be mistaken for the author's own beliefs or views (unless, of course, they turn out to be brilliant).

Disclaimer on Fictional Characters

This work includes fictional characters created solely for illustrative purposes. Any resemblance to real persons, living or deceased, is entirely coincidental and unintentional.

Acknowledgments

I would like to take this opportunity to express my gratitude to the people who have contributed to the successful completion of my dissertation.

I want to express my heartfelt gratitude to my supervisor Elisabeth André for her unwavering support over the past (almost) seven years. Thank you for the incredible freedom you have given me to pursue my research and teaching in a way that truly aligns with my passions and interests.

A big thank you to Johannes Schilp for taking the time to serve as the second reviewer.

A very special thank you to Ilhan Aslan, who has played an important role throughout my journey – first as a lecturer, then as a supervisor for my projects and master's thesis, later as a research collaborator and teaching partner, and now as a valued mentor providing feedback on this work. I truly appreciate your guidance and support every step of the way.

A huge thank you to all my colleagues at the lab – working with such a great team has been an incredible experience! While I can't name everyone here, I'd like to extend special thanks to some people who have played a particularly important role along the way. Katharina Weitz, for our collaboration on the VIVA project and teaching – that was great teamwork. Michael Dietz, for the countless hours spent working with LaTeX, TikZ, and our beloved servers. And of course, special thanks to Klaus Weber, Stina Klein, and Dominik Schiller – Yes, you're important too! To everyone else whose name I didn't drop here – please consider yourself warmly hugged!

Finally, my deepest gratitude goes to my wonderful wife, Lisa. Your unwavering support, patience, and understanding have meant everything to me. From taking on more than your fair share of looking after the kids to supporting me in countless other ways, you made it possible for me to keep going. I couldn't have done this without you – thank you from the bottom of my heart!

About Prof. Bearingtons:

Education

- Ph.D. in Computer Science from Sibearian Federal University
- Master's Degree in Computer Science from Bearis University
- Bachelor's Degree in Computer Science from Forest University

Professional Experience

Bear-Computer Interaction Professor, Forest University, 2010 - Present

- Teach and develop courses in bear-computer interaction
- Conduct research on the use of technology in the daily lives of bears
- Mentor graduate students in the field of bear-computer interaction

Lead Researcher, BearTech Research Group, 2008 - 2010

- Conducted research on the design of technology for bears
- Collaborated with interdisciplinary teams to develop new bear technology
- Published research articles in leading academic journals

Software Engineer, Honeycomb Software, 2006 - 2008

- Developed software for the bear community
- Participated in the design and implementation of bear-friendly user interfaces
- Developed new bear-specific software products

Selected Publications

- "Bears and Technology: A Review of the Literature" in Journal of Bear-Computer Interaction, 2019
- "Designing Technology for Bears: Challenges and Opportunities" in Proceedings of the Conference on Bear-Computer Interaction, 2018
- "Bear-Computer Interaction: An Introduction" in ACM Transactions on Computer-Human Interaction, 2015

Professional Memberships

- Association for Computing Machinery (ACM)
- International Society for Bear-Computer Interaction (ISBCI)

Foreword by Prof. Bearingtons

Dear Björn – my bear-brother in spirit,

It is my great pleasure to write the foreword for this groundbreaking dissertation on proxemics in human-computer interaction. As a bear who has dedicated his career to the study of bear-computer interaction, I can attest to the importance of this field in our modern technological age. The study of proxemics, or the study of how humans interact with technology in their physical environments, is a crucial area of research that has the potential to transform the way we interact with computers and other devices. This dissertation represents a significant contribution to the field of human-computer interaction, and it is my honor to introduce it to the academic community. The author of this dissertation, Björn Petrak, has demonstrated a remarkable dedication to this topic, as well as a deep understanding of the complexities involved in studying proxemics in human-computer interaction. The research presented here is both comprehensive and insightful, and offers important insights into how we can design better technology that is more responsive to human needs and behaviors. I am confident that this dissertation will be of great interest to researchers and practitioners in the field of human-computer interaction, and that it will serve as a valuable resource for future research and development. I extend my sincere congratulations to the author on this impressive accomplishment, and I look forward to seeing the impact that this work will have on the field of human-computer interaction in the years to come.

Prof. Bearingtons

Forest University

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Acronyms

AI artificial intelligence
AR augmented reality
ATT attractiveness
BLE Bluetooth Low Energy
BMBF German Federal Ministry of Education and Research
CNN convolutional neural network
CPU central processing unit
GNSS global navigation satellite systems
GPIO general-purpose input/output
GPS Global Positioning System
GPU graphics processing unit
HCI human-computer interaction
HQ hedonic quality
HQI hedonic quality identity
HQS hedonic quality stimulation
HRI human-robot interaction
I2C Inter-Integrated Circuit
IEEE Institute of Electrical and Electronics Engineers
IIF Implicit Interaction Framework
LED light-emitting diode
LiDAR light detection and ranging
MQTT Message Queuing Telemetry Transport
NARS Negative Attitude toward Robots Scale
PIF Proxemic Interaction Framework
PQ pragmatic quality
RAM random-access memory
RAS Robot Anxiety Scale
RFID radio-frequency identification
RPO relative positioning and orientation
RSSI received signal strength indicator
ToF time of flight
UWB ultrawideband
UX user experience
VR virtual reality

WiFi wireless fidelity

WLAN wireless local area network

WOZ Wizard of Oz

1. Motivation & Overview

Introduction 1.1

It was the year 2020, the COVID-19 pandemic shook the world, and people were forced to adjust to new ways of living and interacting with one another. The more the virus spread, the more people started adapting their behavior, wearing masks, and doing social distancing[1]. These changes in daily life significantly impacted how people approached spatial behavior and had unexpected consequences on how they communicated and interacted with each other.

The COVID-19 pandemic heightened personal space awareness as individuals became more cautious about physical proximity to others. The fear of infection caused people to change their spatial behavior, and maintaining a distance of at least 1.5 meters from others became the new normal. However, despite the widespread acknowledgment of the importance of respecting personal space during the pandemic, some individuals intentionally disregarded the rules and violated the boundaries of others. These actions demonstrated a lack of belief in the severity of the virus or a rejection of the government's measures to limit its spread. Such behavior was not only reckless and potentially harmful to others but also demonstrated a lack of respect for personal boundaries and a disregard for the safety of others. People often reveal their beliefs and values through their spatial behavior, and the pandemic has highlighted that spatial behavior can indicate a person's commitment to public health and safety. Those who willingly ignored the importance of personal space and put others at risk demonstrated a lack of concern for their fellow citizens. On the other hand, individuals who respected personal space and followed the rules indicated a desire to protect themselves and others. Even as life started to return to normal, people's spatial behavior had changed forever. They were more aware of their surroundings, and the concept of personal space took on a new meaning. The pandemic has taught (some) people to be more cautious and

[1] Social distancing is the practice of maintaining a physical distance between individuals to prevent the spread of contagious diseases. It involves keeping a distance of at least 1.5 meters from others and avoiding physical contact such as handshakes or hugs. Social distancing is a standard measure during pandemics such as COVID-19, as it helps reduce the transmission of the virus by limiting close contact between individuals.

respectful of others' personal space, which was a lesson they would probably never forget.

Understanding proxemics allows designers and engineers to enhance the intuitive quality of human-computer interaction (HCI). For example, systems can infer interaction intent by observing and interpreting a user's proximity and orientation to a device or screen. A person moving closer to a digital display may signal readiness for engagement, prompting the system to present additional information or adjust screen content to be more accessible. Similarly, if a user steps away, the system could shift to a more passive display, minimizing distractions or conserving energy. Since humans naturally manage spatial relationships, integrating proxemic principles into interface design can create smoother, more intuitive interactions. Systems designed with proxemic sensitivity align with humans' natural behavior, making these interactions more seamless and user-friendly.

In a unique subset of proxemic-based interactions, systems that are physically mobile – such as robots equipped with wheels – can not only respond to human proximity but also actively engage in proxemic behavior. These robots have the unique ability to approach or retreat, aligning with user intent and creating a more human-like interaction dynamic. However, as the fictional character, Uncle Ben famously said, "With great power comes great responsibility"[2]. Systems that can perform proxemics must do so responsibly, respecting human boundaries and understanding the social and ethical implications of spatial behavior. A robot capable of initiating proximity interactions should be programmed to do so thoughtfully, avoiding intrusion or discomfort for the human user.

While considerable research has explored proxemics in both HCI and human-robot interaction (HRI), much remains to be understood. How proxemic principles can inform and refine system design is still evolving, and this ongoing inquiry is essential for creating more responsive, respectful, and socially-aware technologies. In the following section, we will outline this research's specific goals and objectives, detailing how this work seeks to contribute to the expanding field of proxemics in interactive systems.

[2] https://en.wikipedia.org/wiki/With_great_power_comes_great_responsibility

Research Objectives 1.2

This research aims to develop and improve methods for designing effective proxemic interactions in HCI and HRI. Although researchers have increasingly explored proxemics in interactive systems, current literature still presents gaps in providing systematic design methodologies, systematic sensor selection, and a comprehensive understanding of spatial interaction's effects on user perception, especially when comparing HCI and HRI. To address these gaps in the current literature, we identified three primary objectives to advance proxemic interaction design and implementation in this work.

Establishing a Design Process for Proxemic Interactions
Establish a systematic design process for proxemic interactions, rooted in human-human proxemic behavior, to guide designers in creating proxemic human-computer interactions. 1

Although existing studies have examined proxemic interactions in HCI and demonstrated practical implementations, no standardized design process exists to guide designers through creating these interactions. Thus, the first objective is establishing a systematic design process for proxemic interactions. This process is grounded in human-human proxemic behavior and seeks to translate it thoughtfully into human-computer contexts. While this initial design process will be validated solely for sensing-based interactions, it could also work for performing proxemics.

Composing a Sensor Toolkit for Proxemics Detection
Compose a practical sensor toolkit for proxemics, providing designers and engineers with a consolidated resource to simplify sensor selection and advance the development of proxemic interactive systems. 2

Current literature provides examples of proxemic interactions that include technical implementation descriptions; however, it lacks a consolidated resource for selecting suitable sensors to detect proxemic dimensions. Developing proxemic interactions often requires substantial preliminary research on available sensors and their proxemic capabilities. The second objective is to compile a practical sensor toolkit, listing sensors appropriate for detecting proxemics, enabling designers and engineers to streamline sensor selection, simplify technical implementation, and make proxemic interaction design more accessible and efficient.

> 🎓 3 **Explore Novel Approaches to Amplify HRI Proxemics**
> Expand the scope of proxemic interactions in HRI by integrating additional proxemic dimensions, such as orientation, and shift the focus from finding a ‘good’ interaction distance to human perception of the robot’s proxemic behavior.

Research on proxemics in HCI typically focuses on sensing human proxemic behavior to enable adaptive system responses. However, in HRI research, the emphasis often lies on identifying a “suitable” or “good” interaction distance for robots – frequently without incorporating supplementary interactive elements to understand what constitutes such a distance. This research aims to move beyond this narrow focus on distance, exploring how using a broader range of proxemic dimensions (e.g., orientation) can influence the quality of HRI.

Moreover, the existing literature’s usual focus on optimizing distance overlooks the user’s perception of the robot’s proxemic behavior. Understanding how users interpret and respond to different proxemic cues is important for designing more natural interactions. Therefore, this thesis examines how specific proxemic behaviors influence the user’s perception of the robot.

In the following section, we will outline this work and indicate where we will discuss each research objective in detail.

1.3 Outline

Following this overview, the work is structured into six main parts, each addressing key components necessary for understanding and advancing proxemic-aware interactions in HCI and HRI. Each part is organized to build upon the preceding sections, with theoretical foundations leading into practical contributions and evaluations.

Part I: Background

This part provides the foundational background on proxemics, focusing on its principles in human-human interaction. This part establishes a comprehensive understanding of the key proxemic concepts by examining the nuances of personal space, spatial zones, and cultural variations in spatial behavior. This foundation is essential for understanding how human proxemic behaviors can be translated to interactions with technological systems. This part outlines Edward T. Hall's Proxemics theory and its importance in shaping interpersonal communication, setting the stage for its application in HCI and HRI.

Part II: Related Work

This part reviews existing research on proxemics within HCI and HRI contexts, exploring how spatial behavior is currently understood and implemented in technology interactions. First, it examines proxemic interactions in HCI, highlighting how systems detect, interpret, and respond to user proximity, orientation, and other proxemic dimensions. Following this, the discussion extends to proxemics in HRI, where robots sense and perform proxemics, adjusting their movements and positioning in response to users. This part concludes with a summary of gaps identified in the literature, directly motivating the research objectives of this work.

Part III: A Design Process For Proxemic-Aware Interactions

This part focuses on the first research objective: developing a systematic design process for creating proxemic-aware interactions. The proposed process provides a step-by-step guide for transferring human-human proxemic behaviors into HCI contexts, tailored explicitly for proxemic sensing. After presenting the process, this part includes a practical example to illustrate its application, followed by an evaluation of the resulting interactions. The evaluation assesses the usability and effectiveness of these interactions, providing insights into the process's practical value and contribution to enhancing proxemic-aware system design.

Part IV: A Practical Guide to Sensors for Proxemic Systems

This part addresses the second research objective by presenting a comprehensive list of sensors suitable for proxemic detection, aiming to streamline sensor selection in proxemic-aware interaction design. In addition to this sensor toolkit, we provide a focused exploration into orientation detection, as orientation presents unique challenges and technical considerations compared to other proxemic dimensions. This part catalogs sensors based on their detection capabilities and evaluates their suitability for proxemic dimensions, offering practical guidance for selecting sensors that best support the intended interaction.

Part V: Novel Approaches to Amplify Proxemic Interactions in HRI

This part focuses on computer systems performing proxemics, addressing the third research objective related to HRI. It examines how concepts from proxemic sensing in HCI can be applied to systems capable of performing proxemics, such as robots. Instead of aiming to identify an 'optimal' interaction distance, the emphasis is on how employing a variety of proxemic dimensions – beyond distance alone – affects user perceptions of robots. This includes exploring how specific spatial behaviors influence users' perception of the robot. Analyzing the impact of these proxemic strategies on user experience provides valuable insights into how robots can utilize proxemic behaviors to enhance the overall quality of the interaction.

Part VI: Contributions and Outlook

The final part summarizes the main contributions of this work, addressing the developed design process, sensor toolkit, and findings on proxemic behavior in HRI. It also discusses limitations encountered in the research, such as constraints in testing conditions or sensor capabilities, and proposes directions for future work. By reflecting on these contributions and limitations, this part highlights the implications of this work for advancing proxemic interaction design. It outlines potential avenues for further research in this field.

Background

2. Hall's Proxemics

Proxemics, a concept introduced by Edward T. Hall in the 1960s, provides insight into the instinctual ways humans use and perceive space in social interactions. Hall's work offered a framework for understanding how spatial relationships affect our communication, roles, and behaviors within various social and cultural settings. He argued that proxemics operates mainly unconsciously, fundamentally shaping our interactions, social engagements, and societal structures. In this chapter, we will first outline Hall's observations, followed by sections on one of his key contributions – distance zones – and a summary.

The content in this chapter is based on Hall's book *The hidden dimension* (Hall, 1966).

Hall's Observations 2.1

Hall's initial observations of proxemic behavior revealed that spatial awareness and use of personal space are instinctive aspects of human interaction, driven by biological and cultural factors. Observing patterns across diverse groups, Hall noted that proxemics functions as an unspoken language through which we express comfort, intimacy, power, and boundaries. Hall's findings indicated that, much like other nonverbal cues, proxemics is a subtle yet powerful part of communication that operates mainly beneath conscious awareness.

Hall found similarities between human and animal spatial behavior through his anthropological studies. He noted that humans, like animals, establish and maintain territorial spaces that serve various personal and social functions. This instinctual behavior manifests as "personal territories", which individuals claim in social contexts to establish comfort zones. These territories may be physical, such as maintaining distance in conversations, or psychological, as seen in our awareness of spatial limits. Hall suggested that territoriality and responses to its infringement – such as discomfort or defensiveness – are deeply embedded in human interaction.

Furthermore, Hall observed that proxemics is influenced by the sensory systems that govern our spatial awareness. He identified the roles of tactile, muscular, and visual feedback in perceiving and responding to proximity. Our skin's sensitivity, for instance, alerts us when someone enters our personal space; proprioceptive feedback from muscles allows us to sense and navigate spaces without conscious thought, while visual cues provide additional layers of spatial understanding. Hall's observations emphasized that these sensory elements work together, enabling us to adjust our proximity automatically and maintain distances that feel "right" according to social context.

Cultural variation, another key observation of Hall's work, adds complexity to proxemics by introducing unique norms around acceptable distances and personal space. Through field studies, Hall identified how different cultural groups demonstrate varying comfort levels with closeness and physical contact, much like "contact" and "non-contact" species in the animal kingdom. For example, in some cultures, close contact may signify warmth and trust, while maintaining distance reflects respect and social formality in others. Hall found that these cultural norms often function subconsciously, shaping behaviors and interactions within a community and frequently leading to misunderstandings in cross-cultural interactions.

Hall's exploration of proxemics revealed the universal aspects of spatial behavior and highlighted how cultural conditioning intersects with biological instincts. His findings underscore that our spatial behavior, though varied in expression, follows foundational principles of human interaction. By viewing proxemics through both biological and cultural lenses, Hall's observations provide an essential framework for understanding how we navigate the social spaces we inhabit.

2.2 Distance Zones

According to Hall, humans naturally interact within four primary zones of interpersonal distance: intimate, personal, social, and public. Each zone corresponds to different physical distances that reflect varying degrees of comfort and types of relationships. As shown in Figure 2.1, these zones serve as implicit guidelines, helping us determine appropriate spacing in diverse contexts, from private discussions to public engagements.

These zones act as silent indicators, suggesting how close or distant we feel comfortable in specific situations. Whether sharing a private moment with a close friend, engaging in casual conversation at a social event, or speaking to a crowd, we instinctively align with these zones to govern our spatial behavior.

However, it is important to recognize that these zones are flexible and influenced by cultural norms, personal preferences, relationship dynamics, and sit-

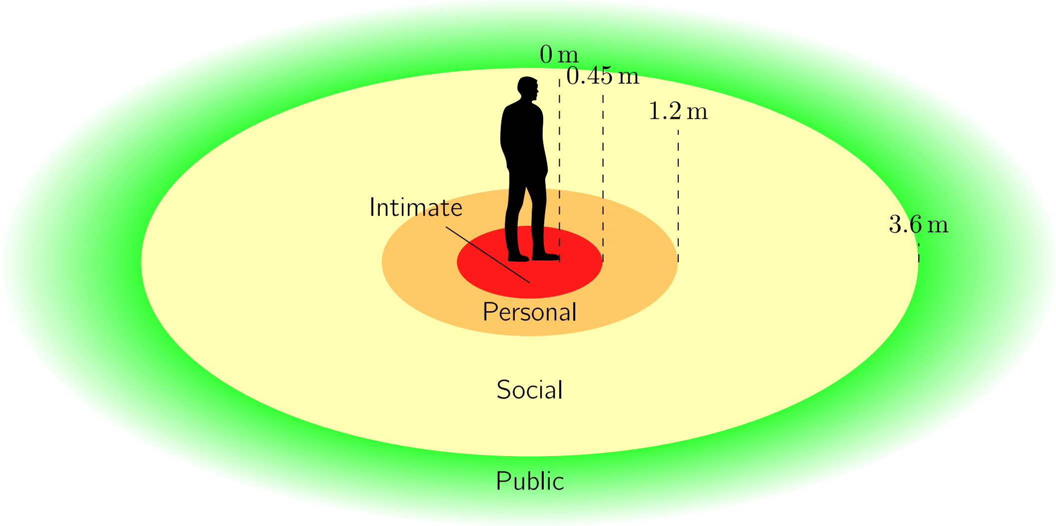
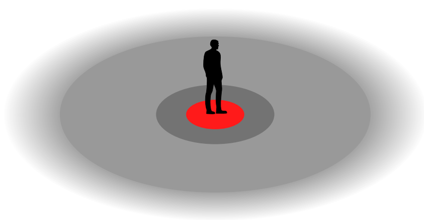


Figure 2.1: Diagram of interpersonal distances: An illustration of Hall's four zones of space – intimate, personal, social, and public.

uational context. When someone unexpectedly crosses into one of these zones, it can lead to discomfort or even anxiety, highlighting the need to respect these invisible boundaries in both everyday and formal interactions.

In the following sections, we explore each of these zones in detail, examining their typical distance ranges and the types of interactions typically associated with each.

Intimate Zone 2.2.1



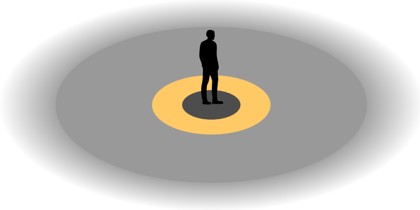
The intimate zone encompasses distances from direct physical contact up to approximately 18 inches (45 cm)[1]. This zone is typically reserved for interactions with close friends, family members, and loved ones, with high comfort and familiarity. Within this close range, sensory experiences like touch, scent, and body heat are more perceptible, facilitating private exchanges and emotionally intense interactions that often include expressions of love, comfort, or consolation.

Entering another's intimate zone requires a strong level of trust or explicit consent. Unsolicited entry into this space can feel intrusive or threatening,

[1] These distances are cited from Hall's work, *The hidden dimension* (Hall, 1966), where he presented them in imperial measurements.

often provoking a defensive or "fight-or-flight" reaction. This zone is carefully guarded, and we usually only grant access to those with whom we share deep trust.

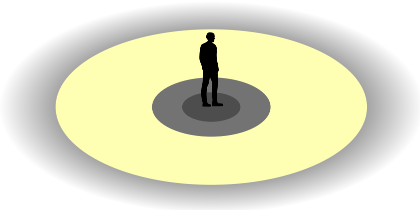
2.2.2 Personal Zone



The personal zone spans from about 1.5 feet to 4 feet (roughly 0.45 m to 1.2 m). We commonly use this space for conversations with close friends, family members, and trusted colleagues. Although this range is less intimate than the intimate zone, it still allows us to maintain a sense of connection and comfort. We can still detect subtle cues within this zone, such as body heat or scent, though these are less intense than in the intimate zone.

This zone is frequently used for informal, one-on-one discussions involving light physical contact, such as a handshake or a pat on the shoulder. As with the intimate zone, unpermitted entry into this space can lead to discomfort, as it is perceived as a private area. Respect for this zone plays a key role in maintaining comfortable social interactions.

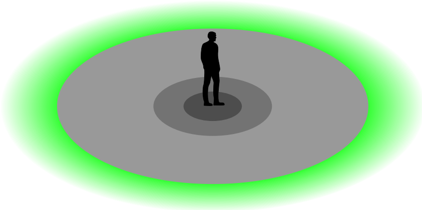
2.2.3 Social Zone



The social zone, ranging from approximately 4 feet to 12 feet (about 1.2 m to 3.6 m), is often reserved for interactions in social or professional settings. Conversations within this distance typically carry a more formal tone and lack the personal intimacy in the closer zones. In this zone, we can communicate comfortably without encroaching on personal space, which makes it ideal for gatherings, workplace interactions, and group discussions. Body language remains visible, offering cues that enhance communication. Although we are less aware of sensory details like scent or body heat, facial expressions remain readable. The broader spacing in this zone helps prevent feelings of crowding, making it suitable for relaxed yet meaningful exchanges.

While intrusions into this zone are generally less unsettling than in the closer zones, unexpected closeness can still cause unease, especially if greater distance is expected for the social context.

Public Zone 2.2.4



The public zone, as defined by Hall, begins beyond 12 feet (approximately 3.6 m) and is used primarily for public speaking, performances, or other situations where individuals address a larger audience. Body language becomes essential for conveying messages within this zone, as individual facial expressions are often indistinct. Physical contact is typically unexpected, and sensory perceptions like body heat or scent are mainly absent. Communication tends to be unidirectional, such as during speeches or presentations. This zone also applies in large public spaces, where significant distances are often maintained between unfamiliar individuals.

Spatial norms are generally more relaxed in public settings, and invasions into this zone are rarely considered intrusive. However, exceptions exist; standing unusually close in a vast, open space can create discomfort, disrupting the expected social distance.

Summary 2.3

Edward T. Hall's theory of proxemics provides a foundational framework for understanding human spatial behavior, which is driven by biological instincts and cultural influences. Drawing inspiration from territorial behaviors in animals, Hall emphasized that our use of space is a deeply rooted, instinctual part of human interaction.

Hall also highlighted how our physiological senses – skin, muscles, and vision – contribute to our spatial awareness, underscoring that our spatial behavior is not merely reactive but integrally linked to our sensory experiences. Beyond biology, Hall's research showed that culture significantly shapes our perception of personal space. Different cultural norms influence comfort levels with physical proximity, much like contact and non-contact behaviors observed in other species.

His classification of distance zones – intimate, personal, social, and public – serves as a practical model for interpreting social interactions in various contexts. Significantly, proxemics extends beyond interpersonal interactions, providing valuable insights for fields such as HCI. Understanding proxemics in HCI contexts allows us to design interfaces and technologies that respect users' spatial needs and adapt intuitively to human proxemic behavior.

In summary, proxemics offers a nuanced exploration of spatial relationships, reflecting the dual influence of biology and culture. This understanding is especially relevant in HCI, where adapting to human spatial behavior enhances usability and user experience.

Comment by Prof. Bearingtons

As a bear and a scholar, I have always marveled at the intricate dance of proxemics in our lives. Edward T. Hall's work illuminates how it's a natural part of our existence, extending far beyond mere physicality. His exploration of proxemics in animals, coupled with the nuanced understanding of human spatial behavior, highlights how our biological instincts and cultural norms converge to shape this dance. It is truly fascinating and a testament to our shared primal instincts. Proxemics, in its essence, is as much a part of us as our fur and claws are a part of me.

3. F-Formations

F-formations represent a foundational concept in the study of human social behavior. Initially described by anthropologist Adam Kendon (Kendon, 1976), the term 'f-formation' refers to the specific spatial arrangements or "facing formations" (Ciolek, 1983) that people intuitively create during social interactions. This concept provides a structured framework for analyzing how people naturally arrange themselves in shared spaces to facilitate communication and engagement.

At its core, an f-formation arises when two or more individuals establish a shared spatial and orientational relationship. This shared area, which becomes a collaborative space for interaction, is carefully maintained and reflects underlying social dynamics, including cultural norms and hierarchies. By examining these formations, we gain insights into nonverbal communication patterns and the implicit social cues that guide group behavior.

The following sections will explore the types and characteristics of f-formations and their implications for social interaction, as well as the concepts of o-space, p-space, and r-space, and then conclude with a summary.

F-Formations in Social Dynamics 3.1

While proxemics emphasizes individual spatial preferences and interactional distances, f-formations focus more on the collective spatial organization within groups. These concepts offer a comprehensive understanding of how space mediates communication and social structuring.

An f-formation is not merely a casual arrangement but an intentional spatial pattern that reflects the social context of an interaction. Kendon identified several common f-formation types, each shaped by the nature of the interaction and the participants' social roles (Kendon, 2010). For instance, a conversation between close friends may differ significantly in structure from a more formal group discussion or a larger communal gathering.

The f-formation chosen by a group can indicate the interaction's purpose, the level of intimacy, and even power dynamics within the group. By examining these formations, we can interpret how spatial arrangements contribute to

(a) Vis-à-vis

(b) Side-by-side

(c) Circular

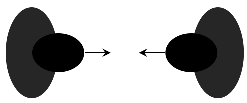
(d) Corner-to-corner

Figure 3.1: Photographs of people forming the four primary f-formation types: (a) Vis-à-vis, showing two individuals facing each other directly; (b) Side-by-side, featuring two individuals standing next to each other facing the same direction; (c) Circular, depicting a group of individuals arranged in a circle or for mutual engagement, and (d) Corner-to-corner, capturing two individuals positioned at corners of a defined space.

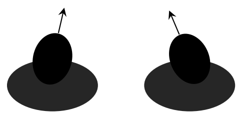
nonverbal cues and influence how individuals participate within a group. This spatial structuring serves as a guide, setting boundaries for participants and establishing a shared "interactional space" where communication unfolds.

Each type of f-formation has distinctive spatial and social characteristics. For example, small group discussions often exhibit circular or semi-circular formations, allowing each participant a clear view of others and facilitating inclusion and collaborative dialogue. In contrast, larger group interactions or formal presentations may involve more linear or side-by-side arrangements, which create a sense of hierarchy or designate specific roles within the interaction. For a visual illustration of these types in real-life scenarios, refer to Figure 3.1 and read the following detailed description of the most important arrangements.

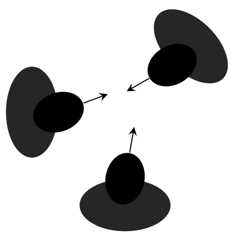
Vis-à-vis:
Also known as face-to-face, this is arguably the most basic and instinctive of all f-formations. It occurs when two people stand or sit opposite each other, usually engaging in a concentrated conversation. One might observe this formation between two friends in deep conversation at a café or during a formal job interview. It allows for direct eye contact and fosters a space conducive to meaningful and intimate dialogues.



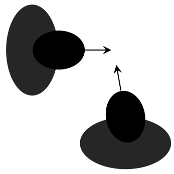
Side-by-side:
In this configuration, two individuals position themselves adjacent, often facing the same direction. This formation is frequently chosen when people are engrossed in a joint activity or are focused on a common point of interest, like two friends watching a film or coworkers collaborating at a shared desk. Interaction in this formation tends to be more relaxed, allowing conversation to unfold while participants remain attentive to the shared focal point.



Circular:
When a group consists of three or more people, a circular f-formation is often the result. Participants position themselves in a circle or semi-circle, allowing everyone to have both visual and interactional access to each other. This arrangement is common in group discussions in social settings or professional meetings.



Corner-to-corner:



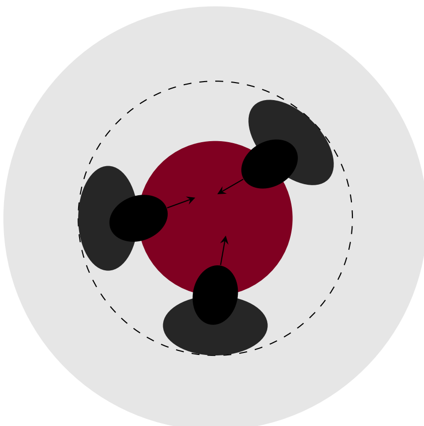
Also referred to as the l-shape formation, this is a less frequent but specialized type of f-formation. Participants are located diagonally or at opposite corners within a given space, like a room. Even though they are not directly facing each other, they can still engage while having a comprehensive view of the surrounding environment. This setup is typical in situations that demand a balance between focused interaction and environmental awareness, such as among security staff or supervisors in a control room.

Having introduced the different formations, we will explore how space is structured within these arrangements by examining the concepts of o-space, p-space, and r-space.

3.2 Introduction to O-Space, P-Space, and R-Space

F-formations comprise three characteristic spatial elements: o-space, p-space, and r-space (Ciolek & Kendon, 1980). Each of these spaces play a specific role in structuring social interactions. As shown in Figure 3.2, these spaces work together to create an organized interaction zone. We will explore each component in detail, highlighting their roles in the social dynamics of f-formations.

3.2.1 The O-Space



The "o-space" forms the central zone of an f-formation, where primary interactions occur. This space is the focal area, allowing participants to engage directly without shifting their positions. Within the o-space, individuals share verbal and non-verbal cues, such as eye contact and gestures, which are essential for effective communication.

The configuration of the o-space adapts to the type of f-formation. In a face-to-face setup, the o-space exists between two individuals; in a circular arrangement, it lies at the center, providing equal visibility to all members. The o-space is flexible and adjusts based on social

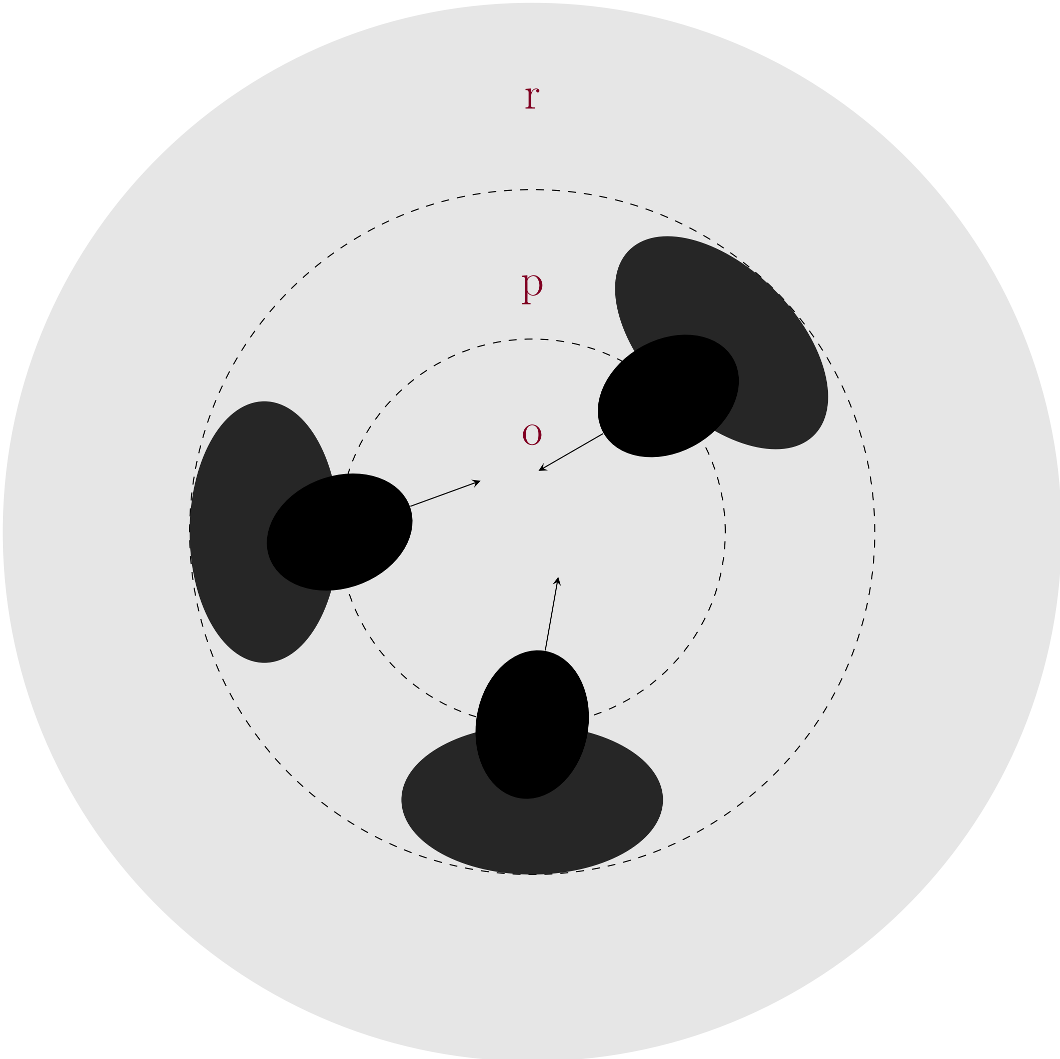
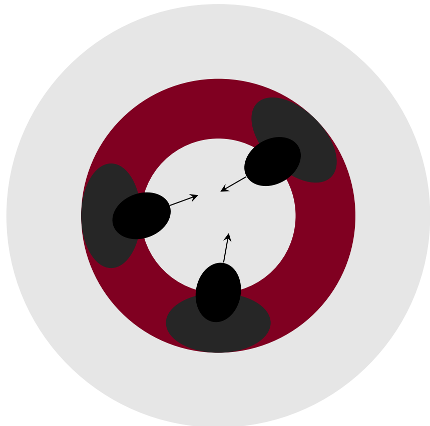


Figure 3.2: An overview of the spatial components in f-formations: o-space, p-space, and r-space.

cues and the interaction context. For example, serious discussions may require a smaller, more focused o-space than casual conversations.

In summary, the o-space is the core of an f-formation, fostering direct social engagement and establishing a shared interaction zone.

3.2.2 The P-Space

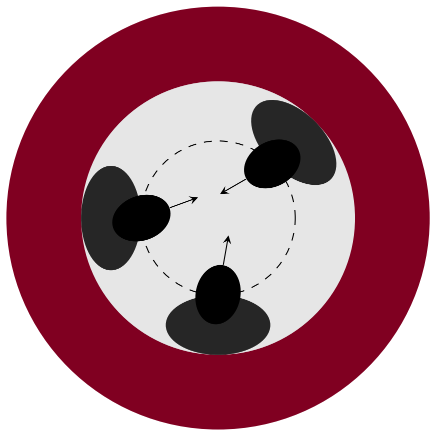


The “p-space” is the surrounding area where participants position themselves, forming a boundary around the o-space. This space includes the participants and their personal belongings, such as bags or chairs, which become part of the interaction’s physical setup.

To enter an f-formation, individuals must first move into the p-space. This space serves as a selective zone that differentiates those actively participating from outsiders. Acting as a barrier, it delineates the boundary of the interaction, defining who is part of the formation and keeping it distinct from the environment.

Thus, the p-space structures f-formations, signaling group membership and establishing a shared physical boundary.

3.2.3 The R-Space



The “r-space” is the outermost area surrounding the o-space and p-space, acting as a buffer that separates the f-formation from external surroundings. People in the r-space are generally not part of the interaction but are close enough to observe it.

This space acts as a flexible boundary; individuals in the r-space may transition into the p-space if they wish to join the interaction. Similarly, objects in the r-space are typically peripheral unless they become relevant to the group’s activity, like an approaching person or a new item of interest.

In essence, the r-space creates a contextual frame around the f-formation, separating it from and connecting it to the broader environment. It adapts as needed based on situational factors.

Summary 3.3

This chapter has examined f-formations and their essential spatial components – o-space, p-space, and r-space. These elements combine to create structured, adaptable spaces that guide social interactions. The o-space serves as the interactional core, where active engagement occurs, while the p-space forms a boundary around participants, defining membership within the formation. The r-space functions as a flexible buffer, separating the formation from its surroundings.

F-formations provide a nuanced framework for interpreting how spatial arrangements reflect and influence social dynamics, adapting to situational cues and interaction needs. This understanding of spatial organization lays a foundation for exploring the role of proxemics in HCI, which we will address in the following parts.

Related Work

II

4. Proxemics in Human-Computer Interaction

Building upon the foundational concepts of proxemics established in the previous part, in this chapter, we explore the role of proxemics in HCI. We examine the impact of spatial relations on the interaction dynamics between users and technology and present the Proxemic Interaction Framework (PIF), a foundational theoretical model in this field. Central to this framework are five dimensions that capture the various aspects of spatial interactions: distance, orientation, movement, identity, and location. Each dimension provides insights into how people naturally manage spatial boundaries and how technology can adapt to these boundaries in responsive, contextually aware ways.

Then, we will examine how these dimensions can be detected and measured, from basic distance sensing to more sophisticated movement and identity detection methods, before reviewing how proxemics has been applied in HCI research over the years, examining example studies and developments in the field. This overview will shed light on the evolution of proxemic principles in interactive technology.

4.1 The Proxemic Interactions Framework

In the vast and evolving field of HCI, the PIF (Marquardt & Greenberg, 2015), developed by Nicolai Marquardt and Saul Greenberg, represents a seminal work. These researchers have crafted a framework to aid in understanding and designing spatial interactions between humans and computers.

At its core, the PIF leverages proxemic factors to facilitate intuitive and natural interactions with computing systems. Their approach suggests that interactions with technology should be as nuanced and context-aware as our interactions with other humans by using proxemic cues to adapt a system's behavior. Central to the framework is capturing and interpreting key proxemic dimensions from sensory inputs. Various technologies such as cameras, sensors, and tracking devices gather the physical context, which is then processed to extract proxemic information like distance, orientation, movement, identity, and location. The framework emphasizes movement and motion as dynamic components derived from temporal changes in distance and orientation.

This sensory information can be fed into a set of behavioral rules. These rules articulate how a system should respond to varying proxemic contexts, ensuring the interaction is dynamic and sensitive to the user's spatial behavior. For example, a system may react differently to a user standing close and directly facing it, compared to one farther away and glancing at it peripherally.

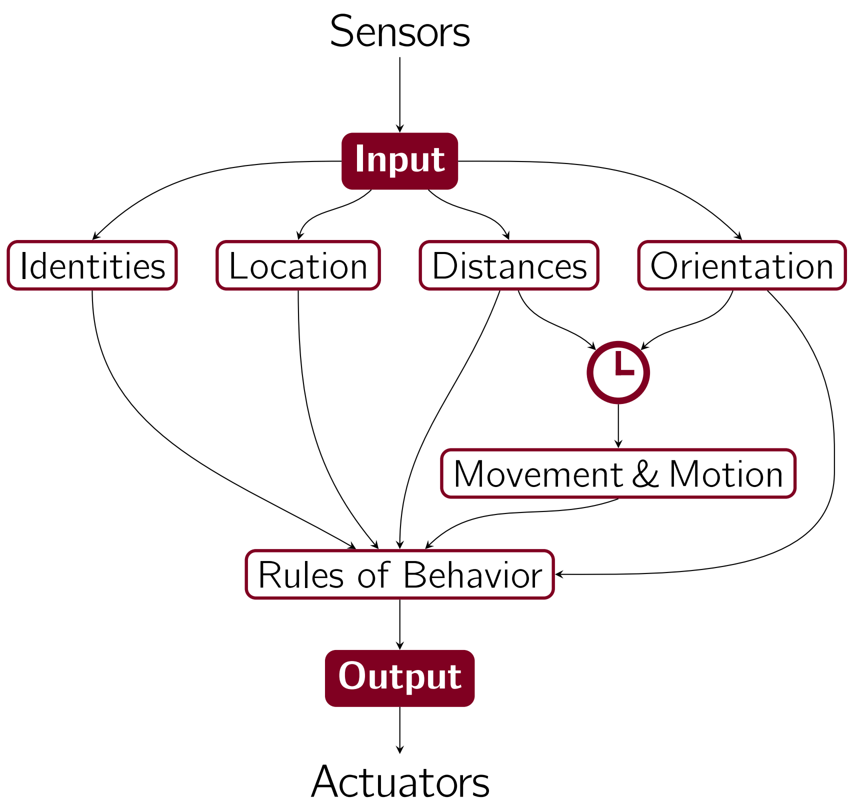


Figure 4.1: Diagram illustrating the Proxemic Interaction Framework. Components such as identities, location, distances, and orientation feed into movement and motion analysis, which informs the rules of behavior controlling the system's outputs. Adapted from Marquardt and Greenberg, 2015, p. 48.

Figure 4.1 offers an overview of the structure of the PIF, providing a general depiction of how the framework is constructed.

Complementing this framework is the Proxemic Interaction Toolkit (Marquardt et al., 2011), designed to translate theoretical concepts into practical applications. This toolkit is a significant advancement in ubiquitous computing systems, easing the task of accessing and interpreting proxemic information. It provides detailed insights into proxemic relationships between various entities in a room-sized environment, including orientation, distance, motion, identity, and location. Notably, the toolkit includes tools for rapid prototyping of proxemic-aware systems and a visual monitoring tool for observing and recording proxemic relationships in three-dimensional space. Its flexible architecture allows for using various sensing technologies, individually or in combination, to enhance its adaptability and effectiveness. The toolkit's practicality is exemplified through its application in student-built systems, such as 'Proxemic Presenter', 'ProxemiCanvas', and 'Proxemic-aware Pong'. These projects demonstrate the toolkit's ability to effectively interpret and mediate proxemic interactions. For more detailed information on these example projects, refer to their paper (Marquardt et al., 2011).

Through the PIF and its accompanying toolkit, Marquardt and Greenberg have provided a foundational structure for understanding and designing spatial interactions in HCI. Their work offers theoretical depth and practical tools for realizing the potential of proxemic-aware systems.

The Proxemic Dimensions 4.2

Understanding and applying the proxemic dimensions is crucial for creating intuitive and responsive systems. These dimensions, rooted in the study of spatial relationships, offer an approach to designing interactions that feel natural and aligned with human instincts and social norms. Following the introduction of the PIF, this section describes the five key proxemic dimensions relevant to the framework: Distance, orientation, movement & motion, identity, and location (Ballendat et al., 2010; Greenberg et al., 2011; Marquardt & Greenberg, 2015; Marquardt et al., 2011).

Distance:
Distance is the physical space between entities, whether people, digital devices, or objects. It is a dynamic element that can significantly influence how interactive systems respond. For example, consider a scenario in a museum where interactive displays provide more in-depth information as visitors come closer. At a distance, the display might show general information about an exhibit. However, as the visitor approaches, it could switch to detailed descriptions or interactive elements, fostering a more engaging and personalized experience.

Orientation:
Orientation pertains to the directional relationship between entities. It is indicative of attention, engagement, and interaction potential. An illustrative example is a conference room equipped with smart sensors. These sensors de-

tect the orientation of participants' smartphones or tablets. If a participant faces the main screen, the system might automatically share the presented content to their device. Conversely, if the participant faces another attendee, the system could facilitate note-sharing or collaborative tools, enhancing the meeting's productivity.

Movement:
Movement captures how entities change their position and orientation over time. This dimension is beneficial in environments where user actions and motions can trigger specific system responses. Consider a smart home scenario where a resident's walking pace and direction are monitored. A leisurely pace towards the kitchen in the morning could prompt the coffee maker to start brewing, while a brisk walk to the door might signal the security system to activate and lock the door.

Identity:
Identity involves recognizing and distinguishing between different entities. This dimension allows systems to provide tailored interactions based on who engages with them. For instance, in a family setting, an intelligent entertainment system could recommend movies based on the specific family member currently watching, determined through facial recognition or device interaction patterns.

Location:
Location refers to the physical context or setting where the interaction occurs. It is about understanding the environmental and situational aspects that might influence the interaction. A practical example is a mobile device that adjusts its functionalities based on its location. When entering a library, the phone could automatically switch to silent mode, or it might activate GPS and traffic updates when it detects that the user is in a car.

Each of these dimensions plays a pivotal role in the design of proxemic interactions. By considering these aspects, developers and designers can create more intuitive, context-aware, and user-friendly interfaces that resonate with natural human behavior and social customs.

4.3 Sensing Proxemics

In the preceding section, we explored the complexities of the five proxemic dimensions, showing their significance in human-computer proxemics (Marquardt & Greenberg, 2012, 2015). A central question arises as we transition from theory to application: How can we accurately measure these dimensions? This exploration is not just an academic exercise but fundamental to the practical implementation of proxemic theory. Understanding the nuances of proxemic dimensions requires tailored approaches, as underscored by extensive research examples. Each project demands a unique set of data, emphasizing the crucial role of context in determining the appropriate sensing technologies. It is not a one-size-fits-all scenario; the specificities of each use case guide the choice of sensors. To illuminate this, references in this section showcase various implementations and their context-specific approaches.

A notable challenge in sensing proxemics is that a single sensor can rarely capture all dimensions. Instead, a synergistic combination of sensors is often employed (e.g., Rekimoto et al., 2003; Surie et al., 2013; Wang et al., 2011). This multi-sensor approach allows for a more nuanced understanding and measurement of proxemic interactions.

A crucial aspect of proxemic sensing is determining whether the target of sensing is a person or a device, as this requirement influences the choice of sensors. In some instances, a device, such as a smartphone or smartwatch, can function effectively as a proxy for a person's proxemics, allowing for the sensing of the device in place of the individual.

Regarding sensing **distance**, the requirements can vary significantly. Some scenarios may only need to detect the presence of a person or device (e.g., Want et al., 1992). In contrast, others might require more precise measurements, like the discrete distances (e.g., Ju et al., 2008) outlined in Hall's dimensions (see Section 2.2: *Distance Zones*). In more advanced cases, continuous distance measurement becomes essential (e.g., Vogel and Balakrishnan, 2004).

Orientation sensing also displays a spectrum of requirements. Some applications need exact angular measurements (e.g., Vogel and Balakrishnan, 2004). In contrast, others only require basic differentiation, such as whether someone is facing towards or away from a sensor, device, or person (e.g., Marquardt et al., 2012).

Identity sensing is equally diverse. Depending on the use case, identifying the exact individual may be crucial (e.g., Want et al., 1992), or it might suffice to categorize (e.g., human, animal, or device) the entity (e.g., Surie et al., 2013). This flexibility in identification is pivotal in designing context-appropriate interactions.

Movement and motion sensing in proxemics can be categorized into two distinct approaches. The first, a discrete method, involves recognizing general movement patterns, such as slow or fast walking, and can also include detecting when someone is moving closer or moving away (e.g., Ju et al., 2008). The second approach is continuous, focusing on precise speed measurements, enabling movement tracking at specific velocities.

Location sensing, a critical dimension of proxemics, varies in complexity. In some contexts, basic detection like identifying the room (bathroom, kitchen, living room) is adequate – in some cases, this could also be achieved by knowing the position of the sensors (e.g., Surie et al., 2013). In more dynamic environments, more comprehensive sensory might be required to capture the contextual nuances of location, such as extracting the information from a camera stream.

One of the key contributions of this work is an in-depth discussion on the types of sensors suitable for sensing various proxemic dimensions, provided in a separate chapter (see Chapter 14: *Sensors for Detecting Proxemics Dimensions*). This discussion will offer a detailed guide to the technological tools available for these measurements, serving as a valuable resource for researchers and practitioners in the field.

In conclusion, the process of sensing proxemics is intricate, requiring a nuanced understanding of the context and the specific proxemic dimensions involved. The selection of sensors and the measurement methodology are customized to each unique scenario.

4.4 An Illustrative Cross-Section for Proxemics in HCI

This chapter provides an overview of the progression of proxemic research within HCI, tracing its development from initial applications of spatial concepts to sophisticated, theory-informed designs. The description is structured around four selected papers, each representing a phase in integrating and interpreting proxemics in HCI. These papers, chosen for their varied approaches to proxemics, illustrate the field's evolving dialogue with Edward T. Hall's foundational theory.

Initial Applications of Spatial Concepts

Early usage of proxemics in HCI can, for example, be observed in works like "Interactive public ambient displays: Transitioning from implicit to explicit, public to personal, interaction with multiple users" (Vogel & Balakrishnan, 2004). This study employs proxemic dimensions such as distance, orientation, and movement to facilitate interactions between users and public displays. Notably, this application of spatial concepts was influenced by intuitive understandings of space and interaction rather than a direct application of Hall's proxemic theory. Despite not grounding these efforts in the formal proxemic framework, the research demonstrates an attempt to use spatial dynamics to improve user experience. This application of spatial dimensions indicates the potential for proxemics to enrich interactive systems, albeit without explicit theoretical underpinning at this stage.

Direct Engagement with Proxemic Theory

In contrast, the work on the 'Range' electronic whiteboard (Ju et al., 2008) suggests a shift towards explicit engagement with proxemic theory. This research is grounded in Hall's work, particularly emphasizing the dimension of distance to shape user interactions. By integrating proximity sensing within the design of the whiteboard, this paper illustrates a conscious application of proxemic principles to enhance HCI. Comparable works often focus on the aspects of distance (Kurdyukova, 2015; Kurdyukova et al., 2012). The focused use of the proxemic dimension of distance to facilitate implicit interactions marks a deliberate move towards theory-informed design in HCI, distinguishing it from earlier, more intuitive applications of spatial concepts.

Adaptation of the Proxemic Interaction Framework

Moving deeper into proxemic research, the paper "Proxemics awareness in kitchen as-a-pal: Tracking objects and human in perspective" (Surie et al., 2013) represents a comprehensive embrace of the PIF. This research not only acknowledges but actively incorporates multiple proxemic dimensions – position, movement, identity, and location – into the design of a 'smart kitchen' environment. By doing so, it showcases the richness and utility of considering a broader spectrum of proxemic elements in HCI. This application of the proxemic framework demonstrates an advanced integration of proxemic theory into the design and evaluation of interactive systems, demonstrating the practical value of a nuanced understanding of spatial dynamics.

Beyond Proximity: Expanding Proxemic Considerations

The chronology progresses with "Proxemics beyond Proximity: Designing for Flexible Social Interaction Through Cross-Device Interaction" (Grønbæk et al., 2020) and their exploration of cross-device interactions, which advocates for a proxemics-based approach that extends beyond simple proximity detection.

This research calls for a nuanced understanding of the interplay between people, devices, and the environment, suggesting new directions for incorporating spatial dynamics into HCI design beyond the scope of the PIF. They also suggest including fixed (e.g., walls, ceilings, and wall displays) and semi-fixed (e.g., tables, chairs, and monitors) features in the interactions. These features are already explored in the proxemics theory by Hall (Hall, 1966) and also discussed by Marquardt and Greenberg (Marquardt & Greenberg, 2015); they're not explicitly included in the PIF. Through the prototypes the authors built to explore the proxemic relations in their setups, they highlight the evolving complexity of proxemics in HCI, emphasizing the need for designs that reflect the full spectrum of spatial interactions.

Summary

Through the lens of these four papers, we observe the development of proxemic research in HCI – from initial, intuitive applications of spatial concepts to sophisticated designs informed by proxemic theory. This evolution underscores a growing recognition of the importance of spatial dynamics in interaction design. While the early work showed promise through the use of proxemic dimensions, subsequent research more directly engaged with Hall's theory, culminating in approaches that seek to broaden the application of proxemics beyond conventional frameworks. This historical overview highlights the development of proxemic research within the scope of HCI, showcasing the field's ongoing evolution towards more theory-informed design strategies.

5. Proxemics in Human-Robot Interaction

Following our exploration of proxemics within the field of HCI, this section expands the discussion to HRI, where spatial dynamics play a pivotal role in shaping practical and comfortable interactions between humans and robots. To begin, we present an overview of key robot categories relevant to proxemic research in HRI before discussing the concept of socially-aware navigation, an area of research that incorporates proxemic principles to enable robots to navigate in ways that respect personal and social space. While socially-aware navigation is a significant aspect of proxemic research, it lies beyond the scope of this work. However, understanding its role is essential for comprehending the broader context in which proxemics operates within HRI.

In the central part of this chapter, we explore the primary factors influencing proxemic interactions in HRI. These factors encompass various aspects, including characteristics of the robot itself, attributes of the human interacting with the robot, and additional contextual elements. Afterward, we look at how a robot's proxemic behavior influences humans. Examining these dimensions provides a broad overview of the research landscape, establishing proxemics as a foundational component of human-centered robot design.

5.1 Key Robot Categories for Proxemics Research

In this section, we explore robot classifications that are most relevant for proxemic research. Before describing the specific categories, addressing the inherent challenges in defining and categorizing robots is crucial. The dynamic and evolving nature of robotics technology complicates these efforts, as the definition of a robot can vary widely across different contexts and over time. Understanding these complexities is essential for identifying which robot types are most relevant to the study of proxemic interactions, setting the stage for a deeper examination of how robots navigate and influence the environments shared with humans.

5.1.1 Challenges in Defining Robots and Robot Categories

What exactly defines a robot? The answer to this question varies widely depending on the source and sometimes evolves. Traditionally, robots have been defined by specific mechanical and functional criteria. For instance, an ISO standard from 2012 once defined robots based on specific capabilities, such as the requirement to have two or more axes of movement, primarily categorizing them into two types: industrial and service robots.

> **Robot**
>
> "*actuated mechanism programmable in two or more axes with a degree of autonomy, moving within its environment, to perform intended tasks* "
>
> *Robots and robotic devices – Vocabulary* (ISO 8373:2012, 2012)

However, an updated version of this ISO standard, from 2021, revised these criteria. The updated definition eliminates the requirement for a specific number of axes and broadens the classification to include an additional type: medical robots.

> **Robot**
>
> "*programmed actuated mechanism with a degree of autonomy to perform locomotion, manipulation or positioning*"
>
> *Robotics – Vocabulary* (ISO 8373:2021, 2021)

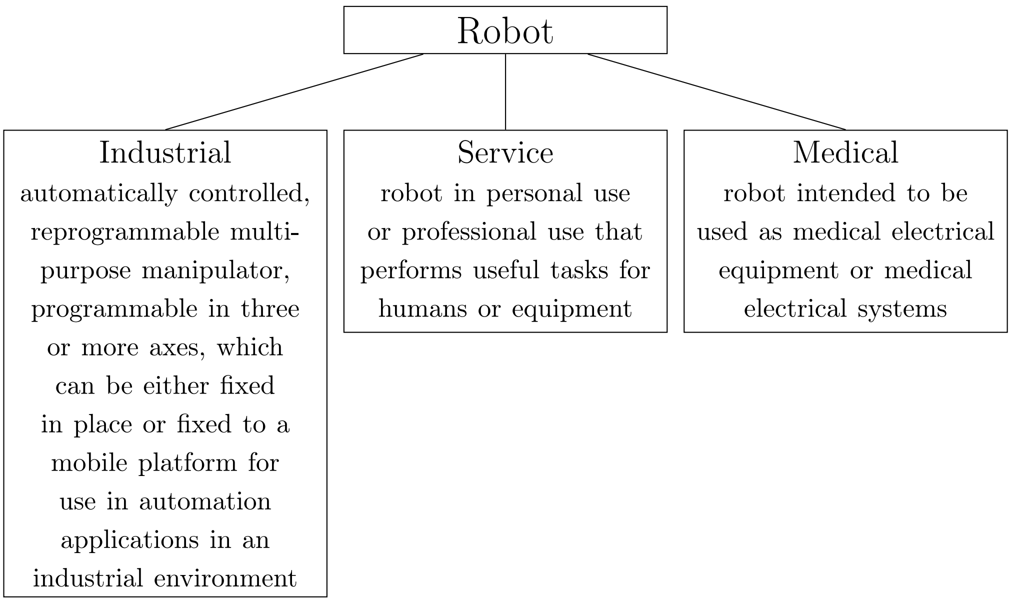


Figure 5.1: Robot types with definitions according to ISO 8373:2021 (2021).

ISO 8373:2021 (2021) provides a structured overview of the three robot types, which are visually depicted in Figure 5.1. The standard also mentions other robot categorizations based on the type of manipulator (e.g., articulated, rectangular, cylindrical) and mobility (e.g., wheeled, legged) – the latter being crucial considerations in the context of proxemics. Given these categorizations, service robots emerge as particularly significant for proxemic research. Unlike industrial robots, which typically operate autonomously within confined spaces, or medical robots, which focus on specific medical tasks, service robots interact directly and frequently with humans.

While helpful, the ISO standard's categorization is limited when considering the wide variety of robot types emerging with technological advances. Therefore, we will explore additional definitions and classifications from other sources to capture a broader spectrum of robotic types and their evolving roles.

Defining a robot is intricate, reflecting the vast diversity in their applications, behaviors, capabilities, and appearances. As illustrated by the evolving ISO standards, definitions must be regularly updated to keep pace with technological advancements and the expanding roles of robots across various sectors.

In his insightful article (Guizzo, 2024) on https://robotsguide.com[1], Guizzo delves into the complexities of defining what a robot truly is. This discussion underscores the inherent difficulties in crafting a universally accepted definition. Guizzo proposes a definition:

> **Robot**
>
> "*A robot is an autonomous machine capable of sensing its environment, carrying out computations to make decisions, and performing actions in the real world.*"
>
> "What Is a Robot?" (Guizzo, 2024)

He acknowledges that this definition balances being overly broad and excessively narrow, yet he also admits, "no definition is perfect". To illustrate this, he points out that his definition could inadvertently encompass non-robotic

[1] "ROBOTS" (https://robotsguide.com) is an editorial product of IEEE Spectrum, the flagship publication of Institute of Electrical and Electronics Engineers (IEEE), the world's largest professional organization for engineering and applied sciences. IEEE Spectrum covers a wide range of technology topics, supporting IEEE's mission to advance technology for humanity. This connection enhances the relevance and authority of the "ROBOTS" website as a reliable educational resource in robotics.

systems such as dishwashers, thermostats, elevators, and automatic doors – items not typically recognized as robots despite fulfilling the criteria.

This predicament highlights a critical challenge: overly specific definitions risk excluding entities universally recognized as robots, while overly broad definitions may include too many non-robotic elements. This dilemma not only complicates the task of defining what a robot is but also impedes our ability to categorize robot subtypes effectively. How can one accurately classify various robot types without a clear, universally accepted definition of a robot itself?

Given the vast potential categories for robot classification, this work will not attempt to categorize every possible type of robot exhaustively. Instead, the focus will be on those classifications most pertinent to proxemics, specifically robots that operate on the ground. This focus excludes aerospace and aquatic robots and types unlikely to engage in social interactions with humans, such as military or disaster response robots.

In the subsequent sections, we will focus on robot types that are particularly pertinent to the study of proxemics. While not exhaustive of all robot varieties, this overview will highlight those most significant for our research into HRI and the spatial dynamics they encompass. As we explore these classifications, it becomes apparent that the boundaries between different types of robots are not always clear-cut; many categories overlap, reflecting the complex interplay between robot design, intended functionality, and their environments.

Comment by Prof. Bearingtons

As an expert bear, I find categorizing robots as befuddling as trying to catch a fish with my paws tied! Just last week, I encountered a tree-felling robot – clever machine, capable of navigating forests and chopping down trees. But where does one categorize such a contraption? Is it a lumberjack or an outdoor Roomba? Sorting robots into categories is as tricky as organizing a picnic in a windstorm – especially when they keep reinventing themselves!

5.1.2 Mobile Robots

Defining a mobile robot precisely can be challenging, as there is no universally accepted definition (Hertzberg et al., 2012). Generally, a mobile robot is characterized by its ability to move autonomously within an environment rather than being anchored to a specific location. The modes of mobility for these robots vary widely, including wheeled and legged locomotion on the ground, as well as aerial movement using wings or rotors (Siciliano et al., 2008; Siegwart et al., 2011).

Research on this category of robots began in earnest in the late 1960s, catalyzing a broad exploration of autonomous mobility and its applications. Examples of mobile robots include everyday robotic vacuum cleaners, the Mars Rover, and various types of drones (Siegwart et al., 2011). However, a broad category, only a select subset of mobile robots, is relevant to the study of proxemics. This subset is particularly significant because these robots can actively engage in proxemic behavior – maneuvering through and responding to human-occupied spaces.

For instance, while the Mars Rover is not directly relevant to proxemics due to its lack of interaction with humans (at least for the next couple of years[2]), other mobile robots like domestic vacuum cleaners or small drones designed for interaction in human environments exemplify the importance of understanding spatial dynamics. These robots must navigate around people, often adjusting their paths or behaviors based on human presence and movements. Additionally, many robots discussed later in this section, which are inherently mobile, highlight the crucial role of proxemics in designing and deploying practical, human-centered robotic systems.

Service and Social Robots 5.1.3

The classification of robots into service represents another fundamental area of study within robotics, particularly relevant to proxemics.

Service Robot

"*Service robots are system-based autonomous and adaptable interfaces that interact, communicate and deliver service to an organization's customers.*"

"Brave new world: service robots in the frontline" (Wirtz et al., 2018, p. 909)

This definition aligns closely with the ISO standards, suggesting a broad scope of functionality. Notably, the work of this definition (Wirtz et al., 2018) also argues that artificial intelligence (AI) assistants, such as Amazon Alexa, would be service robots. While opinions vary within the context of proxemics research, physical presence is critical. Thus, virtual assistants without physical forms are less pertinent to spatial dynamics and human-environment interactions.

[2]https://www.nasa.gov/humans-in-space/humans-to-mars/

Service robots encompass a wide range of applications, from practical devices like robotic vacuum cleaners to those that provide social services. This diversity positions service robots as a broad category, with social robots acting as a distinct subcategory focused on social service. For instance, the VIVA robot, which we discuss later, exemplifies the bridge between service and social robots. These social robots are specifically designed to engage with humans in a profoundly interpersonal manner, as emphasized in a more comprehensive definition:

Social Robot

"*Social robots are designed to interact with people in human-centric terms and to operate in human environments alongside people. Many social robots are humanoid or animal-like in form, although this does not have to be the case. A unifying characteristic is that social robots engage people in an interpersonal manner, communicating and coordinating their behavior with humans through verbal, nonverbal, or affective modalities.*"

"Social Robotics" (Breazeal et al., 2016, p. 1936)

Mahdi et al. (Mahdi et al., 2022) highlight that this definition is broader than previous notions, such as those defining "socially interactive robots" (Fong et al., 2003) or "socially intelligent robots" (Dautenhahn, 1998). The evolution of these definitions reflects a growing recognition of the diverse ways robots can fulfill social roles.

Proxemics is crucial for service robots, which are frequently integrated into everyday human environments to perform various services. Understanding spatial dynamics is crucial for these interactions, ensuring service robots operate effectively and harmoniously within human spaces. This consideration becomes even more critical for social robots. Explicitly designed to engage in and enhance social interactions, these robots must navigate and respond to complex human behaviors and social cues. Proxemics plays a pivotal role in designing and deploying social robots, as it directly influences how these robots communicate and coordinate their behavior with humans, ensuring natural and comfortable interactions.

While it is tempting to delve deeper into subcategories such as entertainment (Tamura et al., 2004; Veloso, 2002) or assistive robots (Brose et al., 2010; Miller, 2006), the complexity and breadth of robot classification can be overwhelming. This sentiment might even prompt Fuchur to advise: "give up, this is a neverending story"[3]. Reflecting this practical limit to the depth of categorization, we will instead focus on another vital type of robot in the next section, particularly relevant to proxemics: humanoid robots.

Humanoid Robots 5.1.4

Last but not least, we will explore the category of humanoid robots, which represents one of the most intriguing and complex types of robots in terms of design and interaction with humans.

Humanoid Robot

"*A humanoid robot is a robot that has a human-like shape.*"

Introduction to Humanoid Robotics (Kajita et al., 2014, p. 1)

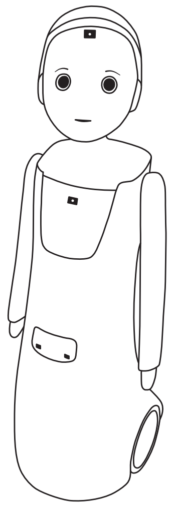
Humanoid robots are designed to resemble the human body, often mimicking facial features, limbs, and movements. This human-like appearance enhances their ability to perform tasks in environments designed for humans and influences how humans perceive and interact with them. Research suggests that we have higher proxemic expectations from robots that appear more human-like, as these forms invite more personal and social interactions (Syrdal et al., 2008).

Anthropomorphism, or attributing human characteristics to non-human entities, is crucial in how interactions with humanoid robots are perceived and managed. This concept is particularly pertinent in robotics, affecting user acceptance and interaction quality. The more a robot is anthropomorphized, the more likely individuals are to expect human-like social cues and behaviors from it (Złotowski et al., 2015).

Since humanoid robots combine the attributes of mobility, social interaction capabilities, and a human-like form, they are at the forefront of proxemics research. They encapsulate the challenges and opportunities of designing robots that can seamlessly integrate into human social spaces. By embodying aspects of both mobile and social robots, humanoid robots are particularly relevant for studies focusing on spatial dynamics and HRI.

The VIVA Robot 5.2

[3] https://theneverendingstory.fandom.com/wiki/Falkor



From August 2018 to December 2021, the VIVA project was funded by the German Federal Ministry of Education and Research (BMBF). Coordinated by navel robotics GmbH, the project involved several academic partners like the University of Bielefeld, the University of Augsburg, and the University of Applied Sciences of Bielefeld and industrial partners like Neuland Software GmbH and Visions4IT GmbH. The primary goal was to develop a robot called VIVA, capable of recognizing and responding to human emotions, fostering trust, and enhancing user well-being ("BMBF Projekt VIVA", 2024; "VIVA: Vertrauen und Sympathie schaffender „lebendiger" sozialer Roboter", 2024).

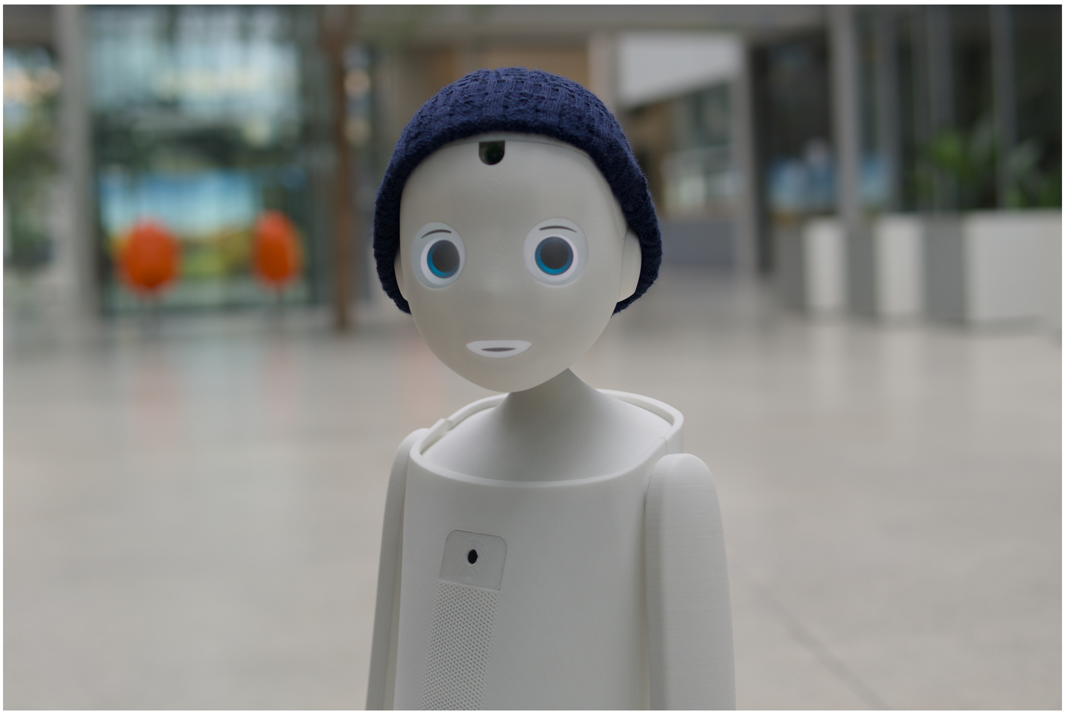


Figure 5.2: Close-up picture of the VIVA robot developed during the BMBF funded VIVA project.

Despite the challenges posed by the COVID-19 pandemic, which necessitated virtual collaboration and evaluations, the project successfully developed multiple prototypes. Following the project's conclusion, the VIVA robot has been further developed and is now known as Navel. This new iteration continues advancing the capabilities established during the VIVA project, focusing on empathetic interactions and user engagement ("Navel – der soziale Roboter", 2024).

The VIVA robot fulfills the criteria of all the previously introduced robot types (i.e., mobile, service, social, and humanoid robots), making it an ideal subject for proxemic research. VIVA's mobility on wheels allows it to navigate and interact autonomously within various environments, which makes it a mobile robot. Since it provides essential support and companionship, enhancing its users' well-being, it also falls into the category of a service robot. Its social robot characteristics enable VIVA to engage in meaningful interactions through verbal and non-verbal communication. Lastly, its humanoid features, such as a human-like appearance and expressive capabilities, facilitate natural and intuitive HRI. This combination ensures that VIVA is a well-suited robot for proxemic interaction research.

The VIVA robot's expressive face, featuring large, round eyes with blue irises and a small, semi-circular mouth, contributes significantly to its ability to engage users emotionally and socially. The robot's eyes and mouth can display various expressions, enhancing its interaction quality and relatability (see Figure 5.2).

Most of this work's HRI research was conducted using the VIVA robot and was part of the VIVA project.

5.3 Socially-Aware Navigation

Before we explore the last and most important section of this chapter, we will examine a common task that robots must perform when navigating environments shared with humans. When robots consider human proxemics in their navigation, this is often referred to as "socially-aware navigation".

> **Socially-Aware Navigation**
>
> "*A socially-aware navigation is the strategy exhibited by a social robot which identifies and follows social conventions (in terms of management of space) in order to preserve a comfortable interaction with humans. The resulting behavior is predictable, adaptable and easily understood by humans.*"
>
> "From Proxemics Theory to Socially-Aware Navigation: A Survey" (Rios-Martinez et al., 2015, p. 146)

A survey paper by Rios-Martinez et al. (2015) provides an extensive overview of how proxemics plays a crucial role in navigation within human environments. People have their personal zones that robots should not enter, and these zones can expand when groups of people interact, forming an f-formation and creating a combined zone that robots should not breach. Another critical zone is the activity space created when interacting with objects, often defined as the space between a person and the object (Lindner & Eschenbach, 2011), which a robot should avoid entering.

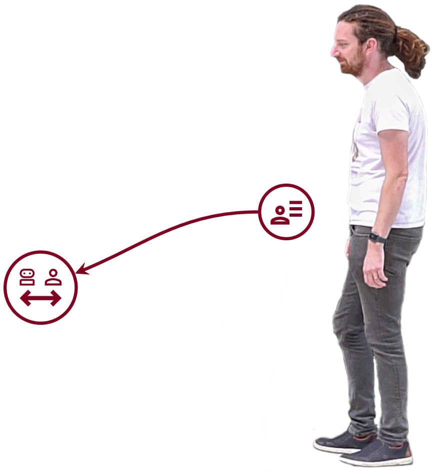
The survey paper also categorizes the different works on socially-aware navigation into two interaction types based on Goffman (2008). The first type is "unfocused interaction", which describes robot behaviors that do not directly interact with humans, such as navigating around and avoiding collisions with humans (e.g., Shiomi et al., 2014; Zeng and Bone, 2013) or passing people (e.g., Neggers et al., 2022; Sisbot et al., 2007). On the other hand, there is "focused interaction" which describes robot tasks that involve direct interactions with humans, such as approaching a human or a group of humans (e.g., Althaus et al., 2004; Carton et al., 2013), as well as tasks like following people (e.g., Algabri and Choi, 2020; Gockley et al., 2007; Zender et al., 2007) or walking side-by-side (e.g., Morales Saiki et al., 2012; Repiso et al., 2017).

For clarity, this work focuses on direct interaction between robots and humans. Therefore, unfocused interactions, where robots aim to avoid direct interaction with humans – even though proxemics plays an important role in navigation – are not within the scope of this work. Only focused interactions, where the robot approaches a human to initiate or engage in an interaction or moves away, which are technically navigation tasks, are relevant. The following section will explore these interactions, examining factors influencing proxemic expectations and behaviors between humans and robots.

5.4 Factors Influencing Proxemics in HRI

This chapter explores the factors influencing proxemic behavior in HRI. We will begin by examining "human factors", which are factors related to humans that influence the proxemic behavior between humans and robots. Next, we will examine "robot factors", which are factors related to the robots themselves that affect proxemic behavior. Following this, we will discuss "connection factors", focusing on how the bonds between humans and robots influence proxemics. We will then explore "interaction factors", considering how the nature of the interaction impacts proxemic behavior in HRI. Finally, we will analyze "environmental factors", the external conditions and settings affecting proxemic behavior.

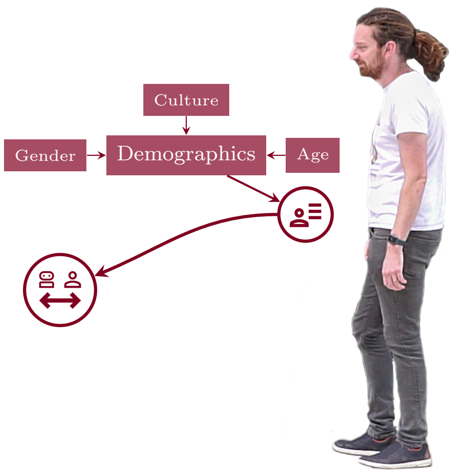
Human Factors 5.4.1



Robot's Proxemic Behavior Human's Attributes

First, we will look at human factors. We sorted these factors into different categories: "demographics", "knowledge and experience", "personality", and "behavior".

Demographics 5.4.1.1



Robot's Proxemic Behavior Human's Attributes

Culture In the paper "Investigating the Influence of Culture on Proxemic Behaviors for Humanoid Robots" (Eresha et al., 2013), the authors explore how cultural backgrounds affect interpersonal distances in HRI. The study involved

Arab and German participants positioning Nao robots[4] both static and dynamic conversational scenarios. Results showed that Arabs preferred closer distances to the robots than Germans – which is in line with observations by Hall in human-human proxemics (Hall, 1966) – in a static scenario where participants placed a robot and themselves next to another robot. However, both cultural groups placed robots at similar distances in a second static scenario involving only robot-robot interactions. The dynamic scenario, where the robots approached the human in a "German" (85 cm) or "Arab" (65 cm) manner, showed no clear preference towards the participants' cultural background.

Following the discussion on culture, "Child's culture-related experiences with a social robot at diabetes camps" (Neerincx et al., 2016) explores how children from Italy and the Netherlands interact with a social robot designed to aid in diabetes self-management. The study was conducted at diabetes camps and involved children participating in activities with the Nao robot. The results revealed cultural differences in proxemics: Italian children were more expressive and physically closer to the robot than Dutch children. However, the Italian children were also older, suggesting that age, not only culture, might influence their interaction with the robot. This suggestion brings us to the next important factor to consider in such studies – age.

Age The role of age as a relevant factor for proxemics in HRI is debated in the literature, with no clear consensus. For example, the paper "Close encounters: spatial distances between people and a robot of mechanistic appearance" (Walters, Dautenhahn, Koay, et al., 2005), investigates interactions between different age-groups and a robot. The study observed children's and adults' proxemics with a PeopleBot™[5] robot. Children interacted with the robot in groups, generally positioning themselves within the "social zone" (1.2 m to 3.6 m), indicating they viewed the robot as a social entity. In contrast, adults interacted individually and preferred the "personal zone" (0.45 m to 1.2 m), suggesting a more familiar interaction distance. These are two completely different study setups, making direct comparisons challenging. However, the results still indicate that there could be age-related differences in human-robot spatial behavior, at least when comparing adults and children.

In another work focusing exclusively on adults, no age-related differences were found in the study titled "Navigating in public space: participants' evalua-

[4] https://www.aldebaran.com/en/nao
[5] https://telepresencerobots.com/robots/adept-mobilerobots-peoplebot/

tion of a robot's approach behavior" (Złotowski et al., 2012). The researchers assessed how the robot IURO's[6] approach trajectories influenced its social acceptance by conducting an online survey with video demonstrations with a prototype of the robot. The general result showed that participants preferred IURO to approach from the front left or front right rather than frontally when walking. At the same time, no specific preference was noted for standing participants. However, results revealed no significant relationship between participants' age and their preferences for the robot's approach direction. Moreover, the study found no significant differences in preferences based on gender.

Gender While Dautenhahn et al. (2006) did not find age-related differences in their work "How may I serve you? a robot companion approaching a seated person in a helping context", they uncovered gender-related differences regarding proxemic preferences in HRI. The study involved trials where a PeopleBot™robot approached seated participants from different directions (front, left, right) to deliver a TV remote control. Overall, the right approach was most favored (59%), followed by the left (28%), with the front being the least preferred (13%). However, results also showed that females more often preferred the frontal approach, while males predominantly preferred the right-side approach.

Also, other works highlight that there are gender differences in HRI, as discussed in the paper "Human-robot proxemics: Physical and psychological distancing in human-robot interaction" (Mumm & Mutlu, 2011). In a controlled lab setting, participants interacted with the robot Wakamaru[7], which varied in likeability and gaze behavior. The study found that men maintained a greater physical distance from the robot than women and increased their distance when the robot maintained mutual gaze, while women's distancing behavior was not significantly affected by gaze. Generally, participants who disliked the robot maintained greater physical distance and disclosed less personal information.

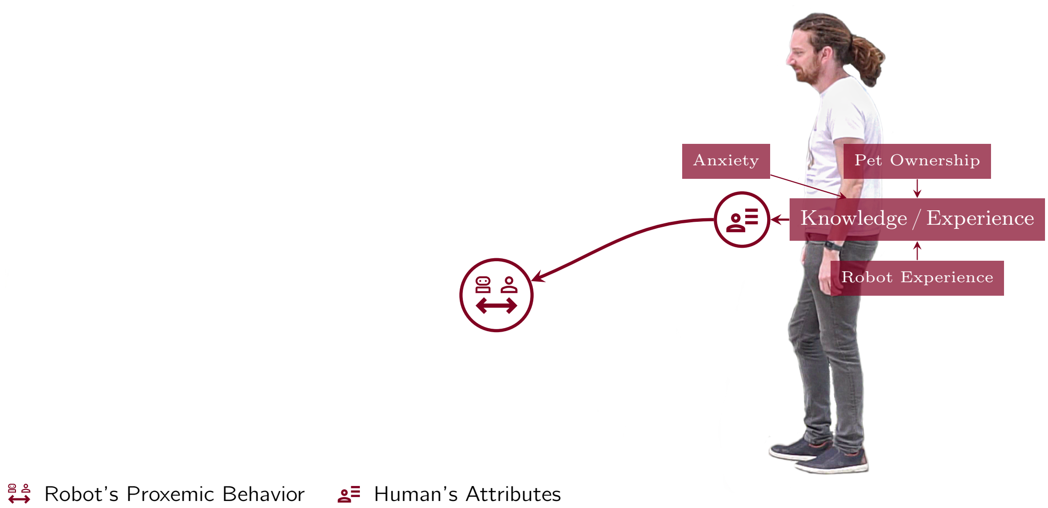
The work "The Relationship Between Robot Appearance and Interaction with Child Users: How Distance Matters" (Lin & Yueh, 2016) investigates how robot appearance affects interactions with children in a library setting. The study involved 77 elementary students interacting with a human-like robot, "Julia", and a machine-like robot, "Book Smile". Results showed that children maintained a closer personal space with the human-like robot. Gender differences were significant: girls interacted at a closer distance and had a more

[6]https://cordis.europa.eu/project/id/248314/en
[7]See Shiotani et al., 2006

positive attitude towards the robots compared to boys. The results suggest that both the appearance of robots and the gender of child users influence proxemic interactions.

Even more studies have investigated gender differences in proxemic HRI. For instance, Syrdal et al. (2007) – which will be explored in more detail later – discovered that women permitted the robot to approach closer from the front than men. At the same time, they observed no differences when the robot approached from the side. Additionally, Takayama and Pantofaru (2009) found that women preferred to maintain a larger distance when the robot's head was oriented towards their face, whereas men were comfortable being closer under the same condition. We will describe this work in more detail in the following section.

5.4.1.2 Knowledge and Experience



Pet Ownership The paper "Influences on proxemic behaviors in human-robot interaction" (Takayama & Pantofaru, 2009) explores how various factors affect personal space preferences around robots. The study involved 30 participants and examined the influence of prior experience with pets and robots on proxemic behavior. Using the PR2 robot[8], the researchers tested three scenarios: participants approaching a stationary robot, an autonomously moving robot approaching, and a teleoperated robot approaching. In different conditions, the robot's head was oriented either towards the participant's face or legs. They found that participants who previously owned pets were more comfort-

[8] https://robotsguide.com/robots/pr2

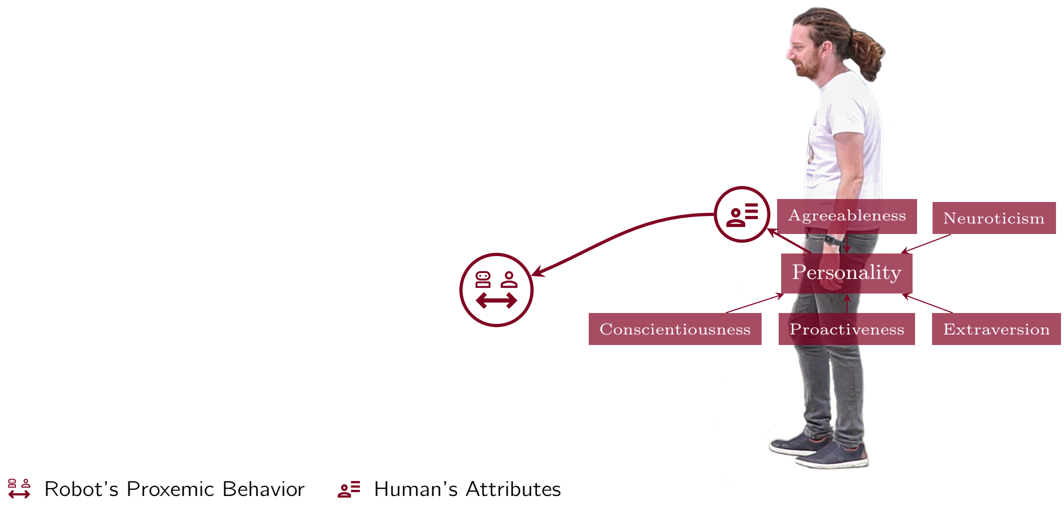
able with the robot being closer to them than those who had never owned pets. These results suggest that past pet ownership decreases the personal space individuals require around robots. However, in the work of Mumm and Mutlu (2011) – previously described in detail – it was found that people who owned pets positioned themselves farther away than those without pets. This finding indicates that the influence of pet ownership on proxemic expectations from a robot is not entirely clear.

Robot Experience The study Takayama and Pantofaru (2009) also revealed significant effects of previous experience with robots on proxemic behavior. Participants with at least one year of experience with robots were comfortable maintaining a closer distance to the robot than those with less or no experience. This indicates that familiarity and comfort with robots through prior exposure can reduce the personal space individuals need when interacting with robots. This finding highlights the influence of general robot experience, although this study did not specifically examine familiarity with the particular robot used.

Anxiety The study Eresha et al. (2013), previously detailed for its insights on cultural differences, also examined the impact of anxiety on HRI. Anxiety was measured using the Negative Attitude toward Robots Scale (NARS) (Nomura, Kanda, & Suzuki, 2006). Results indicated that participants with lower anxiety levels preferred closer interactions, irrespective of their cultural background. This suggests that anxiety could play a significant role in proxemic preferences, potentially influenced by prior experience with robots. Participants with little to no previous experience with robots may exhibit higher anxiety, affecting their comfort levels during interactions.

Personality 5.4.1.3

The paper, titled "'Doing the right thing wrong' - Personality and tolerance to uncomfortable robot approaches" (Syrdal et al., 2006), investigates how human personality traits influence comfort with robot approach directions. The study involved 42 participants and utilized the PeopleBot™robot in a living room setting to approach participants from various directions. Results indicated no consistent significant relationships between the Big Five personality traits (Goldberg, 1999) and preferred approach directions. However, there was a trend where the trait of **extraversion** was associated with a higher tolerance for less comfortable approach directions. Extroverts were more comfortable with approaches generally rated as uncomfortable compared to introverts, although these results were not statistically significant.



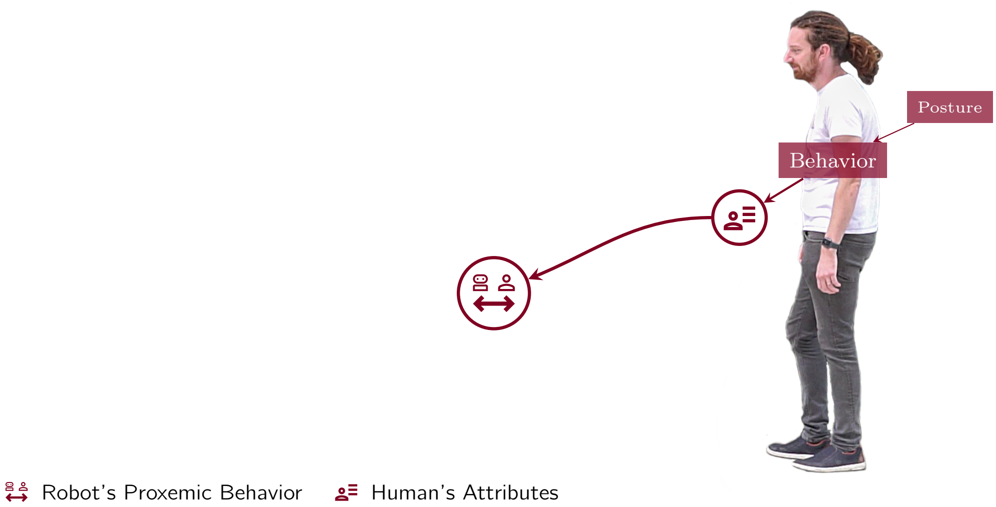
Building on this research, the newer work "A personalized robot companion? - The role of individual differences on spatial preferences in HRI scenarios" (Syrdal et al., 2007) explores how personality traits, again measured using the Big Five model (Goldberg, 1999), affect HRI. The study involved 33 participants who interacted with PeopleBots™in a living room setting, with a subset of 12 participating in a longitudinal study over six weeks. The experimental design included variations in robot control (human vs. robot), interaction type (verbal, physical, and no interaction), and approach direction (front vs. side). Results showed that extraverted individuals preferred the robot to approach closer when they had control over it. At the same time, introverts were more comfortable with the robot approaching autonomously, further adding empirical certainty that **extraversion** is an important factor for human-robot proxemics. Additionally, participants with low **conscientiousness** preferred closer proximity when they had control compared to when the robot was autonomous.

Another paper that looks at personality traits is "The influence of subjects' personality traits on personal spatial zones in a human-robot interaction experiment" (Walters, Dautenhahn, te Boekhorst, et al., 2005), where the authors explore how personality traits affect human spatial preferences when interacting with a robot. The study involved 28 volunteers interacting with a PeopleBot™robot in a simulated living room setting. The results showed that while most participants maintained typical social distances, a significant minority approached the robot more closely than expected. The authors used 12 sub-factors from Eysenck's Three-Factor (i.e., Psychoticism, Extroversion, and

Neuroticism) model (Eysenck, 1991) and formed four new personality factors: "Proactiveness", "social reluctance", "timidity", and "nervousness". Of these, only **"proactiveness"** correlated with proxemic preferences, with proactive individuals preferring to keep more distance from the robot.

Lastly, the previously described work Takayama and Pantofaru (2009) also found that certain personality traits significantly influenced proxemic behavior in HRI. Participants who scored higher on the personality trait of **agreeableness**, based on the Big Five personality traits (Goldberg, 1999), tended to approach the robot more closely. Conversely, individuals with higher levels of **neuroticism** maintained a larger distance when the robot approached them.

Behavior 5.4.1.4



Regarding human behavior – the final category of human factors – in proxemic interactions between humans and robots, limited research specifically investigates or manipulates this aspect within study setups. Two studies are worth noting for exploring human posture (i.e., standing or sitting) in this context. After examining these two studies, we will discuss the robot factors influencing proxemics in HRI.

The first study, titled "Stop! That is close enough. How body postures influence human-robot proximity" (Obaid et al., 2016), examines how different postures of humans and robots influence interpersonal distances. This study involved 22 participants interacting with a humanoid robot, Nao, under various conditions where either the human approached the robot or the robot approached the human, with both agents in either sitting or standing postures. The results indicated that humans maintained larger distances from the robot when standing compared to sitting while being approached by the robot. However, these differences were not found to be statistically significant.

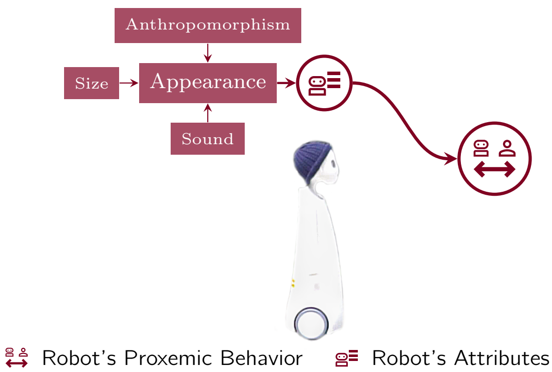
The second study, Syrdal et al. (2006), previously described in earlier sections, explored participants' comfort levels with different robot approach directions based on their posture. The findings revealed that participants preferred front-side approaches when seated and felt least comfortable with rear-side approaches. Conversely, when standing, participants were most comfortable with front-side approaches and least comfortable with rear approaches. This suggests that posture influences proxemic behavior during interactions with robots, though the results are not as definitive as those observed for other factors.

5.4.2 Robot Factors

Having examined the human factors influencing proxemics in HRI, we now focus on the robot factors. We categorize these factors into three main groups: "appearance", "behavior", and "technical".

5.4.2.1 Appearance

Anthropomorphism The study in the paper, titled "Sharing Spaces with Robots in a Home Scenario-Anthropomorphic Attributions and their Effect on Proxemic Expectations and Evaluations in a Live HRI Trial." (Syrdal et al., 2008) explored how the anthropomorphic appearance of robots influences human expectations and evaluations of their behavior in a home-like setting.



Participants interacted with Peoplebots™, one modified with human-like features such as arms and heads, in different scenarios, including no interaction (robot approaching and turning away), verbal interaction (robot following instructions), and physical interaction (robot presenting an object). The results indicated that the robot with human-like features was expected to conform more closely to human social norms, particularly in maintaining personal space (i.e., avoiding intruding on people's personal space).

However, in the study Lin and Yueh (2016) previously described regarding gender differences, the influence of anthropomorphic features on proxemics was evident as children interacted differently with the human-like robot, "Julia", compared to the machine-like robot, "Book Smile". Human-like features in the robot led to significantly closer personal space during interactions, suggesting that anthropomorphic characteristics enhance the robot's perception as a social entity, thereby reducing interpersonal distance.

The last paper "An Exploratory Study on Proxemics Preferences of Humans in Accordance with Attributes of Service Robots" (Bhagya et al., 2019) explores HRI dynamics in four different studies (three of them will be described later). Study 4 examined the effect of a robot's physical appearance on human proxemics preferences. Participants interacted with four different robots: MIRob[9], IRH[10], K-3 mobile manipulator[10], and Fuzz-bot[10]. The results showed that

[9] See Muthugala and Jayasekara (2016)

[10] Further information on the robot could not be found. This may be due to the robot no longer being available, it being a custom-built model, or other reasons not readily apparent.

robots with less human-like appearances, such as the K-3, prompted greater comfortable distances from humans.

All three studies observed that anthropomorphic features influenced the distance participants maintained from the robot. However, the direction of this effect differed between the studies. Various factors could explain this discrepancy, such as differences in the age of participants (children versus adults) or variations in the overall study setting. Nevertheless, anthropomorphism plays a significant role in proxemics, affecting how humans perceive and interact with robots.

Size The first paper, "Psychological Effects of Behavior Patterns of a Mobile Personal Robot" (Butler & Agah, 2001), examines human reactions to different behavior patterns of a mobile personal robot. The study involved a Nomadic Scout II[10] robot, both in its original small cylindrical form and with an added humanoid body attachment to simulate different sizes. The researchers investigated how these variations affected human comfort levels during interactions. The results showed that the smaller robot was generally more comfortable for participants, particularly during close approaches. The humanoid attachment, which increased the robot's size, tended to make participants feel more uncomfortable, highlighting the significance of robot size in proxemic interactions. As described in the previous section, anthropomorphism plays a role, so the difference could also be because of the humanoid appearance or a combination of size and anthropomorphism.

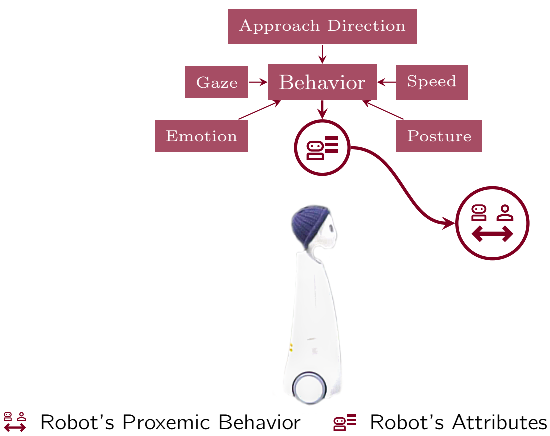
The second work, "Come Closer: Experimental Investigation of Robots' Appearance on Proximity, Affect and Trust in a Domestic Environment" Miller et al., further adds evidence that size plays a role. The authors explore the impact of robot size on human comfort and trust. The study used the TIAGo robot from PAL Robotics[11], which was adjusted to two heights: 1.10 m (short) and 1.45 m (tall). In a 2x2 design, the robot's manipulator position was either extended or retracted. These robots approached participants to determine their comfort distance, anxiety, and trust levels. Results showed that participants maintained a larger distance from the tall robot than the short one. However, the manipulator position did not significantly affect the comfort distance, anxiety, or trust.

[11] https://pal-robotics.com/robots/tiago/ using a TIAGo Base https://pal-robotics.com/robots/tiago-base/

Sound The previously described paper Bhagya et al. (2019) conducted four different studies that investigate how different robot attributes affect HRI. Study 3 focused on the impact of internal noise levels on human comfort distances. Participants approached MIRob under four noise conditions: Zero, Low, Medium, and High, with machine-like noises generated through the robot's speakers. Results indicated that higher internal noise levels increased comfortable distances from the robot. This finding highlights the significance of managing robot noise to improve user comfort during interactions or adapting their distance when reducing the robot noise is impossible.

Another work that looked into differences in sound – in this case, differences in voice style – is the paper titled "Human approach distances to a mechanical-looking robot with different robot voice styles" (Walters et al., 2008). The authors explore how different robot voice styles affect human approach distances. In the study, participants approached a stationary PeopleBot™robot, which used either a high-quality male voice, a high-quality female voice, a neutral synthesized voice, or no voice. Results showed that participants maintained the greatest distance from the robot when it used a synthesized voice, indicating that the nature of the robot's voice significantly influences proxemic behavior. Specifically, the synthesized voice induced a mean approach distance of 80.3 cm, compared to closer distances for the male (51.5 cm) and female (60.3 cm) voices. Participants approached the robot the closest in the no voice condition, with a mean distance of 42.4 cm.

Behavior 5.4.2.2



Posture In work Obaid et al. (2016) that we already introduced for differences in the human posture, they also explored how the robot's posture influences proxemics. When the humanoid robot Nao was sitting, participants approached it more closely than when it was standing. Specifically, participants maintained a shorter distance from the robot when it was sitting, perceiving it as less threatening and more approachable. This suggests that a robot's passive posture (sitting) creates a sense of safety and comfort for humans, leading to closer proxemic behavior. Since there were no significant results for the human posture, the study indicates that robot posture seems to have a more significant influence on interpersonal distances. However, these conclusions are based on a single study.

Approach Direction The factor approach direction was examined in two different works previously described. The first study (Syrdal et al., 2006) showed that the direction a robot approached significantly impacted participants' comfort levels. Front-side approaches (front left and front right) were consistently rated as the most comfortable across various scenarios, while rear approaches were rated as the least comfortable. Front-direct approaches also tended to be less comfortable compared to front-side approaches. These findings suggest that the direction of approach is a critical factor in designing socially acceptable robot behaviors, with participants generally preferring to see the robot approaching from the sides rather than from behind or directly in front.

The second study (Dautenhahn et al., 2006) investigated the preferred approach direction of a robot delivering an object to a seated person and found that 59% of participants preferred the robot to approach from the right side, 28% favored the left side, and only 13% preferred a frontal approach. The frontal approach was not only the least preferred but often described as uncomfortable and sometimes perceived as threatening. Both studies highlight that a frontal approach is not ideal, and robots should approach from the sides or front sides; if that is not possible, the distance should be adapted appropriately.

Gaze The impact of gaze on proxemic behavior has been explored in two studies already described in previous categories. The first study Takayama and Pantofaru (2009) examined the influence of the robot's head orientation on proxemic behavior. They found that the direction the robot's head was facing significantly influenced how close participants were willing to get to the robot. Specifically, women maintained a larger distance when the robot's head was oriented towards their face compared to when it was facing their legs. At the same time, men were comfortable approaching closer when the robot's head was directed at their face.

In the second study by Mumm and Mutlu (2011), the authors discovered that participants who disliked the robot maintained a greater physical distance when it maintained mutual gaze, indicating discomfort with increased closeness. Conversely, participants who liked the robot did not alter their physical distance based on the robot's gaze direction. This study also revealed gender differences, with men increasing their distance from the robot during mutual gaze, while women's distancing behavior remained largely unaffected.

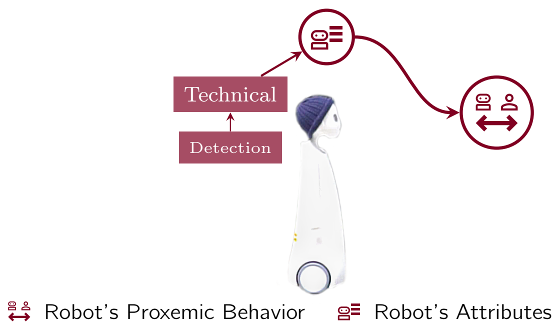
Both studies indicate differences in response to the robot's gaze, showing that one gender increased distance with mutual gaze in one study and the other did so in the other. Therefore, while there is evidence of gender-specific differences in response to robot gaze, it remains unclear how to effectively adapt robot behavior in such situations.

Speed There is limited research on the impact of speed in direct HRI. However, speed was also manipulated in the study by Butler and Agah (2001), discussed in a previous section. In their study, slow speeds such as 10 inches/second ($\sim$ 0.25 m/s) and 15 inches/second ($\sim$ 0.38 m/s) were generally rated as comfortable by participants, whereas the faster speed of 40 inches/second ($\sim$ 1.02 m/s) caused discomfort. Since intermediate speeds were not tested, an optimal speed might lie between these values.

Emotion In the paper Bhagya et al. (2019) – we already described two studies before – the authors conducted two more studies with a robot that displays emotions. The first study investigated the effects of a robot's facial emotions on human-robot proxemics preferences. Thirty-two participants interacted with MIRob, displaying six facial emotions: Happy, angry, sad, fear, disgust, and surprise. Participants approached the robot, and the comfortable interaction distance was recorded for each emotional expression. The results showed that the 'angry' and 'disgust' facial expressions elicited the greatest preferred distances, with mean values of 122.05 cm and similar measurements, respectively, indicating discomfort. In contrast, 'sad' elicited the closest approach distance, with a mean value of 45.59 cm, suggesting a preference for proximity when the robot appeared more vulnerable or non-threatening. The study concluded that facial emotions significantly affect how close humans are willing to get to robots.

The second study explored the impact of vocal emotional tones on human-robot proxemics. Using MIRob, thirty-two participants were exposed to the robot's vocal requests expressed in four emotional tones: Happy, angry, sad, and fear. The robot's speech was synthesized to convey these emotions, and participants' comfortable distances were recorded. Similar to the findings in Study 1, the 'angry' tone resulted in the largest proxemics distance, with a mean value of 127.25 cm, indicating a strong preference to avoid an angry-sounding robot. The 'sad' tone, on the other hand, led to the closest distance, with a mean of 66.63 cm. These results align with the facial emotion findings, reinforcing that both visual and auditory emotional cues from robots significantly influence human comfort and approach behaviors.

5.4.2.3 Technical



Lastly, a good series of papers by Mead and Matarić show that a robot's technical limitations can be significant for proxemic behavior. In their work "Perceptual Models of Human-Robot Proxemics", they demonstrate that interactions are significantly influenced by the robot's ability to recognize and adapt to human speech and gestures. The authors conducted experiments using the PR2 robot, involving 40 participants interacting in human-human and human-robot scenarios. The study setup included controlled and natural distances, with participants discussing cartoons while their speech and gestures were monitored using Kinect sensors and microphones. The results revealed that at natural distances, humans positioned themselves significantly closer to robots (average 0.94 m) than to other humans (average 1.44 m). Recognition of speech and gestures by the robot was notably affected by these distances;

at closer distances (0.5 m), the robot's speech recognition rates improved as humans spoke louder, but this effect diminished at greater distances. Additionally, gesture recognition was more accurate at mid-proximities, where the robot's sensors could better capture detailed movements. These findings highlight that the robot's recognition abilities sometimes take precedence over the human's preferred distance. Optimizing robot positioning to enhance speech and gesture recognition can be crucial for effective HRI, even if it means deviating from the human's preferred proxemic behavior.

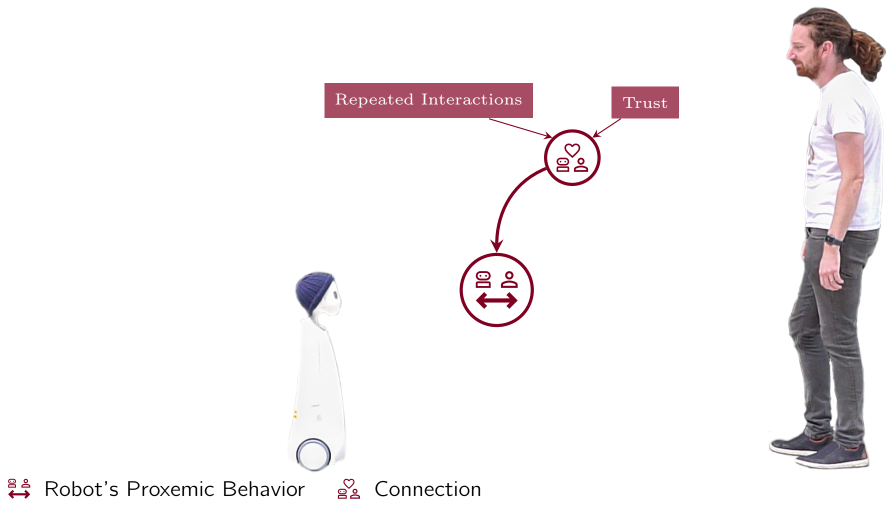
Similarly, in another study (Mead and Matarić (2015) and expanded in Mead and Matarić (2016b)), they explore how humans adjust their proxemics preferences to aid a robot's performance. In the paper with the title "Robots Have Needs Too: How and Why People Adapt Their Proxemic Behavior to Improve Robot Social Signal Understanding" they described the expanded study involving 180 participants and the Bandit robot (which is a Pioneer 3-AT[12] with an added humanoid body), they found that participants changed their preferred interaction distances over time to improve the robot's ability to recognize speech and gestures. This adaptive behavior suggests that users are willing to accommodate the technical needs of robots, prioritizing effective communication over personal comfort. The study highlights the dynamic interplay between human behavior and robotic performance, indicating that user proxemic preferences can evolve to optimize interaction quality. These insights emphasize the importance of considering robot recognition capabilities in designing HRI systems, as user adaptability can significantly enhance the efficacy of these interactions.

Connection Factors 5.4.3

After examining the factors related to humans and robots, we now focus on the connection between them. These connection factors directly influence the proxemic behavior between the interactants.

The study by Walters et al. (2008), previously described, also examined the differences between individuals who had interacted with the robot before and those who had not. The findings revealed a significant connection between **previous interactions** and participant comfort levels, evidenced by shorter approach distances in those with prior experience with the robot. This habituation suggests that familiarity with the robot reduces perceived social and

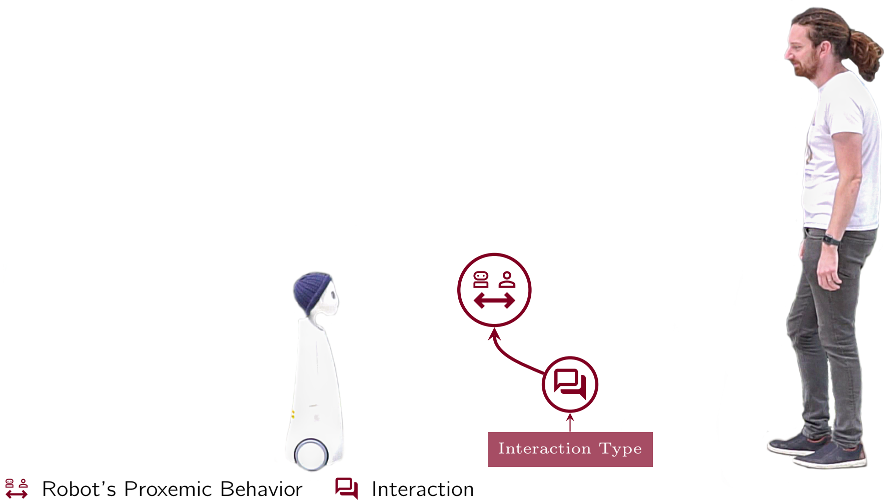
[12] https://www.generationrobots.com/media/Pioneer3AT-P3AT-RevA-datasheet.pdf



spatial barriers, enhancing the human-robot connection and resulting in closer physical proximity during subsequent encounters.

This is also supported by results from the study by Syrdal et al. (2007), in which **long-term interaction** effects were assessed by having 12 participants engage with the robot over six weeks, with sessions occurring twice a week. The experiment measured approach distance preferences during the first encounter (week 1), after a week (week 2), and after three weeks of bi-weekly sessions (week 5). The results indicated that participants allowed the robot to approach significantly closer over time.

Another study by Miller et al. (2020) suggests that even short-term repeated interactions can significantly reduce the distance people allow a robot to approach, particularly for taller robots. Their findings indicate that as individuals become more familiar with the robot through repeated encounters, their initial discomfort decreases, and their **trust** in the robot increases, allowing for closer proximity. These results also match the paper "Small Talk with a Robot? The Impact of Dialog Content, Talk Initiative, and Gaze Behavior of a Social Robot on Trust, Acceptance, and Proximity". The study involved 31 participants interacting with the NAO humanoid robot, examining the effects of talk initiative and gaze behavior across different dialog contents. The results showed that participants who reported higher **trust** maintained closer proximity to the robot.



Interaction Factors 5.4.4

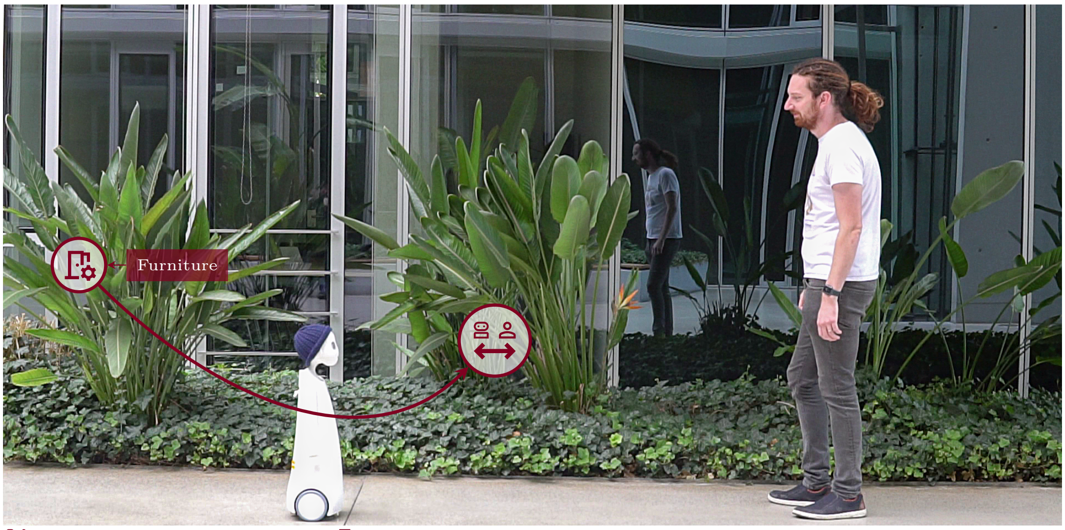
We will now explore interaction factors, which focus on the nature and dynamics of the interactions themselves. These factors are crucial in shaping proxemic behavior between humans and robots.

The study by Syrdal et al. (2007), which we introduced before, also examined how different interaction factors influenced participants' comfort levels with the robot's approach. The authors found that participants generally allowed the robot to approach closer when the interaction involved a physical task compared to verbal or no interaction. These results suggest that engaging participants in physical activity with the robot increased their comfort with its proximity. These results underline the importance of considering **type of interaction** in designing robot behaviors to enhance user comfort and acceptance.

In contrast, a previously described study by (Babel et al., 2021) did not observe any differences in proxemic distances based on interaction type. However, their comparison focused on two verbal tasks: a service task and small talk, rather than contrasting a verbal task with a non-verbal one. Additionally, Takayama and Pantofaru (2009) investigated whether the approach – by either the robot or the human – affects proxemic distances but found no significant differences.

In summary, the current research suggests that **interaction type** may influence proxemic distances. However, there is no conclusive evidence to indicate that the dialogue's content or the approach's initiator significantly impacts these distances.

5.4.5 Environmental Factors



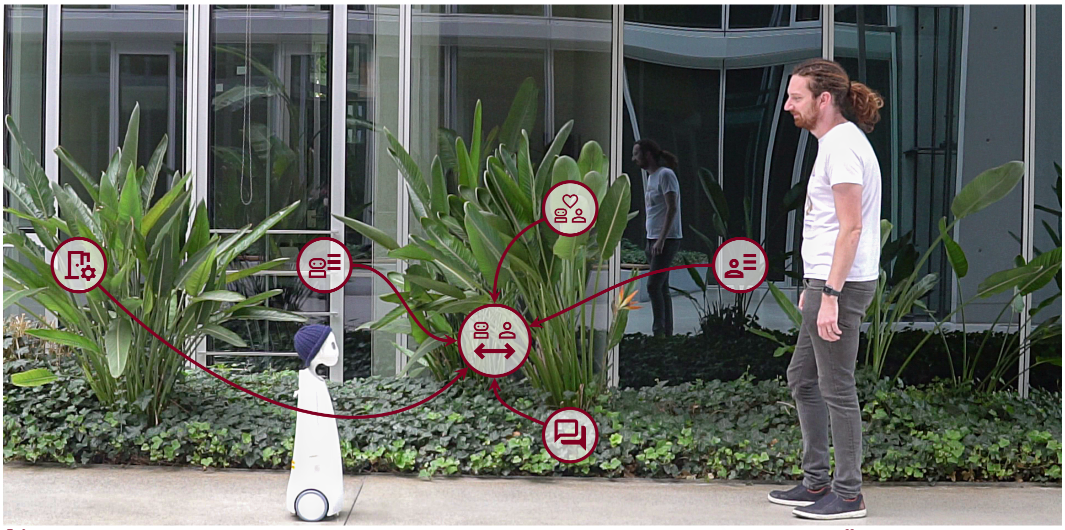
Robot's Proxemic Behavior Environment

Lastly, we will examine environmental factors. These factors pertain to the external conditions and settings that influence proxemic behavior in HRI. There is limited literature on this topic, with the study by Syrdal et al. (2006) being a notable contribution.

The study highlighted the influence of environmental factors on participants' comfort levels during robot approaches. Specifically, the presence or absence of a table significantly affected how comfortable participants felt with different approach directions. When seated behind a table, participants generally felt more secure and preferred front-side approaches, while rear approaches were less comfortable. Without the table, discomfort with rear approaches increased, indicating that physical barriers like tables can provide a sense of security and impact the perceived intrusiveness of a robot's approach. These results underscore the importance of considering the environmental context in the design of HRI scenarios.

5.4.6 Summary

The previous section presented a detailed overview of the diverse factors identified in research as influential to human-robot proxemics. These factors span a range of categories, each shaping the spatial dynamics in HRI in distinct



Robot's Proxemic Behavior Robot's Attributes Human's Attributes Connection
Interaction Environment

Figure 5.3: Overview of influencing factors in HRI proxemic research.

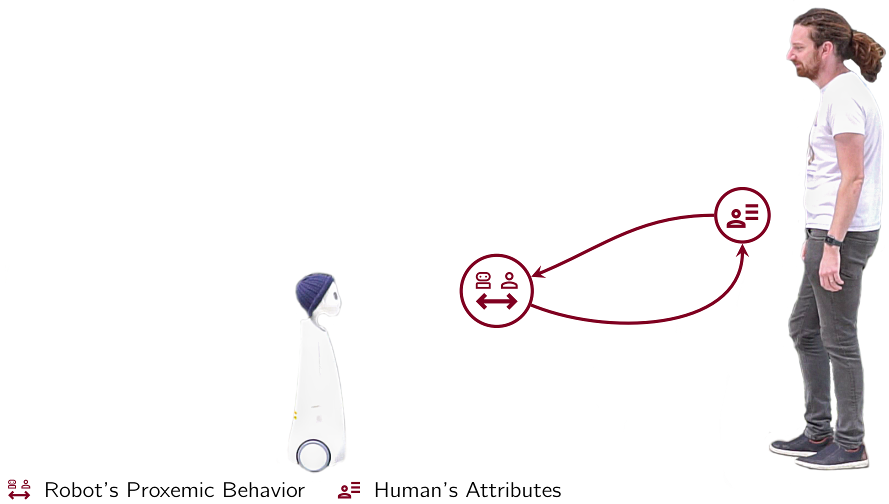
ways. Figure 5.3 summarizes these findings, illustrating the extent of research across various influencing dimensions.

Research has mainly focused on human-related factors, such as personality traits and demographic characteristics, as well as robot-related factors, including appearance and behavior, which have been extensively examined for their impact on proxemics. However, areas like connection factors, which often necessitate long-term research to explore relationship-building and attachment dynamics, remain less thoroughly investigated. Similarly, interaction factors and environmental factors influencing proxemic behavior are also underrepresented in the current body of research.

5.5 Proxemic Behavior Influencing Humans

This chapter explores how proxemic behavior influences humans. First, we explore how proxemic behavior shapes human behavior, which is detectable by the robot and can be fed back into an adaptive process for the robot's proxemic behavior. Second, we explore how specific behavior influences humans' perception of robots.

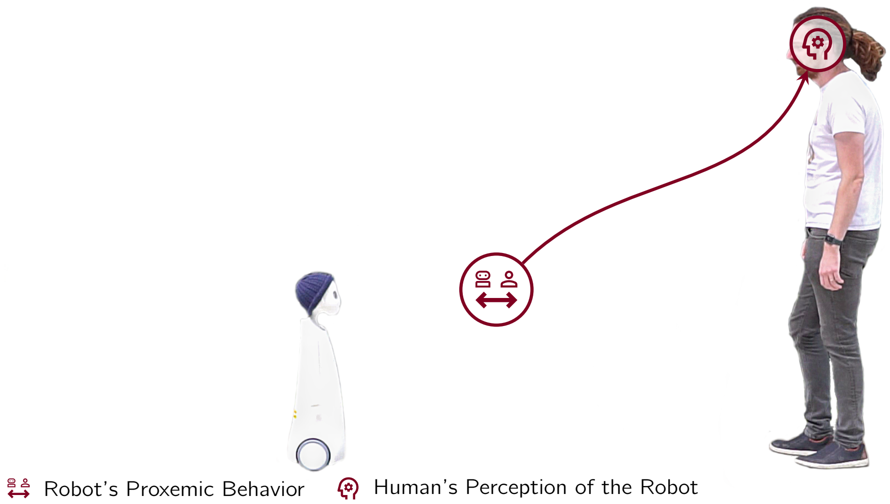
5.5.1 Human's Behavior



The paper "Robot behavior adaptation for human-robot interaction based on policy gradient reinforcement learning" by Mitsunaga et al. (2005) explores how robots can learn socially appropriate behaviors through reinforcement learning. The study focused on the proxemic dimensions of interaction distance and motion speed, where the robot adjusted the distance to a person and how fast it moved based on human responses. Other behavioral factors were also adapted, such as gaze meeting ratio and waiting time. The robot received positive rewards when humans remained engaged, and negative rewards were received if they, for example, stepped back or avoided eye contact, showing discomfort. The robot learned to maintain an optimal social distance and move at a comfortable speed through policy gradient reinforcement learning. According to the authors, the results showed that the robot successfully adapted to human preferences, leading to more natural and engaging interactions.

In another work by Patompak et al. (2020) titled "Learning Proxemics for Personalized Human–Robot Social Interaction", the authors also explore how robots can learn appropriate social distances for human interaction. Using the Pepper robot, the study implemented a reinforcement learning-based navigation strategy that adapts to individual proxemic preferences. The algorithm optimized two key dimensions, Interaction Degree (ID) (quality of engagement) and Unacceptable Degree (UD) (discomfort due to intrusion), alongside other social factors like gender, relationship level, and relative distance. In simulations, ID and UD were computed based on a predefined social force model, considering human position, movement, and social attributes. In real-world experiments, however, feedback was collected solely through verbal responses, which guided Pepper to adjust its interaction distance dynamically. Results showed that the robot successfully personalized interaction distances, according to the authors, reducing discomfort and improving engagement quality.

Human's Perception of the Robot 5.5.2



In most of the previously described works, the authors focused on factors that influenced proxemic expectations and did not measure how specific proxemic behavior is perceived by the humans and affects their ratings of the robot (Bhagya et al., 2019; Lin & Yueh, 2016; Mead & Matarić, 2016a; Neerincx et al., 2016; Syrdal et al., 2006, 2007; Takayama & Pantofaru, 2009; Walters et al., 2008; Walters, Dautenhahn, Koay, et al., 2005; Walters, Dautenhahn, te Boekhorst, et al., 2005). Butler and Agah (2001) and Dautenhahn et al. (2006) let participants rate different behaviors on a 5-point Likert scale on how comfortable they feel with the behavior of the robot but did not rate the robot directly. Złotowski et al. (2012) let participants rate if they 'liked' an approach trajectory in a video on a 5-point Likert scale. However, if authors tried to measure the influence of the behavior on how the human perceives the robot, it's mostly very limited:

- In addition to looking at distance differences, Eresha et al. (2013) also measured the influence of distance on evaluating the robot with questions such as "The robots seemed friendly to me". However, the authors do not report the results of the questions in detail in their paper, and they report that some of the participants did not even notice the differences in distance.

- Obaid et al. (2016) only checked the influence on Robot Anxiety Scale (RAS) (Nomura, Suzuki, et al., 2006) ratings of the participants for each condition but found no significant differences.
- In the work by Mumm and Mutlu (2011), the authors manipulated the robot's likability. They assessed the effectiveness of this manipulation by allowing participants to rate the likability on a 7-point Likert scale, demonstrating that their manipulation was successful.
- Babel et al. (2021) let the participants rate different behaviors on different scales (e.g., trust, robot acceptance). However, they didn't manipulate proxemic behavior. They only checked if people maintained different distances for different tasks and if it correlated with the trust rating of the participants in the robot.
- Miller et al. (2020) also asked for ratings in different dimensions (e.g., anxiety, trust) but also didn't manipulate the proxemic behavior and instead had it as a dependent variable.
- Mead and Matarić (2015) have explored the interplay between proxemics and performance of the robot's gesture and speech recognition systems on different factors like competence and anthropomorphism. However, this does not allow any direct conclusions on how proxemic behavior affects the evaluation without other factors.
- In the work by Henkel et al. (2014), the authors explored how changes in behavior during an approach influenced how the human perceives the robot. They had three conditions – no change, linear change, logarithmic change – and manipulated the proxemic dimension speed and the dimensions of head gaze behavior and submissiveness. The robot that dynamically adapted its behavior using a logarithmic scaling function was perceived as more intelligent, likable, and socially aware. Here, the authors focused on the scaling function and how that influenced the perception of the robot. Thus, the exact influence of the proxemic behavior remains unclear.

5.5.3 Summary

After creating a detailed overview of the factors influencing proxemics in HRI, we then examined the research on how a robot's proxemic behavior affects humans in this section. In the first part, we reviewed work that aimed to

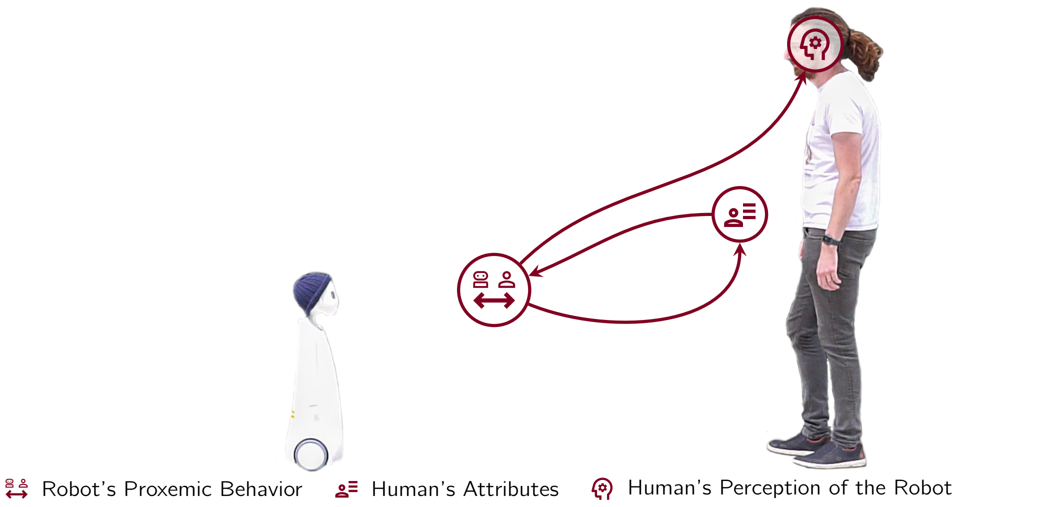


Figure 5.4: Overview of robot's proxemic behavior influencing humans in HRI.

learn appropriate proxemic behavior by generating feedback for reinforcement learning through the detection of human behavior. This indicates that the robot's proxemic behavior affects human behavior in a manner that can be incorporated back into a learning loop. In the second part, we looked at the literature that explored how specific proxemic behavior by the robot influences how the robot is perceived by the human, usually by giving explicit feedback via a questionnaire or interview.

Figure 5.4 summarizes these two categories of proxemic behavior that influence humans. Research is very limited for both categories. This indicates that, compared to the factors influencing proxemic behavior by the robot, the perception of specific proxemic behavior is less researched.

6. Summary

Research on proxemics in HCI has laid the essential groundwork, primarily through frameworks like Marquardt and Greenberg's PIF. This framework introduced a proxemics approach detailing which proxemic dimensions of users can dynamically influence interactions with a system. By examining multiple proxemic dimensions – such as distance, orientation, movement & motion, identity, and location – the framework has inspired a broad range of applications that adapt computer system responses based on human spatial behavior. This work has enabled system designers to measure specific factors, enabling context-aware responses that enhance user interaction.

However, while the framework's flexibility has facilitated its adaptation to diverse contexts, much of the existing research focuses on applying proxemics to novel environments rather than establishing a systematic design process for creating proxemic interactions. Despite the widespread adoption of proxemic concepts, there is currently no systematic method to guide designers through each phase of designing and implementing these interactions effectively. This absence of a standardized design process makes it challenging to achieve meaningful, context-sensitive interactions consistently. Therefore, we formulated research goal one as follows:

Establishing a Design Process for Proxemic Interactions
Establish a systematic design process for proxemic interactions, rooted in human-human proxemic behavior, to guide designers in creating proxemic human-computer interactions. 1

Building on this, another significant limitation within proxemics research is the lack of consolidated resources for sensor selection in implementing proxemic systems. While past studies provide examples of proxemic systems that utilize various sensor combinations to capture multiple dimensions, the lack of a comprehensive, curated toolkit for proxemic sensor options requires designers and engineers to conduct extensive preliminary research. Identifying suitable sensors often involves reviewing numerous studies or technical specifications to determine which sensors are compatible with proxemic requirements. This fragmented approach hinders the efficiency of system development and limits accessibility for practitioners unfamiliar with the range of sensor options available. As such, the need for an organized resource leads to research goal two:

> 🎓 2 **Composing a Sensor Toolkit for Proxemics Detection**
> Compose a practical sensor toolkit for proxemics, providing designers and engineers with a consolidated resource to simplify sensor selection and advance the development of proxemic interactive systems.

When applying proxemics concepts to HRI, researchers have primarily focused on a single dimension: proximity (i.e., distance). Typically, proxemics in HRI has been limited to simplistic distance-based models, where the robot approaches the user to a predefined "ideal" distance, or vice versa. Such models generally focus on achieving an acceptable proximity for comfort and interaction. Although some research provides standardized proximity values for specific contexts, as seen in studies by Walters and colleagues (Walters et al., 2009), later work by Mead and Matarić highlighted that static distance values may not translate well to actual interactions. Mead and Matarić's findings emphasized that real-life interactions – lasting several minutes with dynamic exchanges – resulted in average distances significantly greater than those documented in earlier, more controlled studies (Mead & Matarić, 2016a). This discrepancy underlines the limitation of relying solely on predefined proximity distances, as real interactions often involve richer, multidimensional proxemic cues.

However, while valuable, achieving the "right" distance is insufficient to create natural interactions between humans and robots. Existing research often prioritizes finding an ideal interaction distance but rarely considers how users perceive these distances or how variations in proxemics could influence user perceptions. For instance, a robot's ability to dynamically adjust its proximity based on contextual cues may serve as a subtle yet powerful communication tool, signaling states such as friendliness, caution, or urgency. Rigidly adhering to static distance values overlooks the potential for robots to actively leverage proxemic interactions to shape user perceptions and enhance the interpretability of their behaviors. This gap underscores the importance of studying how different proxemic interactions influence user perceptions of the robot beyond just achieving an optimal distance. By exploring the effects of dynamic proxemic behaviors on user experience, we can better understand whether these variations contribute to more meaningful, responsive, and effective interactions in HRI. To address these problems in the literature, research goal three is as follows:

Explore Novel Approaches to Amplify HRI Proxemics

Expand the scope of proxemic interactions in HRI by integrating additional proxemic dimensions, such as orientation, and shift the focus from finding a 'good' interaction distance to human perception of the robot's proxemic behavior.

3

In summary, these identified gaps in proxemics research underscore the significance of the proposed research goals. By addressing these goals, this work aims to establish a systematic process for designing proxemic interactions, compile a toolkit for efficient sensor selection, and explore ways to further improve proxemics in HRI by moving the focus from finding an optimal distance to user perception of proxemic behavior.

Comment by Prof. Bearingtons

Bear-stonishing goals here! This work promises to dig deep into the field, crafting a design process, assembling a sensor toolkit, and bridging HCI with HRI. Quite a *pawsome* venture into uncharted territory! I'm keen to see how these *fur-midable* tasks are tackled and what insights will be unearthed – surely it will be something worth *bearing* in mind for the future!

III A Design Process For Proxemic-Aware Interactions

7. Overview

In the first of three main parts of this work, we address the first research objective:

Establishing a Design Process for Proxemic Interactions
Establish a systematic design process for proxemic interactions, rooted in human-human proxemic behavior, to guide designers in creating proxemic human-computer interactions.

1

We propose a design process that draws on the implicit and proxemic interactions seen in human-human exchanges, translating these behaviors into principles for human-computer interaction. We achieve this adaptation by integrating established frameworks from existing academic literature, enabling a robust foundation that connects theoretical insights with practical applications.

Following the introduction of the proposed process in Chapter 8: *Proposed Process*, we explore a concrete example of its application by designing a plant-watering system in Chapter 9: *Exemplary Process Execution*. We conceived the system to assist users in maintaining optimal watering habits for their plants, utilizing the principles of proxemic interactions to enhance user experience and engagement.

We then present the prototypes developed for this system in Chapter 10: *Developed Prototypes*, showcasing how the design interactions are applied practically. We conclude this part with an evaluation in Chapter 11: *Evaluation*, examining whether the designed proxemic-aware interactions effectively support users in their plant-watering tasks, aiming to validate the utility and impact of the proxemic design approach in this context.

Finally, a concluding section will reflect on the research objectives, assessing the extent to which they were achieved. This reflection will include an analysis of the process's effectiveness and any insights gained, ultimately clarifying the contribution of this part in Chapter 12: *Conclusion*.

Parts of the work in this part are published in the following publication:

Bittner, **B.**, Aslan, I., Dang, C. T., & André, E. (2019). Of Smarthomes, IoT Plants, and Implicit Interaction Design. *Proceedings of the Thirteenth International Conference on Tangible, Embedded, and Embodied Interaction*, 145–154. https://doi.org/10.1145/3294109.3295618

8. Proposed Process

This chapter will present a comprehensive approach to designing proxemic-aware interactions within the field of HCI. We will begin with an overview of the key steps and concepts involved in the design process, followed by an in-depth exploration of each stage. Finally, we will integrate these steps to provide a complete picture of the process, setting the stage for the next chapter to examine an exemplary application of this methodology.

8.1 Introduction

When designing proxemic-aware interactions, it is crucial to consider how implicit interactions, like proxemics, naturally occur in everyday human behavior. As discussed in the background, proxemics refers to how people intuitively manage their personal space and the distance they maintain with others or objects without consciously thinking about it. This concept can be leveraged in interactive systems to respond to users' behaviors without requiring explicit input, such as pressing a button. For instance, a system could detect when a user squints or moves closer to a screen, indicating that the text might be hard to read, and automatically adjust the font size accordingly.

Similarly, proxemic-aware systems can adapt content based on the user's distance from a screen or device, creating a more seamless and intuitive user experience. The Implicit Interaction Framework (IIF) by Ju (2015) provides a foundational understanding of these interactions and guides their incorporation into the design process.

However, ensuring that these implicit interactions align with user expectations and are genuinely helpful poses a challenge. Simply brainstorming and implementing different options is unlikely to yield a user-friendly result. Therefore, it is essential to involve users from the outset. We propose using the experience prototyping method introduced by Buchenau and Suri (2000), which allows designers to observe how users naturally interact with new types of products. This approach provides valuable insights that can be analyzed using the IIF.

In the final step, we utilize the PIF to investigate the specifics of proxemic interactions and to integrate these insights into the product design. The following sections will detail these methods and outline the process for designing proxemic-aware systems.

8.2 Experience Prototyping

The concept of experience prototyping, as explored by Buchenau and Suri (2000), emphasizes engaging stakeholders in the experiential aspects of a product, space, or system – meaning that they should actively experience the interaction. Unlike traditional prototyping, which often focuses on technical and functional features, experience prototyping aims to capture interactions' subjective, sensory, and contextual elements. According to the authors, this method is particularly valuable in designing complex, dynamic systems where the experience extends beyond a single artifact and involves a holistic interaction. This is especially relevant for proxemic and implicit interactions, where the design must account for the nuances of human behavior and spatial dynamics.

Buchenau and Suri identify three primary applications of experience prototyping in design activities:

- **Understanding Existing User Experiences:** This application is critical for uncovering the essential aspects of current experiences and the contextual factors that influence them. For instance, designers might simulate users' experiences with a computer system to empathize with their emotional and social concerns. This understanding could be vital in proxemic interactions, where user comfort and natural behaviors are central to the design.
- **Exploring and Evaluating Design Ideas:** Experience prototyping allows design teams to actively engage with prototypes, testing and iterating on different solutions. This process helps designers understand various design concepts' practical implications and user experiences. In the context of proxemic-aware systems, this can involve exploring how users interact with different spatial configurations or interface designs.
- **Communicating Ideas:** Experience prototypes are powerful tools for conveying design concepts to clients and stakeholders. By providing a tangible and immersive experience, they help create a shared vision and facilitate informed decision-making.

Among these, "Understanding Existing User Experiences" is particularly relevant to our process since it is precisely what we want to do – understand existing proxemic interactions by people. By closely examining how users naturally interact with products, especially regarding spatial relationships and implicit cues, we can better design systems that respond appropriately to user behavior. We could also use the process to add proxemic interactions to an existing product.

The authors describe various techniques suitable for experience prototyping, highlighting the importance of an adaptive and creative approach. Notably, they discuss:

- **Role-playing and Bodystorming:** These methods involve acting out scenarios to explore user needs and potential design solutions. Role-playing is particularly useful for proxemic interactions as it allows designers to observe how users naturally manage personal space and react to others' proximity.
- **Low-fidelity Prototyping:** Using simple materials and mock-ups, designers can quickly iterate and explore ideas without the constraints of high-fidelity tools. This approach enables rapid experimentation and refinement of concepts. However, compared to the previous method, we cannot see the 'system's' reaction to the users' proxemic behavior, so it's much less useful for our process.

The authors caution that experience prototyping comes with challenges, including ensuring that prototypes appropriately represent different user experiences and balancing active participation with observation. They emphasize the importance of using multiple prototypes and methods to capture the full scope of user interactions.

In conclusion, Buchenau and Suri position experience prototyping as an essential approach for tackling modern design challenges, particularly in complex and interactive systems. By enabling a deeper understanding of user experiences, fostering innovative exploration, and facilitating clear communication of design ideas, experience prototyping helps designers move beyond individual artifacts to consider the broader context and experience of use – which is precisely what we want to do by adding proxemic-awareness to our product's interaction capabilities.

8.3 Implicit Interactions

In HCI, explicit interactions are often used, such as when interacting with graphical user interfaces. The user presses a button and receives a system response. Implicit interactions, on the other hand, do not require these explicit actions. For example, an automatic door opens when one approaches without pressing a button. This type of interaction is particularly suitable for networked artifacts, as the computers within these artifacts are often not visible, and explicit interaction may not be possible. Ju describes in the theory of implicit interactions that people rely on implicit interactions to communicate. By recognizing and analyzing these everyday interactions, designers can learn to create better products. The challenge lies in identifying implicit interactions and making them useful for the product. The IIF presented by Ju is intended to help designers understand implicit interactions, thereby enabling the development of novel interactions with devices. It thus aids in transferring human-human interactions to human-device interactions. The framework is based on the theory that implicit interactions function through regular communication patterns, making interactions designed based on these patterns recognizable and functional as intended (Ju, 2015).

The framework models interactions between two entities, such as between a person and an interactive object. Thus, it only helps in understanding interactions between two parties and cannot be used to analyze more complex interactions involving multiple people or objects.

Interactions in the framework are assessed based on the following two criteria:

- **Attention Demand:**
  The user's attention demanded by the computer system is described through cognitive and perceptual focus, concentration, and awareness. Attention is represented by two types: *foreground interactions*, which require the user's attention, and *background interactions*, which escape attention.
- **Initiative:**
  Initiative describes who initiates the interaction from the system's perspective. It is a *reactive interaction* if initiated by the user and a *proactive interaction* if initiated by the system.

Considering these two factors, each with two types, the range of interactions is classified into four categories, each accompanied by an example interaction from a delivery service:

- **Foreground-Reactive**: Actively ordering some food.
- **Foreground-Proactive**: The delivery service recommends what to order.
- **Background-Reactive**: The delivery service delivers a configured order daily.
- **Background-Proactive**: The delivery service delivers something because it assumes you are hungry.

Many details are not modeled in the framework, such as the exact appearance of an object being interacted with. The focus is on attention and initiative to simplify the transfer from human-human interactions to human-device interactions. The framework only models how the interaction proceeds, not who is interacting (Ju, 2015). An example interaction pattern visualized with the IIF can be found in Figure 8.1.

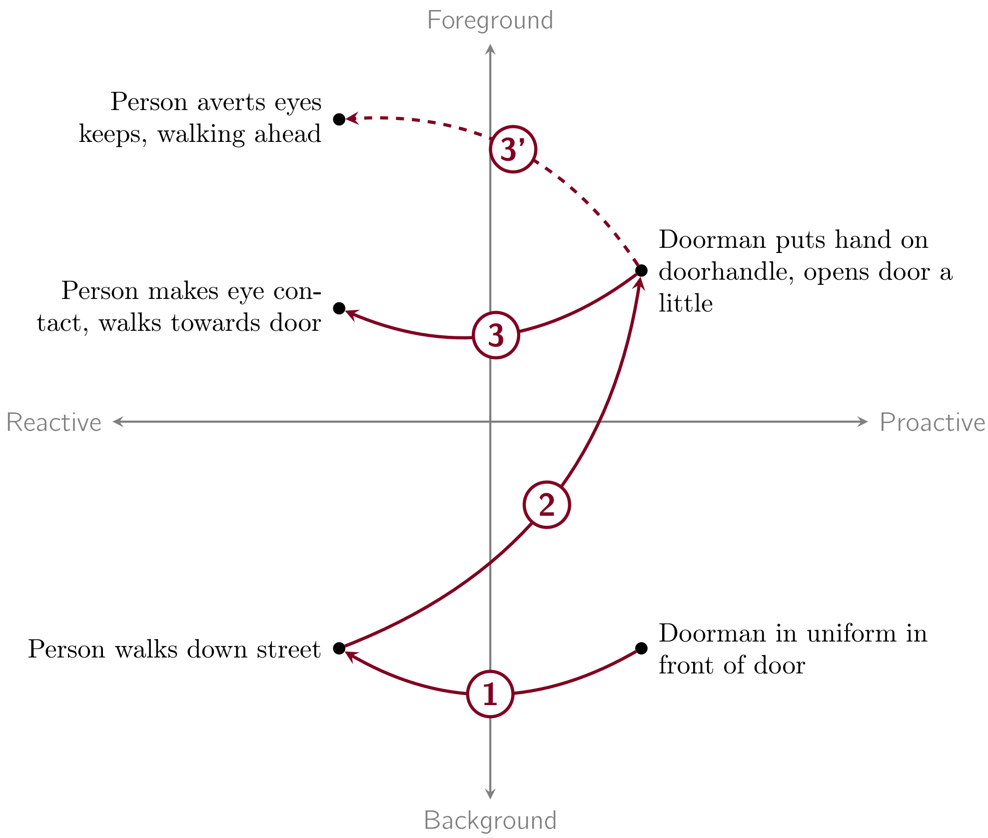


Figure 8.1: Illustration of the IIF: A doorman exemplifies proactive engagement by intuitively opening the door, based on Figure 3.1 in Ju (2015).

More information and examples can be found in the works Ju (2015), Ju and Leifer (2008), and Ju et al. (2008).

8.4 Proxemic Interactions

Proxemic interactions have been explained in detail in Chapter 2: *Hall's Proxemics*). For our process, we will use the PIF introduced in the Section 4.1: *The Proxemic Interactions Framework*. An overview of this framework can be seen in Figure 4.1 on page 26.

While the IIF helps us understand the implicit interactions we want to analyze during role-plays, the PIF allows us to focus on the fine-grained proxemic details where the IIF is insufficient. The PIF defines the dimensions 'identity', 'location', 'distance', 'orientation', 'movement and motion' as relevant for proxemic interactions.

How these frameworks are incorporated into the process will be discussed in detail in the next section.

8.5 The Process

The proposed process for designing proxemic-aware interactions integrates all the methods described in the previous sections and consists of four distinct steps. Each step is crucial to comprehensively understanding how to realize an effective proxemic-aware interaction with a system. A visual representation of the process can be seen in Figure 8.2, and the four steps are described in the following sections.

Step 1: Role-plays

As previously discussed, role-plays help us understand how a natural interaction between a user and the system might look. By conducting role-plays, we aim to observe people's behavior as they would naturally act without overthinking. Several points must be considered when planning and conducting these role-plays:

1. **Participant Selection:** Since we want to see people's natural behavior, it's beneficial to use participants who are not deeply involved in the system's development. This avoids any preconceived notions or adaptive behaviors influenced by previous discussions.

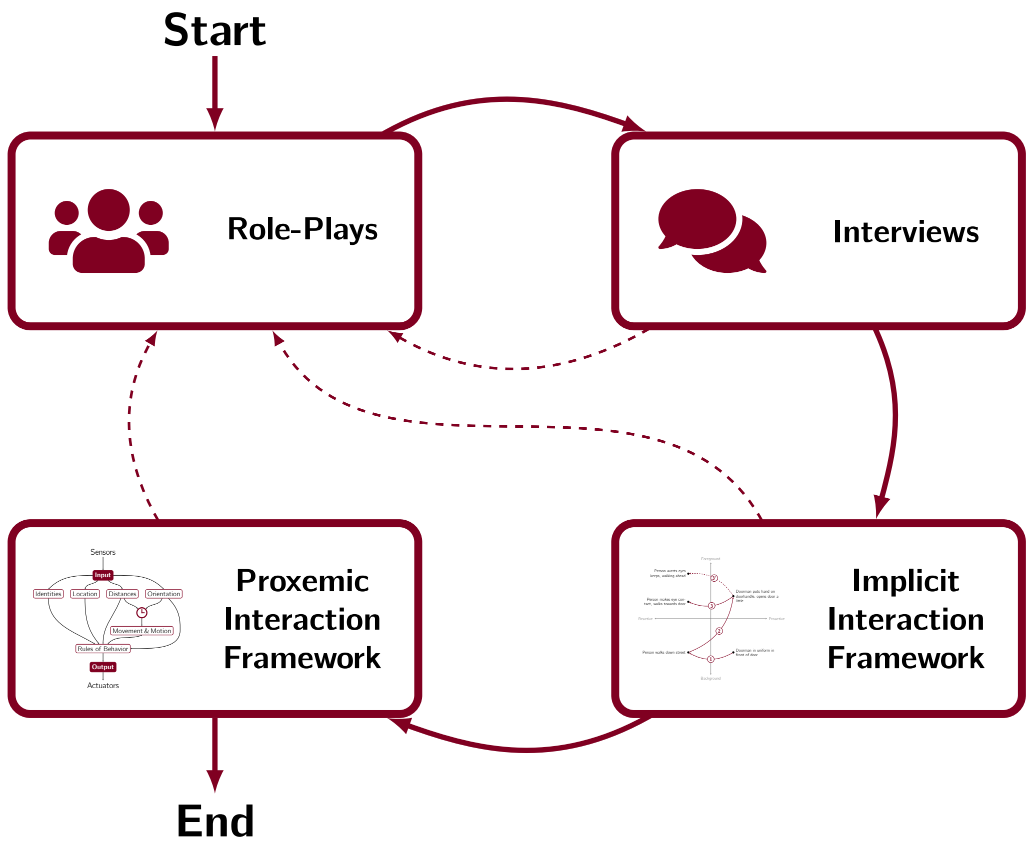


Figure 8.2: A visual representation of the proposed process for designing proxemic-aware interactions, illustrating its four steps: *Role-plays*, *Interviews*, *IIF*, and *PIF*.

   - Conduct role-plays with participants who were not involved in the design process and only provide them with the necessary information about the system.

2. **Scenario Variety:** Different scenarios help us see how role-players behave in various situations. While there is no set rule for the number of scenarios, even simple systems should allow for at least three different scenarios.
   - Perform role-plays with multiple scenarios based on the system's complexity.
3. **Role Rotation:** To avoid repetitive perspectives, use different people for different scenarios or rotate roles among participants.
   - Use different participants for different scenarios or rotate roles.
4. **Clear Goals and Rules:** Define clear goals and rules for each participant in the role-play to ensure they understand what to do and what is not allowed.
   - Ensure every participant knows their goals and the scenario's rules to facilitate accurate observations without the need for intervention.

5. **Interaction Possibilities:** Consider limiting or increasing interaction possibilities in different scenarios based on system capabilities or human limitations.
   - Adapt role-play conditions to reflect technical limitations or unique abilities, such as blindfolding participants or limiting verbal communication.

Preparation is essential for these scenarios. Make sure you have the right number of participants, clear introductory texts, defined goals and rules, as well as any necessary equipment.

Step 2: Interviews

After each role-play scenario, interview all participants to gain deeper insights into the interactions. This helps clarify any actions or decisions noted during the role-play. Typical questions might include:

- "Did you have any problems in the scenario?"
- "Did you not understand any interaction?"
- "Did you notice any other issues?"

Interviews can be brief when everything goes smoothly, but they are essential for uncovering overlooked aspects. Follow-up interviews right after each scenario enable participants to give more precise feedback.

If unresolved issues or new questions arise from the interviews, additional scenarios can be prepared before moving to the next step.

Step 3: Implicit Interaction Framework With the role-plays and interviews completed, the next step is to analyze the interactions using the IIF. This involves reviewing videos to identify implicit interactions, such as changes in distance or orientation, and considering the framework's dimensions:

- **Initiative:** Who initiates the interaction? Is the system proactive or reactive, and when does it switch?
- **Attention Demand:** Is the interaction in the background or foreground?

Different scenarios might yield different interactions. The goal is to determine the most effective interactions based on participant understanding and interview feedback. If a clear best option emerges, proceed with it. Otherwise, further role-plays or evaluations may be necessary. The final analysis should result in detailed interactions as illustrated in Figure 8.1.

Step 4: Proxemic Interaction Framework

The final step is the analysis using the PIF. While the IIF provides an overall understanding of the interactions, the PIF allows for a detailed examination of proxemic aspects. For instance, the IIF might describe an interaction where a person is 'approaching' the system without specifying what 'approaching' entails. The PIF helps define the specific situations in which the system should respond based on proxemic interactions.

This involves analyzing all proxemic dimensions defined by the PIF: 'identity', 'location', 'distance', 'orientation', 'movement and motion'. Terms like 'looking at', 'approaching', 'moving away', 'walking', 'rotating', and 'entering the room/building' indicate that proxemics are involved. Identifying these interaction elements allows us to determine their precise meanings. Here are two examples that describe a fictitious *cake system* and where an analysis with the PIF is useful.

- **Implicit interaction: Person is approaching the cake**:
  Here, we need to know when the cake system should react to the person's approach. Is the person approaching when he enters the kitchen (technically getting closer to the cake on the table) or only when the person is getting close and within reach? The cake system's reaction could differ, with the person approaching having the body and head *orientated* towards the cake or away. Which person is approaching may be relevant (i.e., the dimension *identity*). For example, the system could behave differently when it is the person's birthday.
- **Implicit interaction: Person is looking at the cake**:
  Here is the central dimension *orientation*. Assuming the person orients their face and eyes toward the cake, the following question arises: Should the system be triggered whenever the person looks from any distance toward the cake? Maybe observing it from far away is fine, and nothing should happen, but if the person is getting too close (and it is not their birth), the cake will try to shoot the person with the chocolate confectionery.

Through this analysis, a precise understanding of proxemic-aware interactions is achieved. If uncertainties remain, further role-plays can be conducted.

In the next chapter, this process will be applied to the development of a proxemic-aware plant care system, which will serve as an example.

9. Exemplary Process Execution

This chapter will apply the proposed process introduced in the previous chapter to a practical example: a supportive system for watering plants. This project aims to assist users in their plant-watering routine without replacing or altering their methods. Instead, it will utilize implicit and proxemic interactions to offer support.

The following sections will introduce the project's concept and then guide you through the four steps of the process for designing proxemic-aware interactions for the plant watering system.

9.1 The Project

New embedded technologies have been transforming how we, as home inhabitants, envision our everyday routines and modes of interactions with networked things in our future homes and buildings. While the automation of many routine tasks in the home is already possible and more automation may be part of a desirable future, Calvo and Peters (2014) have criticized an exclusive focus on technology design for productivity in their book 'Positive Computing'.'. They motivated a sensitivity to human well-being and potential as additional design goals.

Indeed, future scenarios imply that inhabitants of smart homes will not have to care about anything but interact with everything in a magical manner and be well. However, an increase in automation can be considered as a source for one of the main contemporary design challenges, with previous research arguing, for example, that autonomous technologies often lead users to feel a loss of control (Barkhuus & Dey, 2003). To make autonomous systems less obnoxious, Ju and Leifer (2008) have proposed to design human-like forms of interaction (i.e., combine explicit with implicit interactions) for which the IIF by Ju (2015) provides support. Mennicken et al. (2014) have recommended focusing on collaboration between inhabitants and homes as a direction to deal with the problems of automation. Ultimately, not all routine tasks in homes are viewed as "a waste of time" but some routines may even be considered healthy rituals. For example, Elings (2006) found various studies from different countries showing how plant interactions promote human well-being. Thus, a routine task, such as watering the houseplants, should not be automated blindly but designed carefully.

That is why we follow the suggestion by Calvo and Peters and build a system designed for human well-being. An implicit interaction-based, proxemic-aware system is suitable for that approach. In the following we will give a short overview of 'Positive Computing' and the relevant dimensions for our work and then briefly describe the requirements of the watering plants system before continuing with describing the steps we took with the proposed process.

9.1.1 Positive Computing

Calvo and Peters write (Calvo & Peters, 2014, p., 63):

> As devices get embedded into the fabric of our lives and become inextricable parts of the experiences that shape us, their inevitable impact on our wellbeing grows ever greater.

The interconnection of many artifacts increases the influence of digital devices, significantly affecting our well-being. To reduce or avoid stress and suffering caused by digital technologies, 'Positive Computing' should focus less on productivity and efficiency and more on enhancing human values, such as wellbeing (Calvo & Peters, 2014).

In the application of 'Positive Computing', the design of systems considers their impact on the user and their psychological needs, aiming to influence the user's well-being. This can be achieved by avoiding negative feelings, such as reducing overwhelm, and by actively improving specific factors like autonomy, competence, and motivation. These three factors will be examined in this project and are explained below.

Autonomy
: Autonomy is one of the three key components of Self-Determination Theory, which is crucial for positive well-being and motivation. Users should feel that the outcomes result from their actions when interacting with a digital device. Increased system automation can reduce user influence, potentially leading to feelings of helplessness. Therefore, the use of technology must be balanced to support the user while ensuring they retain control (Calvo & Peters, 2014, pp. 22, 261–263).

Competence
: Competence is another factor in Self-Determination Theory. Users should

feel that their abilities contribute to the outcomes. Overwhelming tasks can make users feel their skills are insufficient, while tasks that are too simple may lead them to believe that results are not due to their abilities. Therefore, goals must be realistic and appropriately challenging. Additionally, efforts can be made to enhance a person's skills, thus giving them a greater sense of accomplishment (Calvo & Peters, 2014, pp. 22, 263–265).

Motivation

Motivation is a crucial factor as it drives individuals to take action. Without motivation, users will not engage with the system, rendering other factors ineffective. Hence, the goal should always be encouraging users to interact with the system, perhaps by rewarding correct actions (Calvo & Peters, 2014, pp. 131, 149).

9.1.2 Watering Plants System

To develop a system that effectively supports individuals in watering their plants, we aim to leverage implicit interactions, particularly proxemic interactions. This approach will seamlessly integrate into users' routines without causing significant disruptions. While some individuals possess the skills to care for their plants without assistance, others may lack this proficiency, often leading to overwatering or underwatering. Recognizing that many people own multiple plants, our proposed system will encompass a network of technical and human participants designed to provide tailored support and ensure optimal plant care. This holistic approach will address the diverse needs of plant owners, promoting healthier plant maintenance practices across varying levels of expertise. The participants in the interaction are described below.

The Human The system incorporates a single individual whose objective is to water their plants.

The Watering Can The system also includes a watering can to be connected to the plants, facilitating proxemic interactions through this connectivity.

The Plants The system may comprise multiple plants, each capable of communication with the other plants and the watering can.

With these simple requirements, we start the process to determine what the concrete interactions should look like.

9.2 Step 1: Role-Plays

In the process, we conducted two iterations of role-plays, which are described in detail in this section.

9.2.1 First Iteration

Figure 9.1: The plant (left person) in the first role play indicates that it needs water and is being watered by the user (right) with the watering can (middle).

We conducted a few straightforward scenarios to gain initial insights into how a fundamental interaction might unfold. These provided valuable information on aspects requiring closer examination in a subsequent iteration. Each scenario was filmed and reviewed afterward for further analysis.

The role-play exercise was conducted with four participants and included seven short scenarios. Each scenario featured a user (played by the author), a watering can, and one or two plants (referred to as artifacts). It was acknowledged that the author's prior knowledge might influence the insights gained; however, this was acceptable as the first iteration aimed to provide an initial overview of the interaction possibilities.

The artifacts were restricted from moving from their locations or speaking with the user. However, single words or sounds were permitted, as well as any verbal communication among the artifacts themselves. Additionally, at the beginning of each scenario, the participants were briefed on the situation and what they needed to pay attention to. In each scenario, at least one plant required watering.

The first four scenarios aimed to determine how the plants indicate their need for water or lack thereof and whether their gestures differ when one or more plants are in the room. The plants raised their arms when they needed water, as shown in Figure 9.1. If they did not need water, the plants made no gestures. The gestures did not differ when there were single or multiple plants in the room.

In the previous scenarios, the plants responded to the user lifting the watering can. In the subsequent two scenarios, they needed to attract the user's attention when urgently requiring water, but the user did not water them proactively. In the first of these two scenarios, one plant communicated its need for water to the watering can, which then alerted the user by repeating the word "Hey". In the second scenario, the plants' behavior was observed when the watering can was out of reach. One plant sat on the ground to draw the user's attention.

The final scenario examined how to inform the user which plants needed watering when they could not indicate this themselves. The watering can nod towards the plant that needed water.

Although the role-play provided some initial insights, several questions remained unanswered. Since all participants knew each other's needs, it was always clear what the others intended to convey with their gestures. It would be interesting to see how the artifacts communicate their needs to others when only their needs are known initially. Furthermore, the behavior was partially influenced by the author, who had premeditated some actions. For instance, a plant stopped indicating its need for water when the user stood before it with the watering can, and the user caused it to raise its arms again by interrupting the watering process. This leaves questions about how long the plants will indicate their need for water.

Due to the scenarios' simplicity, the interviews did not yield reportable insights. A second role-play was subsequently conducted to address the unanswered questions.

9.2.2 Second Iteration

The second role-play aimed to address the unresolved questions in the first role-play. Additionally, new participants were sought to ensure their behavior was not influenced by prior knowledge. The author did not actively participate in the role-play to minimize his influence on the results. This role-play aimed to answer the following specific questions:

- How long do plants perform their gestures to communicate their water needs to the user? Do they continue until the user notices or until they receive enough water?
- How do the artifacts ensure that the plants receive the correct amount of water?
- Who and how draws attention to the plants that the user forgets to water?
- How do the artifacts behave when one of the plants is visibly defective?

The participants were interviewed after each scenario to gain further insights or understand specific behaviors. The following sections outline the sequence of scenarios conducted to answer these questions.

9.2.2.1 Procedure

Four scenarios were played out, each designed to answer one of the specific questions. Depending on the scenario, five or six participants played the roles of a user, a watering can, and three to four plants.

At the beginning, participants were briefly instructed that they would alternate playing one of the three roles and were given an overview of the scenario setup: First, the group was informed about the sequence of the upcoming scenario, followed by individual briefings for each participant regarding their specific needs. The artifacts were then placed in the room, and the role-play began as soon as the user entered. After each scenario, we individually interviewed participants about this scenario.

Participants were also given preliminary information before the first scenario, applicable to all four scenarios. The user's goal was always to meet the needs of all artifacts. Once they believed they had accomplished this, they were to return the watering can to its original place. The watering can's goal was to fulfill the needs of the plants. Additionally, all artifacts were to try to achieve their objectives while supporting the user, being as unobtrusive as possible, and minimizing disruption. Furthermore, artifacts were not allowed to change their position independently. The plants' specific needs varied across the scenarios and are detailed in the following comprehensive description of each scenario.

1. Scenario 9.2.2.2

Scenario Overview In the first scenario, we blindfolded all artifacts to simulate the limited perception of actual artifacts, which can only sense their environment through sensors and communication with other system components. Additionally, participants could not see each other's gestures and had to come up with their own ideas to have their needs met. The user wore headphones to prevent hearing what the artifacts said, as verbal communication in the role-play represented internal communication between system components. The user had to rely on interpreting the artifacts' gestures. Three plants participated in this scenario, with two needing to be watered and the third not to be watered.

Figure 9.2: The plant (on the right) in the first scenario has been watered and shows its satisfaction by raising its arms.

Role-Play Outcome The scenario began with the user entering the room and picking up the watering can. This action was communicated by the watering can to the plants, prompting one plant to droop its head. The user brought the watering can to this plant and watered it. The watering can announced that it was watering the plant and stopped after a while. The plant then expressed its happiness. Next, another plant knelt and drooped all its limbs. The user also watered this plant, which the watering can again announced. The watered plant slowly straightened up, expressed happiness, and raised its arms, as shown in Figure 9.2. After a short pause, the watering can asked if all the plants are happy. The plants began counting to determine their number (as they were unaware of this), concluding that all were satisfied. The user then set the watering can down, and all artifacts thus achieved their objectives.

9.2.2.3 2. Scenario

Scenario Overview To ensure the user was unaware of the communication between the artifacts in the second scenario, the artifacts used their smartphones to communicate via a group chat. This allowed a plant placed in an adjacent room to participate in the communication, which would not have been possible with verbal communication. Besides the plant itself, no one knew about this additional plant. Two plants in the main room needed water, while the third was not to be watered.

Role-Play Outcome At the beginning of the scenario, when the user entered the room, one of the plants wrote this in the chat. Two plants wrote that they needed water. One signaled this to the user by raising a hand while the other drooped its head. The user then watered these two plants one after the other. The watering can wrote in the chat during the process, indicating it was watering. One plant showed its satisfaction by nodding, and the other by smiling as they were watered, and both thanked the user in the chat afterward. While the other plants were watered, the plant in the adjacent room tried to attract attention through messages. After it communicated its location in the chat, two plants pointed towards the door to the adjacent room. The user found the additional plant and watered it until it was happy and expressed its thanks via a message. The user then set the watering can down, and the plants clarified in the chat whether everyone was satisfied. Since this was the case, all objectives were also achieved in this scenario.

9.2.2.4 3. Scenario

Scenario Overview As in the first scenario, the user in the third scenario wore headphones to block out the now again verbal communication between the artifacts. This time, the plants aimed to receive a specific amount of water. We distributed glasses to the plants, and a watering can filled with water was given to the watering can. The amount of water in the can was deliberately insufficient to satisfy all the plants, to observe the impact on the user's watering behavior and how the artifacts managed this. Two plants aimed to receive exactly half a glass of water, while the third needed to have its glass wholly filled.

Figure 9.3: The plant (on the right) in the third scenario shows the amount of water it needs by pointing at the glass.

Role-Play Outcome After the user entered the room and picked up the watering can, the first plant raised its glass to indicate it needed water. When the user approached with the watering can, the plant pointed to the middle of the glass (see Figure 9.3), which was then filled to the indicated level. Next, the neighboring plant raised its glass, and the user moved to it. This plant did not indicate a specific amount, so the user filled the glass until the watering can was empty. The watering can then showed the user it was empty by pointing to the can. The user looked around, saw the third plant waving its glass, and refilled the watering can. The user then approached the last plant, which had indicated it needed water. Like the first one, this plant showed how much water it needed, and the glass was filled to the mark. The user then set the watering can down, looked around again, and nodded in satisfaction. However, the plant that needed a full glass ended up with only about three-quarters full, so the objectives were not completely met. The user was unaware of this. It was also noted that no verbal communication occurred, even though the artifacts had the option.

4. Scenario 9.2.2.5

Scenario Overview In the final scenario, the setup was the same as in the previous one. This time, one plant required half a glass of water, another needed no water, and a third plant was tasked with repeatedly requesting one-third of a glass of water to simulate a defect. The goal was to observe how the user and the other artifacts behaved when one exhibited a defect.

Role-Play Outcome As with the other scenarios, this began with the user picking up the watering can. Initially, all the plants verbally communicated their needs to inform the other artifacts. The defective plant pointed to its glass and signaled to the user, just as in the third scenario, how much water it needed. After the glass was filled accordingly, it expressed thanks, and the user turned to the next plant, which indicated it needed half a glass of water. The first plant again signaled that it needed a third glass of water, prompting the user to water it again. The user turned away, but the plant signaled for water once more and was watered again. This cycle repeated several times until the other plants began to ask if everything was all right. The defective plant continued to insist it needed water, and the other plants decided to inform the user to stop watering it. The artifacts agreed that the watering can should take on this task. When the user approached the defective plant with the watering can again, it shook itself, indicating to the user to stop. Consequently, the user moved away from the plant. Despite further attempts by the defective plant to get more water, the user denied it additional water and concluded the care of the plants by setting the watering can down.

9.3 Step 2: Interviews

The participants in the role-play were individually interviewed immediately after each scenario, with the questions tailored to their specific roles in the scenario. We transcribed the interviews as the basis for the subsequent thematic analysis, as described by Braun and Clarke (2006). The data analysis revealed two thematic areas relevant to the design of interactions with artifacts: 'Communication Between the Artifacts' and 'Communication With the User'. An overview of all the areas and subareas can be seen in Figure 9.4. Quotes from the interviews are provided in the following section with the information in brackets to which scenario the quote refers (e.g., "I was a plant" (1)).

9.3.1 Communication Between the Artifacts

Communication between the artifacts was present and discussed in the interviews in all scenarios. This topic arose when addressing Group satisfaction and Problem recognition. Additionally, Water quantity and the Effect on the user was also discussed.

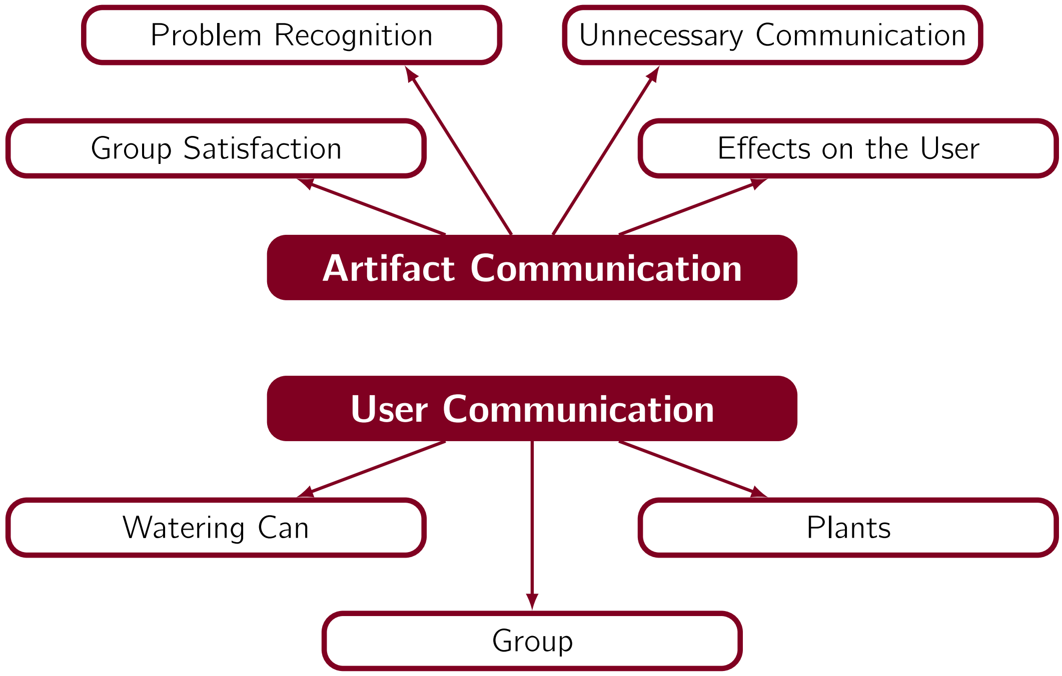


Figure 9.4: An overview of the topics that emerged when analyzing the interview data.

Group satisfaction Since the artifacts were supposed to fulfill their needs, they also considered whether the other artifacts were satisfied. In the first scenario, the plants began to clarify if everyone was happy, during which a problem was reported by one of the plants: "But then it was about when he [the user] asked if all the plants are happy, we didn't know if all the plants are happy because we didn't know who all are" (1.). Since the participants were blindfolded, they first had to determine how many participants were in the room. For another plant, clarifying satisfaction seemed important so that the user would know when he was done because "only when we plants knew among ourselves whether we had all had our needs met, did the watering can somehow communicate that to the user. [...] only then did the user somehow understand that it was over [...]" (1.). In another situation, when a plant was not fully satisfied, communication could have helped to solve the problem, according to the affected plant: "If we had communicated, it would have worked." (3.).

Problem recognition When one of the plants in a scenario was 'defective' and kept requesting water, it took a while for everyone to realize that something was wrong. "Before that, it could be that (...) it needs it in bursts or something" (4.), one of the plants speculated. The other artifacts eventually clarified through communication that the plant was likely broken. When asked when she noticed that something was wrong with the other plant, one plant replied: "Yes, when she [the malfunctioning plant] – when we asked her – or when she kept saying the same thing and when we then tried to communicate with her, and she didn't give any different feedback." (4.). The watering can, which was somewhat perplexed by the situation, found the inquiries of the other plants "good" and "helpful" (4.), so the situation was eventually resolved.

Water quantity While the participants found communication among themselves useful and helpful for the previous topics, there were situations where communication offered no advantages. In one scenario, the artifacts were allowed to talk to each other, but no verbal communication took place. One of the plants explained it as follows: "I knew we were allowed to talk, but it wasn't really necessary. (short pause) And it doesn't really bring much to communicate with the other plants, as the user has to fulfill the tasks. (short pause) In my opinion, at least in this task." (3.). Another plant, unsure if talking was allowed, said afterward: "Even though we didn't talk, everything was still fulfilled. At least for me, my needs were met without talking." (3.). In this case, communication seemed necessary for the plants only if problems had arisen: "If there had been problems, I could have talked to the watering can. Or with other plants, so they could help me somehow." (3.).

Effect on the user Since the user was unaware of the communication between the artifacts but knew they were communicating, the interviews explored whether this impacted the user. However, the participants agreed that not seeing the communication "didn't really" (1.) or "didn't play a role" (2.).

9.3.2 Communication With the User

The second important thematic area was the communication between the artifacts and the user. This can be subdivided into three topics: Communication with a plant, Communication with the watering can, and Communication with a group of artifacts.

Communication with a plant First, the plants needed to indicate whether they required water. The plants that did not need water did nothing and reported that they "did not really communicate with him [the user]" (2.). It seemed more reasonable for them to communicate with the user only when he attempted to water them: "[...] if he looks at me and plans to water me, then I will resist, so to speak." (2.).
On the other hand, the plants that needed water tried to communicate with the user in different ways. "[...] I bent over like this (bends over), and then I

was watered" (1.), one of the plants described her attempt to attract attention and the user's reaction. The user in the scenario also said that "this gesture (droops head) [...] was actually quite clear" (1.). Other plants tried more energetically, waving or similar actions to draw attention. One user found the active gesture more understandable, as he noted in the interview: "Since participant A. [the plant – ed.] approached me and communicated directly with me, I understood it better than a 'withdrawal"' (2.). He even became more explicit and demanded that the plants "communicate the state [...], that they want to be watered [...] and not just change their appearance. So, approach me directly [...]".

Next, the focus was on how the plants would communicate the required amount of water to the user. Some plants indicated the amount before watering, and the user found it "very good" and easy to understand "how much they want" (3.).
Another plant did not indicate how much water it needed, leading the user to eventually decide that "it's enough – or must be enough" (3.). Other participants also found it unclear whether the plant was satisfied, as reflected in several statements. One plant remarked: "I think she – maybe she had too much water – no, too little water [...] Maybe she wanted a completely full glass. (short pause) That means maybe she should have indicated this more clearly" (3.). The watering can also speculated that the plant might not be satisfied: "When the watering can was empty, I think the plant could have used a bit more. We might have had to go back" (3.). It would have been more understandable for the participants if all plants had indicated how much water they needed before watering.

Finally, the focus was on how the plants would indicate their satisfaction. One plant stated that she "grew taller [and] then he [the user] stopped [watering]" (1.). Although this approach worked well in the described case, the user wished for "a clearer signal from the plants when they are satisfied [...]" and that they should "also say when they don't want to be watered anymore" (2.). The watering can also felt that the plants "could have spoken or said thank you, so you really know: now it is really finished" (3.).

Communication with the watering can While the watering can mostly took a "passive role" (1.) and generally 'did not communicate much with the user' (2.), there were two situations where communication between the watering can and the user seemed useful.

On one hand, the user found it “good with the watering can [...], that it realized by itself: It needs water” (3.) when it was empty.
In another case, a defective plant kept requesting water, and the watering can signaled to the user by shaking that he should not water the plant further. The watering can said that the user “correctly interpreted [it] when I shook myself” and even mentioned that it “maybe should have [...] signaled even earlier” (4.). One plant believed “that it is best if the watering can signals it because it is misleading if other plants intervene at that moment [...]” (4.).

Communication with a group of artifacts Lastly, it became apparent that it is helpful for the group to communicate with the user when it is “difficult” (4.) to convey information alone. This was the case in the role-play when a plant in another room still needed watering. To draw the user’s attention, “somehow another component or second plant” was needed (2.). The user also explained that it only became “clear” to him “when the second hand went up” (2.).

9.3.3 Summary

The interviews revealed when communication between artifacts or from artifacts to the user is helpful or can be omitted. The artifacts mainly communicated with each other to determine if everyone was satisfied. It was also noted that communication between artifacts was beneficial for identifying and solving problems. However, communication among themselves did not seem necessary when informing the user about how much water each plant needed. Additionally, the communication between artifacts had no impact on the user.

Regarding communication with the user, it was found that plants needing water should explicitly indicate this, while plants not needing water should do nothing. To receive the correct amount of water, the plants should ideally indicate how much they need before the watering begins and clearly state when they are satisfied so the user can be sure that the plant does not want more water.

There was very little communication between the watering can and the user. The watering can only communicated with the user in case of problems with the plants or when it was empty. The only situation in which the artifacts communicated as a group with the user was when they wanted to draw attention to another plant.

Step 3: Implicit Interaction Framework 9.4

In this section, we define the interactions with the system. For this purpose, first, we analyze the participants' behavior in the role-plays using the IIF and then transfer the behavior to the computer system. The design assumes a functioning system and does not include representations of errors that occur, for example, in the event of a defect or interactions for such cases.

The typical behavior of the user and the plant in the role-plays is first described to identify the interactions. The process was expanded to include the plant indicating when it has received enough water, as required by the participants (see Communication with a plant, page96). For this purpose, the display of the water amount was combined with the nodding of the head as confirmation from two different scenarios of the role-plays into one process. Here, the interaction between the user and plant participants is considered since the IIF can only model the interaction between two participants. The watering can appears as an additional object.

Environment: Room with plant and watering can
Roles: Plant, User
Procedure:

User:	Enters the room and takes the watering can in hand
Plant:	Raises its arms
User:	Searches the room for plants that need water and goes to the plant after noticing its raised arms
Plant:	Indicates with its finger on the glass how much water is needed
User:	Fills the glass with the watering can
Plant:	Nods its head when it has received enough water
User:	Stops watering and puts the watering can down

In this setting, the plant recognizes the user's intention to water when they take the watering can and proactively indicates that it needs water. Once the user notices the plant and approaches it, the plant responds and indicates precisely how much water it needs so that the user gives it the right amount. As soon as the plant has received enough water, it confirms its satisfaction to the user. Figure 9.5 shows the interaction pattern of this interaction.

If the interactions are abstracted from specific actions like 'raising arms', the process is as follows:

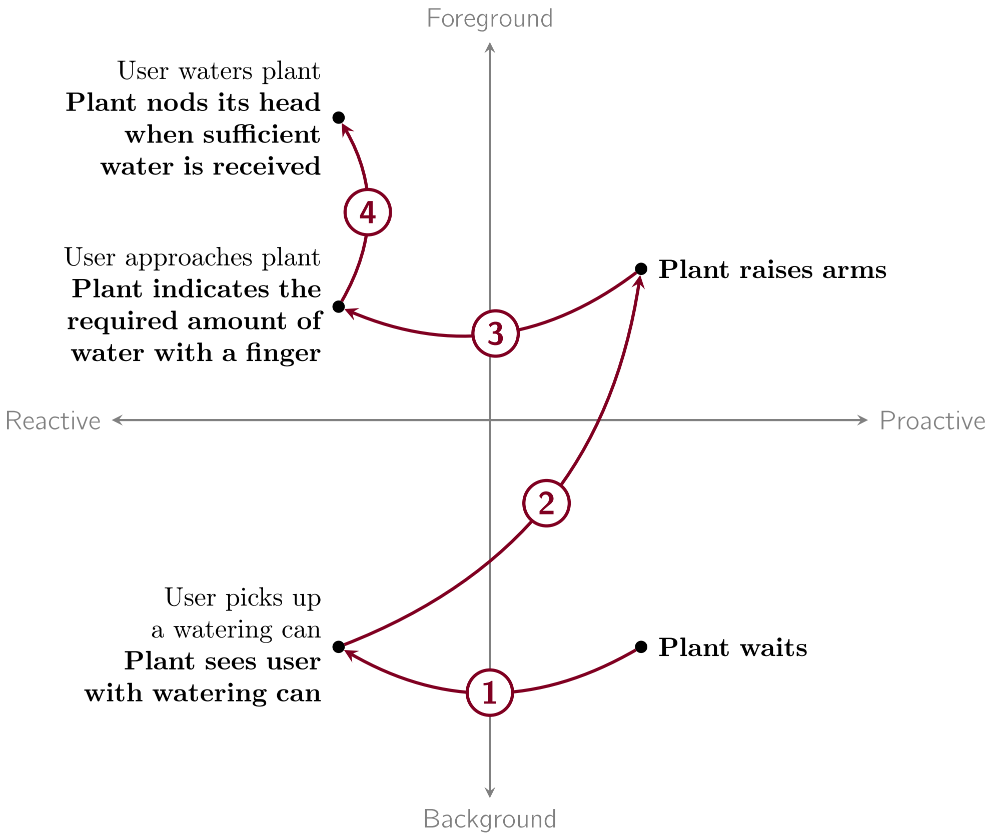


Figure 9.5: Interaction patterns illustrated with the IIF of the described example of a concrete interaction in the role-playins.

ENVIRONMENT: Room with plant and watering can

ROLES: Plant, User

PROCEDURE:

User:	Enters the room and takes the watering can in hand
Plant:	Indicates that it needs water
User:	Searches the room for plants that need water and goes to the plant after noticing the indication
Plant:	Indicates the amount of water it needs
User:	Waters the plant with the watering can
Plant:	Indicates that it has been sufficiently watered
User:	Stops watering and puts the watering can down

When comparing the two created interaction patterns (see Figure 9.5 and Figure 9.6), it is observable that the fundamental interaction pattern does not differ. The exact representation of the information does not impact the type of implicit interactions. Therefore, we use this fundamental interaction in the abstracted version for the further design process. The specific implementation

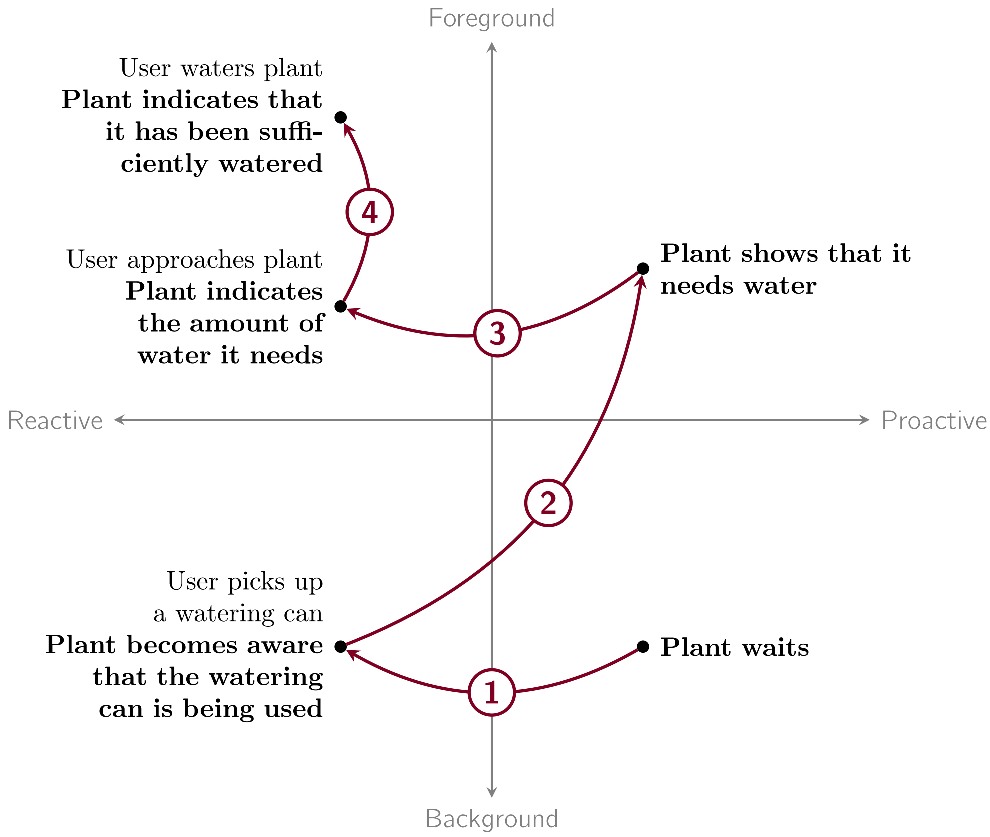


Figure 9.6: Interaction patterns illustrated with the IIF of the described example of an abstracted interaction in the role-playins.

or mapping of the information representation will be determined later when developing the prototype.

9.5 Step 4: Proxemic Interaction Framework

As the role-plays showed, several proxemic properties play a role in interactions. As noted in the analysis described in the previous section, the plant changed its display when the user approached it. Therefore, the behavior of the artifacts in this regard will now be examined in more detail using the PIF.

Figure 9.7 shows six steps of the user's interaction with the system, described below.
In the first step (a), the user enters the room. Thus, the three plants in the room, the user, and the watering can are known participants in the system. Since neither the user's distance to the other participants nor their orientation or movement suggests that they intend to water the plants, no system reaction occurs.
Between steps (a) and (b), the user walks past one of the plants, even entering

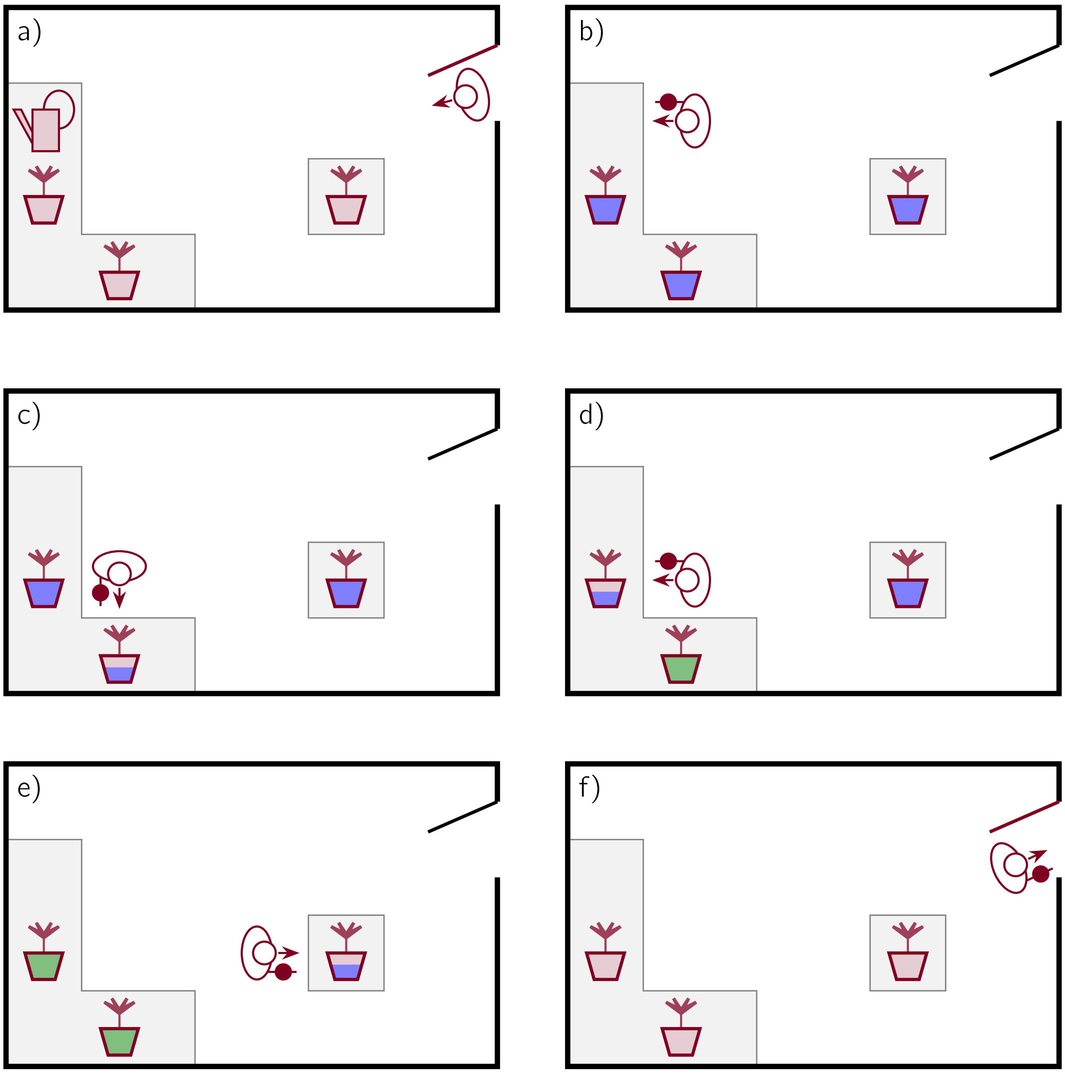


Figure 9.7: Illustration of the supportive plant watering interactions, finalized using the PIF.

its personal zone (see Section 2.2.2: *Personal Zone*, page 12), but orientation and movement indicate that the plant is not their target, so the system does not react here either.

In step (b), the user stands in front of the watering can and takes it in hand. Now, the user's intention to water the plants is recognizable. All plants in the same room indicate that they need water, and the user can see at a glance that they need to take care of all three plants.

The user now walks through the room and, in step (c), stops between two plants so they are simultaneously within the personal zones of both plants. However, they first orient themselves to one of the plants. Consequently, this plant changes from indicating the need for water to indicating the required amount of water. The other plant, however, continues to show its need for

water.
In step (d), the user has now turned to the second plant, which is why it now indicates the required amount of water. The other plant no longer needs to communicate the required amount of water.
A similar behavior of the plants can be observed in step (e). Like the previously cared-for one, the recently watered plant no longer displays the amount of water once it notices that the user is turning away or moving away from it. The last plant, however, changes from indicating the need for water to indicating the required amount of water when the user focuses on it through orientation and distance.
Finally, as shown in step (f), the user leaves the room. All plants switch back to passive mode and no longer display any information. The same behavior would occur if the user puts the watering can down. If there are plants in the adjacent room that the user now enters, they will behave in the same way as the plants previously considered after step (b).

The main factors in the interactions are distance and orientation and whether a user with a watering can is in the same room (i.e., identity and location are also relevant). This information helps finalize the interaction design between a user, his watering can, and the plants.

9.6 Conclusion

In conclusion, the example run of the proposed process successfully demonstrated that implicit and proxemic interaction patterns can be effectively identified through different scenarios in role-plays, supplemented by post-session interviews. These patterns have proven invaluable in guiding the design of a proxemic-aware interaction, which can now be implemented in interactions between humans and computer systems. Using short and straightforward scenarios in the initial role-plays was particularly beneficial, especially when there was uncertainty about which scenarios would yield the most insightful results. Moreover, the interviews provided essential input for refining the design, offering diverse perspectives, and highlighting potential improvements when certain aspects of the interaction did not work as intended. It was also noteworthy that participants were highly motivated to complete the tasks as optimally as possible, often suggesting how they could have performed better.

While adapting and designing the interaction based on the role-plays was relatively straightforward, it remains to be seen how well this design will perform in real-world use cases. The following chapters will explore this further by describing the developed prototype and the study that was conducted.

10. Developed Prototypes

In this chapter, we will describe the prototypes we developed based on the interaction model refined through our process. We created two prototypes utilizing the same interaction pattern to assess whether the development process results in a usable product. By employing different prototype versions, we aim to reduce the risk of negative evaluations that could stem from the specific technologies employed.

We will begin by discussing how to effectively map the information intended for display to the user (e.g., a plant's water needs). Following this, we will provide a detailed explanation of the two prototypes. The first prototype incorporates a physical interface within the watering can and plant pots, utilizing light-emitting diodes (LEDs) for communication. In contrast, the second prototype leverages augmented reality (AR) technology to present the information to the user via a smartphone. We developed both as Wizard of Oz (WOZ) prototypes so that the interaction can be evaluated without spending too much time on a fine-tuned product.

10.1 Mapping

After defining the processes for interactions and information displays, the next step is determining how to convey this information to the user effectively. This section will cover how the plants communicate their water needs and current water levels and provide positive feedback or warnings to the user. Additionally, a method for displaying the overall satisfaction of all the plants in a room will be discussed.

10.1.1 Water Requirements

The display of water needs should allow the user to quickly recognize whether a plant requires water without needing to approach it physically. During the role-playing exercise, different approaches were explored for how plants could attract the user's attention. Some plants raised their arms, while others merely drooped their shoulders. However, the interviews revealed that users prefer a clear and straightforward indicator. Therefore, a single-color display will indicate whether a plant needs water. Since blue is commonly associated with water, it has been chosen to represent the plant's water needs.

Furthermore, in the role-playing exercise, plants that did not need water remained inactive and were, therefore, ignored by the user as intended. However, as Ju points out, it is beneficial to have an indicator that signals whether a device is currently functioning (Ju, 2015, p., 45). If a plant malfunctions and fails to display anything, it could be mistaken for a plant that does not show a need for water. If the user relies on the system, this error might only become apparent when it is too late and the plant has gone without water for an extended period. Additionally, such an indicator would allow the user to distinguish between digitized and non-digitized plants easily at a glance and immediately know which plants require manual watering. To ensure the user does not lose track, plants should continue to display their water needs even after being watered, but in green. Green was chosen because it is a positive, affirming color, and many plants are green when healthy.

In addition to the two scenarios described, a third color has been designated to indicate when a plant urgently needs water. Red, commonly used as a warning color, has been selected for this purpose. Thus, each plant's display should consistently appear in one of the three colors – red, blue, or green – when communicating its water needs to the user, particularly after the user has picked up the watering can.

10.1.2 Water Level

In one scenario during the second role-playing exercise, the plants held a glass and aimed to have it filled to a certain level, such as halfway. The plants would point to the glass, indicating the desired water level for the user to fill. However, In real plants, it is impossible to directly observe the current water level due to opaque pots and soil. Therefore, a method for displaying the water level in the developed system needed to be devised. The concept of analog water level indicators, common in plant care, was considered (see Figure 10.1). These indicators consist of a small stick within a transparent casing that moves up and down according to the water level in the pot, showing how much water is present. The casing has two markings indicating the minimum and maximum water levels. The tip of the stick should always be between these two markings and ideally within a designated optimal range between them.

Figure 10.1: Analog Water Level Indicator

The digital water level display aims to implement this concept as a metaphor, showing the user the water level and two markers. These markers and the midpoint between them define the thresholds at which the plant will communicate its water needs to the user using a red, blue, or green display. Plants with a water level below the minimum marker will display red; from the minimum marker up to the midpoint, they will display blue; and above the midpoint, they will display green. The markers also determine the values the user should receive additional notifications at during the watering process. Confirmation that the plant has been adequately watered will occur when the midpoint between the two markers is reached, indicating the water level is in the optimal range. Conversely, when the maximum marker is reached, the user will be warned against further watering.

Confirmation/Warnings 10.1.2.1

The user receives a positive confirmation when they water a plant and it reaches an adequate water level. However, if the user waters a plant with too much water, they receive a warning. Additionally, the user is warned if they approach a plant with a high water level while holding the watering can, as this likely indicates an intention to water that plant. A simple solution, similar to the previous indicators, should be implemented to convey confirmation or warnings to the user in these three scenarios. Thus, two colors will be used and displayed directly on the plant. The red and green colors are again suitable for signaling confirmation and warnings. These important messages should not be conveyed through a simple continuous light but through repeated blinking to ensure the user notices the information. This also makes it easier to distinguish from the water needs display. An idea from the role-playing exercise is incorporated to emphasize the warning further: when the user needs to stop watering a plant, the watering can will shake. Therefore, in this scenario, the handle of the watering can will vibrate, providing the user with haptic feedback in addition to visual cues.

10.1.2.2 Group Satisfaction

During the role-playing exercise, it became clear that users should be notified when all plants are satisfied. This helps prevent the user from overlooking any plant. To achieve this notification, information is required on the number of plants in the system or the room and their respective statuses. To provide the user with a consistent visual experience, the same color mapping used for displaying water needs on individual plants will be applied here. The goal for the user is to see a green overall indicator.

The overall status is determined by the worst status among all plants whose satisfaction is monitored. For instance, if a single plant urgently needs water, the overall status indicator will be red. The indicator will turn blue once no plants urgently need water, but not all are satisfied. Finally, when all plants are satisfied, the indicator will turn green. The display should be placed in a central part of the system, such as on the watering can itself, where the user can easily see it while watering. This way, when the user picks up the watering can, they can immediately check if any plants in their system need watering.

10.2 Physical LED Prototype

The LED prototype consists of several components developed to achieve the working system. We will begin by outlining the hardware components required to construct the prototypes, providing a detailed overview of the necessary equipment. Following this, we will examine the specific components that we developed for the prototype and show their communication mechanisms. Finally, we will examine the WOZ interface that was implemented. The WOZ is a small application that enables an operator to simulate the proxemic information for the prototype, thereby eliminating the need for physical sensors. The prototypes required significantly less development time by using a WOZ interface, and the users in the study had the impression of a fully functioning system.

10.2.1 Hardware

For the development of the prototypes, we used multiple Raspberry Pi Zero W (see Figure 10.2) in each of the developed artifacts. The board has 512 MB of random-access memory (RAM) and a 3.3 V general-purpose input/output

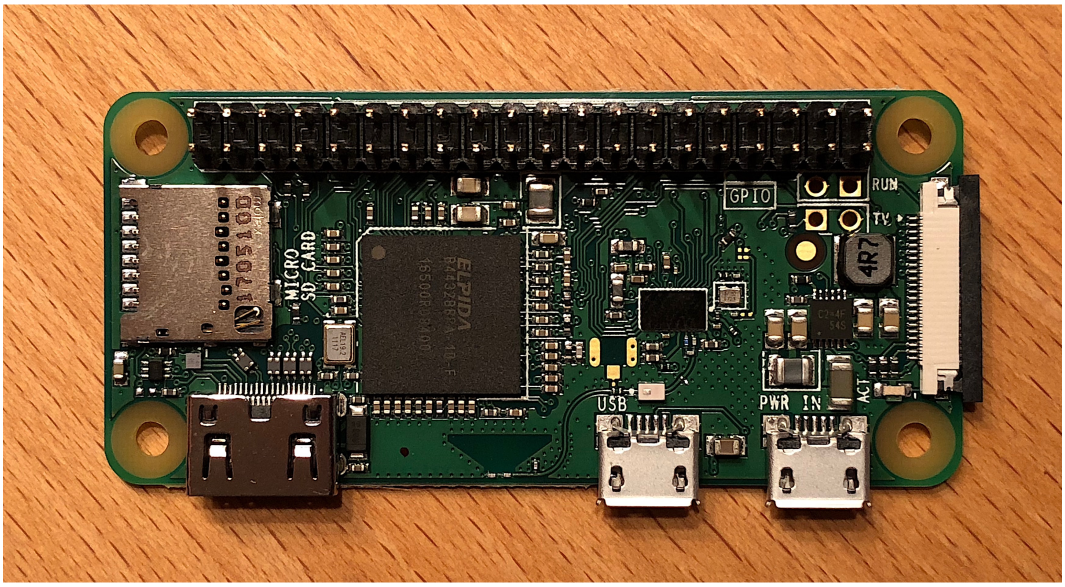


Figure 10.2: Raspberry Pi Zero W

(GPIO) interface. It also has a built-in wireless local area network (WLAN) antenna and can be used inside the watering can without any cables. Also, the other specs and interfaces like Inter-Integrated Circuit (I2C) are sufficient for our purpose (Barnes, 2017; "GPIO Electrical Specifications (Raspberry Pi input and output pin voltage and current capability)", n.d.).

We used the following sensors, actuators, and electrical components to enable the artifacts to communicate their needs.

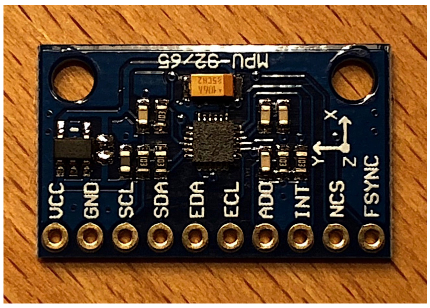


Figure 10.3: MPU-92/65

9-Axis Motion Sensor The MPU-92/65 (see Figure 10.3) is a sensor that provides data across nine axes for motion tracking. It integrates a 3-axis gyroscope, a 3-axis accelerometer, and a 3-axis magnetometer. This combination allows the sensor to measure gravitational force and magnetic field strength along three axes, enabling the calculation of the sensor's orientation. Additionally, acceleration data is provided along the three axes, making it possible to detect whether the sensor is in motion. For example, the sensor can be connected to a Raspberry Pi via the I2C bus, allowing the raw data to be read for further processing (InvenSense Inc., 2014).

NeoPixel LEDs NeoPixels are LEDs manufactured by Adafruit[1], based on the WS2812B protocol. Each LED is individually controllable with 256 levels for the colors red, green, and blue, allowing them to display $256^3 = 16,777,216$ different colors. In theory, an unlimited number of LEDs can be controlled through a single data connection when connected in series. However, in practice, the number is limited by the available RAM and power supply. As the protocol dictates the data transmission speed, the speed at which colors can change decreases with each additional LED because more data cannot be transmitted in the same amount of time. Adafruit offers various types of NeoPixels, including individual LEDs and multiple LEDs arranged in a strip, on a stick, in a ring, or in other forms (as shown in Figure 10.4), where the data lines between the individual LEDs are already connected.

The protocol specifies a power supply with an input voltage V_{in} of 3.5 V to 5.3 V, so the NeoPixels in this project are powered with 5 V. The data line must operate at a minimum of $0.7 \cdot V_{in}$, requiring at least 3.5 V when the input voltage is 5 V. Since the Raspberry Pi's GPIO pins can only provide a maximum of 3.3 V, either V_{in} must be reduced, or the Raspberry Pi's data signal voltage must be increased. In most cases, an insufficient signal leads to flickering LEDs, so in the prototypes, the data signal voltage was increased using a logic level shifter (Worldsemi Co.,Limited, n.d.).

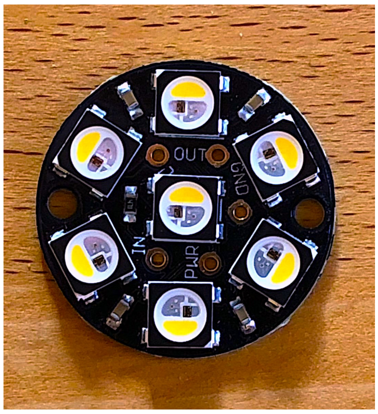


Figure 10.4: Seven connected NeoPixel LEDs

Logic Level Shifter A logic level shifter, such as the 74AHCT125 (see Figure 10.5), is used to convert the voltage of a signal to a different level. The 74AHCT125 is particularly well-suited for increasing voltages below 5 V up to 5 V, as it can accept an input signal between 0 V and 5 V and convert it to a supply voltage ranging from a minimum of 4.5 V to a maximum of 5.5 V. The logic level shifter is connected to a power source with the desired voltage, which in the case of

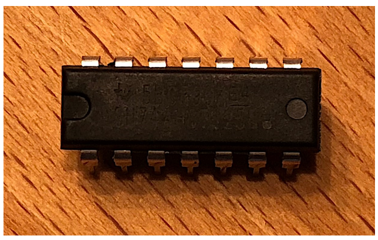


Figure 10.5: 74AHCT125 logic level shifter

[1] https://www.adafruit.com

the NeoPixel is the 5 V power supply from the Raspberry Pi. The 3.3 V data signal from the Raspberry Pi is then connected to one of the inputs, and the 74AHCT125 converts this 3.3 V signal into a 5 V signal, which is sufficiently high for the NeoPixel LEDs (Diodes Inc., 2013).

Vibration Motor A vibration motor is ideal for providing haptic feedback to the user. Inside its casing, a small motor rotates a weight. The weight is unevenly distributed, creating an imbalance that causes vibrations transferred to the casing, making it vibrate. The vibration motor used (see Figure 10.6) operates at a voltage range of 2.5 V to 3.5 V. At the 3.3 V´ provided by the Raspberry Pi pins, the motor produces around 15, 000 revolutions per minute, generating a noticeably strong vibration (Pololu Corporation, 2024).

Figure 10.6: Vibration motor

Components 10.2.2

After introducing the individual hardware components, their application and interaction within the different parts of the overall system will now be explained. Additionally, the functions enabled by each element will be discussed, ensuring that the complete system can provide all the interactions described in the previous chapter.

Server 10.2.2.1

The server is the central hub for all other components of the system. It also hosts a Message Queuing Telemetry Transport (MQTT) broker[2], which is essential for communication between the artifacts. Since the individual elements are intended to be networked in both solution approaches, the server is used in both prototypes (i.e., the LED version and also the AR version). We developed the server using Node.js, allowing it to run on almost any hardware with network capability, such as a Raspberry Pi 3 Model B.

The server manages and updates information regarding components currently connected to the system. Each participant must send a message containing information about its type (i.e., watering can, plant, user) and a unique, configured ID to the topic "devices/new" after establishing a connection to the

[2]https://mqtt.org/faq/

server. Additionally, participants should define their "Last Will" so that they are removed from the list in case of a connection loss. Once a participant subscribes to the topic "devices/connected", it receives a list of all connected devices from the server. This functionality is mainly used in the WOZ interface, which will be described later.

10.2.2.2 Watering Can

Figure 10.7: Watering can with illuminated LEDs

The connected watering can is designed to track when the user waters the plants. Additionally, it provides a vibration function to alert the user and displays the overall status of the plants in the current room in the LED prototype. The watering can is equipped with the motion sensor (MPU-92/65), the vibration motor, and NeoPixel LEDs with logic level shifters to enable these functions. All components are controlled by a Raspberry Pi Zero W, which is powered by a battery.

All hardware, except the vibration motor, is mounted in an extension at the bottom of the watering can. The vibration motor is attached to the handle so the user can feel the vibration when holding the can. Holes were drilled in the bottom of the can for the LEDs, sealed with transparent material to protect the hardware from water damage. Figure 10.7 shows the modified watering can with the integrated hardware.

The motion sensor detects when the user tilts the can. To calculate the tilt angle, it reads the sensor's gravitational values 25 times per second. If the can is tilted more than 45°, it sends its current position every 0.75 seconds to the topic "watering_can/{ID}/pour", which the plants can subscribe to and respond accordingly. To ensure a consistent water flow, the can's opening has been narrowed to deliver constant water per unit of time.

The vibration motor subscribes to the topic "plant/+/warning" and receives all plant warnings. It then vibrates for one second to alert the user when a warning occurs and the watering can is near the plant that issued it.

When the can receives a notification from the WOZ interface that it has been lifted, it sends a message to "watering_can/{ID}/movement", informing the plants. The plants then have two seconds to relay their status, after which the can displays the overall status using its LEDs. This status display can be turned off for use with the AR prototype, where the overall status is shown in the smartphone app.

Plant 10.2.2.3

The plant should be able to communicate its water needs and current water level to the user, update it during watering, warn the user when necessary, and indicate its satisfaction after receiving sufficient water. Each plant in the LED prototype requires LEDs for display, a logic level shifter, and a Raspberry Pi Zero W for control. Each plant uses two NeoPixel strips with eight LEDs, connected to form a column of 16 LEDs. Holes were drilled in the plant's outer pot to make the internal LEDs visible as individual lights. The plant is placed in an inner pot, which fits inside the outer pot, leaving enough space between the two for the hardware. A larger hole at the back of the outer pot allows the Raspberry Pi to be powered via cable.

Figure 10.8: Plant in the LED prototype

The water level is configurable to allow for different water levels in the study. The water level can range from 0 to 16, corresponding to the 16 LEDs that displays it. Starting from the bottom, the number of illuminated LEDs matches the water level. The minimum and maximum water levels are set at 6 and 14, respectively, indicated by markings above the sixth and 14th LED. The target level during watering is 10, located midway between the limits. Figure 10.8 shows a plant displaying a water level of 4. When the plant needs to indicate its water requirement, all LEDs light up in the color corresponding to its current status. During a warning or confirmation, all lights blink simultaneously in the same color.

The plant monitors messages from the watering can and user to display its water needs and water level. The plant updates its display if the user is close enough or the can is nearby during watering. When the target water level is reached, the plant blinks green; if it is overwatered, it blinks red and sends a warning.

10.2.3 Wizard of Oz Interface

Figure 10.9: Screenshot of the WOZ interface for the physical LED prototype.

We created a web interface for the LED prototype, which can be accessed via the server. This interface allows the system to receive proxemic data that the individual artifacts cannot independently measure and functions as a WOZ interface. Figure 10.9 illustrates the layout of this interface.

A list is sorted by type on the right side, showing all connected participants. To keep this list updated, the interface includes an MQTT client subscribing to the topics described above, ensuring it stays informed about all participants. When opening the interface, a second client is created to simulate a user, registering as a participant of the "user" type. All connected clients can be dragged onto the black area on the left side, which symbolizes the room's layout, where all participants must be positioned as they are in the actual space. Whenever a participant is moved, their new position is sent to the topic "master/{COMMAND}/{PARTICIPANT_ID}", which should be subscribed to by the participant with the corresponding ID, so they are informed of their new position. The watering can can be "attached" to the user on the interface with a small button and will then move together with the user. When the user picks up the watering can, this button must be pressed, and the plants will then receive the corresponding information via MQTT. The connection can also be severed when the user sets down the watering can.

The green circles around the plants symbolize the area where the displays should show the water level when the user with the watering can enters this zone. Therefore, to display the water level of a plant, the user must be placed within the corresponding zone in the WOZ interface.

Furthermore, each element in the participant list has a button that can be used to identify it. When one of these buttons is pressed, a message is sent to the corresponding participant, causing its LEDs to blink briefly several times. This feature is useful during system setup to verify the positioning of the plants and avoid confusion easily.

10.3 Augmented Reality Prototype

We developed the AR application for smartphones using Apple's ARKit[3]. Information is displayed virtually next to the plants, using horizontal surface detection to identify where the plants are located. The user (i.e., a study operator) can then select and place preconfigured objects from a list next to the plants. The application is based on an Apple sample program[4], which was customized and extended for this project. The display functions similarly to the LED prototype, with a water level ranging from 0 to 16, represented by a 3D model created for this project. There are 17 different objects for the water level and four additional objects in red, blue, green, and transparent for indicating water needs, confirmations, and warnings. The objects are swapped as needed, creating

Figure 10.10: Plant in the AR prototype

[3] https://developer.apple.com/augmented-reality/arkit/

[4] Handling 3D Interaction and UI Controls in Augmented Reality: https://developer.apple.com/documentation/arkit/handling_3d_interaction_and_ui_controls_in_augmented_reality

the appearance of the water level filling as the plant is watered. An example of this virtual display can be seen in Figure 10.10.

Since the user indicates their intent to water the plants by opening the application, information is displayed without lifting the watering can. The water needs are initially shown with the 3D model filled in the appropriate color. Using the environment scanned by ARKit, the distance to virtual objects is calculated, and the application detects when the user is coming closer to the plant. The user's orientation, determined by the smartphone, eliminates the need to generate proxemic data in this prototype artificially.

All plant information is processed on a single device rather than multiple devices. The only communication between participants is the warning message sent to the watering can and the notification from the watering can to the plants when watering occurs. The application calculates the plant closest to the smartphone and updates its water level accordingly. The minimum and maximum water levels, target, and blinking for confirmations and warnings are the same as in the LED prototype. Unlike the LED prototype, the overall status in the room is not displayed on the watering can using LEDs. Instead, a ring at the bottom of the smartphone display shows the corresponding color.

11. Evaluation

The overall goal of the (repeated measures) user study was to explore the user experience (UX) of the two systems. This way we wanted to ensure if the design process produced an interaction that is well perceived by the participants. In addition we tested whether using the system affects the well-being determinants of autonomy, competence, and motivation. We measured these additional factors because caring for plants is an important activity for many people, and we did not want to restrict too much with our design.

Figure 11.1: Screenshots of the user study. With a) showing a participant testing the LED system and b) showing a participant testing the AR system with the participants view of the AR through the smartphone display.

Participants and Apparatus 11.1

We recruited 24 participants (12 females, 12 males) aged between 17 and 59 ($M = 28$, $SD = 11$). All participants reported no color vision weakness and were familiar with mobile devices. The participants rated their skills and interest in houseplant care with a 7-point Likert scale (-3 $\widehat{=}$ beginner/unimportant, 3 $\widehat{=}$ professional/important) in average more than beginners ($M = -1,04$, $SD = 1,68$). However, they indicated an interest in plant care ($M = 0,38$, $SD = 1,58$). The study was conducted in a living room to provide an environment where users typically interact with houseplants (see Figure 11.1). For each run, three plants were placed in the room at a distance of $2\,\mathrm{m} - 3\,\mathrm{m}$ from each other. The watering can was placed on a table near the plants. The plants had different initial water levels (i.e., very low, low, sufficient) to show the user the existing conditions. For testing the AR system, an iPhone X was used to display the information in the AR condition.

11.1.1 Questionnaires

We chose the attrakDiff (Hassenzahl et al., 2003) questionnaire to evaluate the different systems considering UX. The questionnaire measures pragmatic quality (PQ), hedonic quality (HQ) resulting from a combination of hedonic quality stimulation (HQS) and hedonic quality identity (HQI), and overall attractiveness (ATT). HQS measures the perceived ability of a product to meet a person's desire for self-improvement, HQI measures the perceived ability of a product to communicate a valuable identity to others (Hassenzahl et al., 2003). The attrakDiff questionnaire is particularly suitable for our study as it focuses on hedonic qualities (with HQS, HQI, and ATT), which may play a more significant role in one's own home than, for example, in a work environment. In addition, participants were asked to self-assess how using the respective system would affect the three positive computing factors: motivation, competence, and autonomy on a 7-point Likert scale. Motivation and competence were chosen to explore whether users would be more motivated to care for their plants with the systems and improve their skills. An effect on these two factors was measured with the questions *"How do you think your motivation to water your plants would change with the use of the system"* and *"How do you think your ability to give your plants the right amount of water would change with the use of the system"* (strongly worsened, enormously improved). The question of autonomy was intended to check whether the system restricts users in their tasks. It was addressed with the question *"Who has control of the watering process?"* (the system, the user).

11.2 Procedure

We briefly described that the study aims to test two systems that help water houseplants. Before the participants tested the two systems one after another, they were asked to read a brief description of the system and the task they would perform. With the support of the system, the task was to water all three plants up to the required amount of water. After completing the task, they rated the system's attractiveness using the attrakDiff questionnaire. This process was repeated for the second system. Afterward, the participants answered questions about the positive computing factors. At the end, participants were asked which systems they preferred and had to give reasons for their preference. Each participant completed the study in about 30 minutes.

Results 11.3

First, the general trends in the “quantitative” data (collected with the questionnaires) are identified using graphical representations, and then statistical analyses are performed to test for significance. Afterward, we describe the results of the qualitative data analysis, aiming to provide reasons for specific results and observations.

General Trends 11.3.1

Figure 11.2 presents an overview of how each item of the attrakDiff was rated on average for both conditions. In most items, the LED system was rated better than the AR system. Especially with the items belonging to PQ, the LED system performs much better. The only exception where the AR system was rated better is the item “undemanding-challenging”, which is part of the HQS measurement. Figure 11.3 provides an overview of mean values for each of the independent variables measured by the attrakDiff questionnaire (i.e., PQ, HQI, HQS, ATT). As indicated, the biggest differences can be seen in the PQ, where the LED prototype performs much better. It also has better results in HQI and ATT. Only in HQS, both systems are rated almost equally. Figure 11.4 shows the mean values of the evaluation of the positive computing questions. Here, the trend continues that the LED system performs better.

Statistical Analysis 11.3.2

We conducted a paired-samples t-test to test the differences between the two systems (i.e., LED, AR) across the dependent variables measured by the attrakDiff questionnaire (i.e., PQ, HQI, HQS, ATT) and the three positive computing factors (i.e., motivation, competence, autonomy). The t-test showed a significant effect on the dependent variables measured with the attrakDiff on PQ $t(23) = 4.71$, $p < .001$ and ATT $t(23) = 3.51$, $p = .002$. No significant effects were found on HQI $t(23) = 1.83$, $p = .081$ and HQS $t(23) = -0.10$, $p = 0.924$. For the factors of positive computing, there was a significant effect on motivation $t(23) = 3.98$, $p < .001$. Competence $t(23) = 1.92$, $p = .067$ and autonomy $t(23) = 1.25$, $p = .224$ showed no significant effects. To further evaluate if the process to design interactions worked, we also compared all scales for both prototypes to the scale mean of 0. Besides autonomy, all scales were rated significantly higher than 0 for both prototypes. Details can be found in Table 11.1.

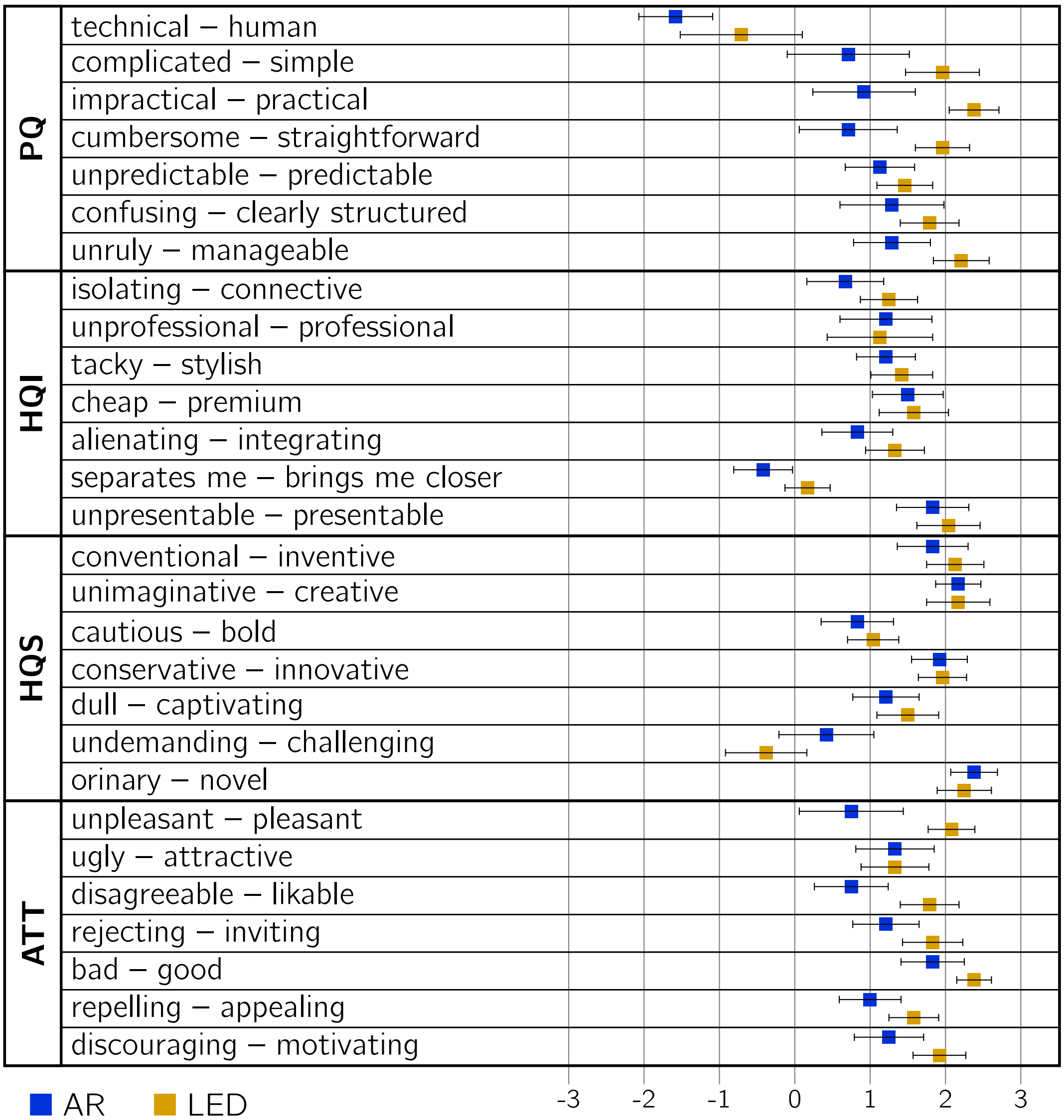


Figure 11.2: Overview of mean ratings for each item of the attrakDiff questionnaire. The items are sorted from left (negative) to right (positive). Error bars denote 95 % confidence intervals.

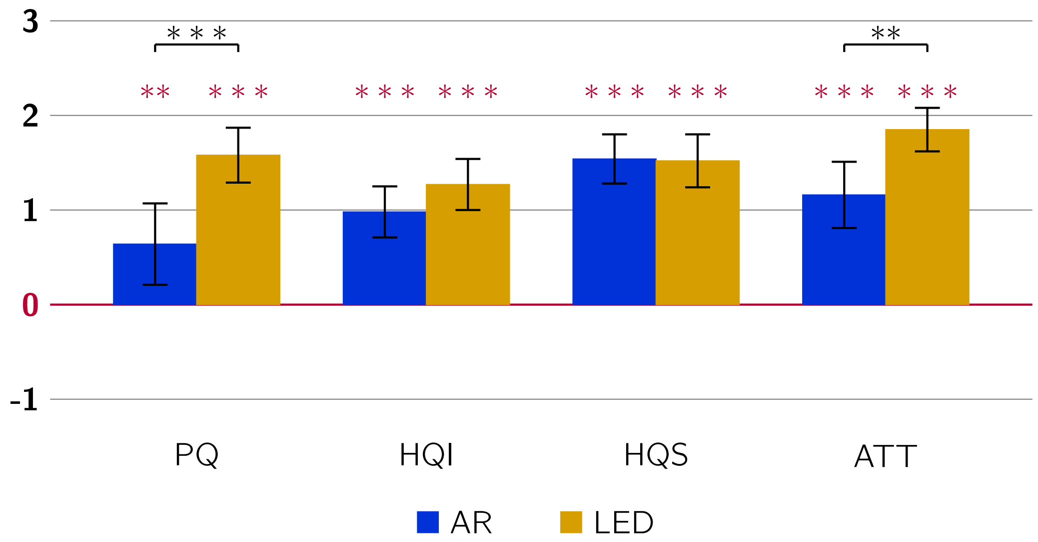


Figure 11.3: Overview of mean values for each condition and dependent variable measured by the attrakDiff questionnaire. Error bars denote 95 % confidence intervals. Scale ranges from -3 to 3. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$, *against scale mean of 0.

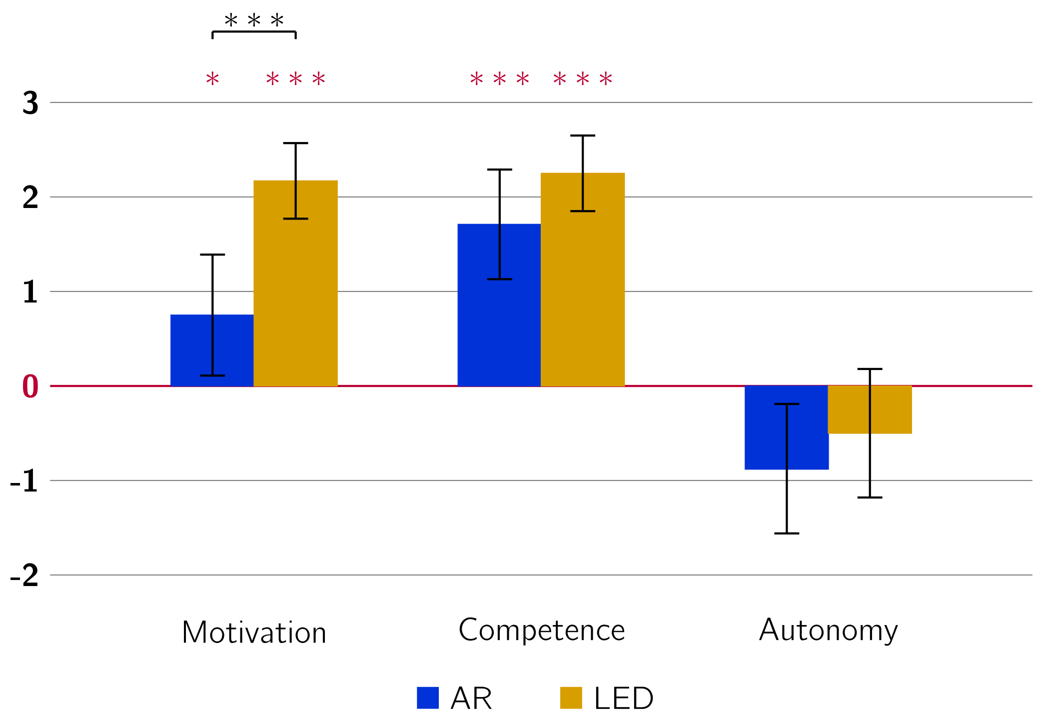


Figure 11.4: Overview of mean values for each of the three positive computing factors based on the participants' self-assessment. Error bars denote 95 % confidence intervals. Scale ranges from -3 to 3. $^{*}p < .05$, $^{**}p < .01$, $^{***}p < .001$, *against scale mean of 0.

Item	M	SD	$t(23)$	p
PQ_{AR}	0.64	1.09	2.87	$.004^{**}$
PQ_{LED}	1.58	0.72	10.80	$< .001^{***}$
HQI_{AR}	0.98	0.66	7.21	$< .001^{***}$
HQI_{LED}	1.27	0.68	9.24	$< .001^{***}$
HQS_{AR}	1.54	0.65	11.57	$< .001^{***}$
HQS_{LED}	1.52	0.70	10.69	$< .001^{***}$
ATT_{AR}	1.16	0.88	6.45	$< .001^{***}$
ATT_{LED}	1.85	0.58	15.45	$< .001^{***}$
$\text{Motivation}_{\text{AR}}$	0.75	1.59	2.30	$.015^{*}$
$\text{Motivation}_{\text{LED}}$	2.17	1.01	10.54	$< .001^{***}$
$\text{Competence}_{\text{AR}}$	1.71	1.46	5.74	$< .001^{***}$
$\text{Competence}_{\text{LED}}$	2.25	0.99	11.15	$< .001^{***}$
$\text{Autonomy}_{\text{AR}}$	−0.88	1.72	−2.48	.994
$\text{Autonomy}_{\text{LED}}$	−0.50	1.69	−1.45	.919

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, one-sample, right-tailed

Table 11.1: Statistical data of participants' ratings of the prototypes tested against the scale mean of 0.

11.3.3 Analysis of Qualitative Data

20 of the 24 participants (83 %) said they preferred the LED system. 17 of these 20 people perceived the AR system's smartphone as limiting, and participants stated that "it is impractical to hold a watering can and a smartphone". Further reasons were that "looking through the screen [of the smartphone] is unreal" and that the LED system is "less complicated", "more intuitive" and "easier to use". Participants who preferred the AR system justified their selection because it is "possible to use any flower pots" and "the display is visible from all sides". It was also mentioned that you could decide for yourself when you want to see the display and thus have the possibility to improve your abilities, for example, by using the display only for controlling and not during the complete watering process.

12. Conclusion

In this part, our goal was to fulfill the first research objective:

> **Establishing a Design Process for Proxemic Interactions**
> Establish a systematic design process for proxemic interactions, rooted in human-human proxemic behavior, to guide designers in creating proxemic human-computer interactions.
>
> 1

To achieve this, we proposed a design process derived from existing academic frameworks and applied this process to designing a supportive plant-watering system. We developed prototypes and conducted a user evaluation to assess whether the designed interactions effectively supported users in their tasks.

To begin with, we proposed a design process that integrates role-play techniques to translate human-human proxemic interactions into computer systems. By incorporating the IIF alongside the PIF, we ensured that proxemic interactions could be systematically transferred through the five dimensions defined by the PIF. This alignment allowed us to meet our initial goal of creating a systematic design process.

To validate the practicality of the process, we conducted an exemplary run by designing a plant-watering system and building two prototypes with different interaction modalities – one physical and one using AR. The user study showed that the system overall functioned well, with users benefiting from intuitive proxemic interactions that required minimal instruction. While both prototypes demonstrated effectiveness, differences in user ratings highlighted that implementation factors – such as the AR version's perceived UX – affected user satisfaction more than the interactions themselves.

User feedback after the study revealed minor issues, primarily relating to system autonomy. Initially, participants preferred a higher level of automated control, but some later felt this was excessive. Importantly, this feedback did not relate to the core proxemic interactions, indicating that minor adjustments to system control could improve UX without altering the proxemic interaction design.

In summary, the proposed process successfully supports the development of proxemic interactions within a proxemic-aware system. However, to fully understand this approach's broader applicability, further research is needed to confirm whether these findings scale to more complex systems that actively perform proxemic interactions rather than simply being proxemic-aware.

Comment by Prof. Bearingtons

Excellent work! I must say, you've laid out a *beary* impressive design process. I'll definitely be using this approach for my next proxemic-aware system – a smart honey dispenser that detects when I'm close and automatically warms up a fresh dollop of honey. Nothing beats a honey dispenser that respects my space... until I'm ready for a closer encounter with breakfast!

A Practical Guide to Sensors for Proxemic Systems

IV

13. Overview

In this second main part of the work, we address the following research objective:

> **Composing a Sensor Toolkit for Proxemics Detection**
> Compose a practical sensor toolkit for proxemics, providing designers and engineers with a consolidated resource to simplify sensor selection and advance the development of proxemic interactive systems.
> 2

We begin by examining the capabilities of technical systems to detect various proxemic dimensions. As defined by the PIF, these dimensions encompass identity, location, distance, orientation, and movement. The focus is to identify and categorize sensors that can reliably detect these dimensions, supporting the design of systems that leverage proxemic data for enhanced interaction.

First, we present a catalog of proxemic sensors in Chapter 14: *Sensors for Detecting Proxemics Dimensions*, offering an overview of options for detecting each dimension. Following this, we dive into the specific challenges of detecting orientation in Chapter 15: *A Deep Dive Into Orientation Detection*, as this particular dimension poses unique difficulties within the sensor list. Addressing these challenges helps refine the toolkit, ensuring designers can access practical solutions even for the more complex aspects of proxemic sensing.

This part concludes with a summary of the key findings in Chapter 16: *Conclusion*, synthesizing insights from the sensor catalog and orientation detection analysis. This final section is a comprehensive reference for designing systems that leverage proxemic detection capabilities.

14. Sensors for Detecting Proxemics Dimensions

This chapter presents a comprehensive list of sensors capable of detecting various proxemic dimensions, such as identity, location, distance, orientation, and movement & motion. Before introducing the sensor list, it is important to understand several key aspects, including how these sensors were identified, the specific definitions of the proxemic dimensions they address, the overall goal and purpose of the list, and its limitations. Additionally, we provide special considerations for camera sensors, as they are unique in their ability to detect a wide range of proxemic dimensions effectively. However, they often require an additional software stack to function correctly.

Once these foundational elements are explained, the chapter will present the sensor list itself, along with instructions on how to interpret the data. This will ensure that informed decisions can be made when selecting sensors for your specific proxemic applications.

14.1 Overview of Sensor List

This section provides an overview of the considerations relevant to the sensor list presented in Section 14.2. We will cover how the sensors were identified, the precise definitions of the proxemic dimensions, the overall goal of the list, its limitations, and specific information regarding the use of cameras in proxemic sensing.

14.1.1 Identification of Sensors

We compiled the sensor list presented in this work through a comprehensive literature review and targeted research. Relevant information was gathered from academic databases such as Google Scholar and IEEE Xplore, utilizing key search terms like "proximity sensors" and "embedded sensors". This process enabled the identification of sensors suitable for detecting various proxemic dimensions.

Sensors are classified into specific proxemic dimensions based on a combination of data sheet analysis, documented use cases, and their properties. We conducted additional research into existing projects and scholarly work to ensure their applicability in diverse contexts, which further informed the sensor selection and classification process.

Moreover, investigating commercially available products provided insight into the current state-of-the-art technologies. This industry research helped bridge the gap between academic findings and practical implementations, ensuring that the sensor list reflects experimental and real-world applications.

14.1.2 Definitions of Proxemic Dimensions

For a detailed description of the proxemic dimensions, refer to Section 4.2: *The Proxemic Dimensions*. However, additional considerations are necessary to fully understand the context in which these dimensions are used for sensor classification:

- **Distance:** This dimension refers to the physical space between an individual and the sensing system. In some cases, direct measurement of a person's distance may not be feasible, requiring the use of a proxy device carried by the individual. Distance can be represented through precise measurements or generalized zones, such as Hall's proxemic zones.
- **Orientation:** Refers to the direction in which an entity or object is facing relative to the sensing system.
- **Movement & Motion:** This dimension encompasses the detection and interpretation of changes in an entity's position, orientation, and motion, including the direction and velocity of movement over time.
- **Identity:** Identity refers to the unique characterization of entities within the space, enabling clear differentiation between them.
- **Location:** This dimension describes both qualitative and quantitative aspects of an entity's position within a space. Unlike distance, location refers more to the contextual and physical layout of the environment. Since this dimension is often implemented through software, it is theoretically relevant but not a primary focus in the sensor list.
- **Presence:** Although not an official PIF dimension, presence has been included in the list as some sensors detect the mere existence of an entity without measuring precise distance. In certain use cases, this information alone is sufficient. Any sensor capable of detecting distance can inherently detect presence as well.

The primary goal of this list is to provide a comprehensive resource for selecting sensors that support proxemic sensing capabilities in system development. The intended audience consists of developers working on computer systems that interact with or sense human proximity, particularly in embedded systems where computational resources may be limited. More advanced applications, such as robotics, camera-based sensing, and computer vision techniques, may offer higher-quality data (see Section 14.1.4: *Special Considerations for Camera Sensors*). However, these could be complemented by the sensors listed here.

The list is designed to assist developers in identifying appropriate sensors based on their specific proxemic sensing requirements. By providing a curated selection of sensors, the aim is to streamline the development process, reduce the time spent on sensor research, and enable developers to focus on system design and integration.

While the list is intended to serve as a starting point for proxemic-aware projects, the following section will address certain limitations.

Limitations of the List 14.1.3

As mentioned, this list primarily aims at embedded systems developers with limited computational resources. These systems are typically designed for applications such as smart home devices, which only require basic proxemic sensing capabilities. Therefore, the list may not be suitable for applications that demand high-precision or advanced proxemic sensing solutions.

Additionally, the list focuses on simpler systems, usually involving a small number of devices (e.g., one computer system interacting with one human, potentially using a proxy device). While the sensors listed are adequate for such setups, more complex systems – incorporating multiple devices, combining data from various sensors, and sharing information across devices – can achieve significantly enhanced sensing capabilities, which are not the primary focus of this list.

Lastly, the list assumes relatively common environmental conditions. Some sensors, such as cameras, require adequate lighting to function correctly, while others, such as ultrasonic or infrared sensors, may face limitations in certain conditions. These environmental factors should be considered when selecting sensors for specific applications.

14.1.4 Special Considerations for Camera Sensors

Cameras offer flexible, software-driven capabilities for detecting proxemic dimensions, eliminating the need for additional hardware to be carried by the target. While not traditionally considered embedded sensors, their effectiveness largely depends on the software implementation. Below are key considerations for using cameras to detect proxemic dimensions:

- **Presence:** Detecting the presence of a person, robot, or animal can be achieved through background subtraction. Simple implementations, such as those using OpenCV (Culjak et al., 2012) on a Raspberry Pi[1], are feasible.
- **Distance:** Stereo cameras can estimate distance by creating a 3D pixel cloud from pixel offsets between two images. However, this requires significant processing power, ideally performed on a graphics processing unit (GPU) (Nair et al., 2018).
- **Orientation:** Detecting orientation can be done using OpenPose (Cao et al., 2019), which utilizes a skeleton model and deep learning (de Paiva et al., 2020). A GPU is recommended for real-time processing, though a central processing unit (CPU) can be used for simpler cases.
- **Movement & Motion:** Stationary cameras can detect motion through background subtraction, while stereo cameras can calculate pixel offsets for moving objects (Kwon et al., 2005). Advanced setups like Kinect or Intel RealSense can enhance accuracy.
- **Identity:** Camera-based identification uses neural networks with confidence values, making results probabilistic[2]. While useful, this method lacks the reliability of explicit identification methods like Bluetooth or wireless fidelity (WiFi).
- **Location:** Determining location with cameras involves integrating environmental context via neural networks (e.g., convolutional neural networks (CNNs)), which requires significant computational power, typically performed on a GPU.

[1] https://pyimagesearch.com/2015/05/25/basic-motion-detection-and-tracking-with-python-and-opencv/

[2] Example implementation: https://github.com/samihormi/Multi-Camera-Person-Tracking-and-Re-Identification

Sensor List 14.2

In this section, we present the list of sensors. Each sensor entry in the list will include information on which proxemic dimensions it can detect, its capabilities, and any special considerations for its usage.

The Sensor List 14.2.1

In Table 14.1, we present the actual list of sensors, formatted as a table for easy reference. The list of sensor include Bluetooth / Bluetooth Low Energy (BLE), Camera, global navigation satellite systems (GNSS), Gyroscope, Infrared Sensor, light detection and ranging (LiDAR), Microphone, Photoelectric Sensor, Pressure Sensor, radio-frequency identification (RFID), time of flight (ToF) Sensor / Laser distance measurement, Ultrasonic Sensor, ultrawideband (UWB), and WiFi.

Name	Description	Dimensions	Comment	Example Applications
Bluetooth / BLE	A wireless technology that estimates proximity by measuring the signal strength of BLE transmissions. As the distance decreases, the signal strength increases, providing a relative measure of proximity.		• Bluetooth alone detects movement toward or away from the device. • Movement can be tracked using a BLE beacon with a gyroscope or multiple beacons.	• Corona-Warn-App (Meyer et al., 2021) • Beacon Technology: Provide local-specific information (Martins et al., 2020) • Indoor Positioning System (Spachos & Plataniotis, 2020)
Camera	Captures visual data to detect objects. When paired with depth-sensing, such as high-depth cameras, it provides accurate 3D spatial information for precise proximity measurements.		• A camera can capture all dimensions but requires significant software integration, detailed in the next section.	• Digital Art[3] • Proxemics Detection (Chakraborty et al., 2013)
GNSS	A satellite-based navigation system that includes multiple global networks like Global Positioning System (GPS) (USA) or Galileo (EU). It uses signals from several satellites to determine precise location data, providing accurate geolocation, including latitude, longitude, and altitude, across different regions worldwide.		• Only suitable for outdoor use. • Positioning is not fully accurate. • Distance is estimated via software. • Accuracy: up to 0.9 m, typically 3 m to 5 m. (Bajaj et al., 2002)	• Drone navigation (Patrik et al., 2019) • GNSS tracking system (Tavasci et al., 2024)
Gyroscope	Measures angular velocity and rotational movement. It offers real-time data on an object's orientation, detecting changes in movement around specific axes.		• Must be mounted directly on the object. • Only measures angular velocity; orientation and motion are determined by software.	• Motion recognition (Huang et al., 2023) • Wearable sensors for health, fitness and sports (Jalal et al., 2020)

Presence / Distance / Orientation / Movement & Motion / Identity / Location

Not Supported / Partially Supported / Supported

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[3] https://taunoerik.art/2022/09/04/artwork-that-knows-when-you-are-taking-a-picture-of-it/

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Name	Description	Dimensions	Comment	Example Applications
Infrared Sensor	Detects infrared radiation emitted or reflected by objects, measuring variations in infrared energy to identify proximity or temperature changes.		• Active sensors provide accurate distance measurement. • Infrared is used for non-continuous recognition; ToF sensors are better for continuous tracking.	• Power saving with presence detection (Nwoye et al., 2017) • Obstacle avoidance (Adarsh et al., 2016)
LiDAR	Emits laser pulses and calculates the time for the reflection to return, allowing precise distance measurement and the creation of detailed 3D maps.		• Orientation and motion require significant software implementation. • Combines object detection and tracking, e.g., Kalman filter algorithms[4]. • Location can be detected in real-time by software.	• Marker-less motion detection (Li et al., 2022) • Object tracking (Huang et al., 2017) • Visitor guidance (e.g., ski resort[5])
Microphone	Converts sound waves into electrical signals. These signals can be analyzed to detect sound intensity, direction, and frequency for acoustic sensing.		• Requires a quiet environment. • The object must emit audible sounds during movement. • Distance and motion can be detected with a microphone array, using signal processing algorithms.	• Hearing aid sound source localization (Van den Bogaert et al., 2011) • Security systems: use of microphone arrays for noise detection and event localization (Dostalek et al., 2009)
Photoelectric Sensor	Uses light to detect objects. It consists of an emitter and a receiver that detects changes in the light beam, providing reliable presence or absence detection.		• Simple and efficient, ideal for basic tasks due to its limitations.	• Object-on-surface detection (Chunjiao, 2013) • Elevator door control

Presence / Distance / Orientation / Movement & Motion / Identity / Location
Not Supported / Partially Supported / Supported

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[4] https://yagmurcigdemaktas.medium.com/3d-multi-object-tracking-using-lidar-for-autonomous-driving-9b988162d8a4
[5] https://www.blickfeld.com/de/blog/digitalisierung-skigebiet-mit-lidar/

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Name	Description	Dimensions	Comment	Example Applications
Pressure Sensor	Measures force applied to a surface by converting it into an electrical signal, useful for detecting physical pressure or weight variations.		• Distance is zero when the sensor is pressed. • A sensor array is required to detect motion. • Challenging to track movement with multiple individuals.	• Kinetic floor tiles for electric energy production that also process position data (Visconti et al., 2022) • A practical application scenario is to recognize people in discrete distance zones
RFID	Wireless technology that uses electromagnetic fields to identify and track RFID-tagged objects. The system communicates with tags to retrieve information from a distance.		• Signal strength can't be detected continuously. • Discrete distance zones detect objects within range. • Requires an attached RFID tag.	• Anti-theft system in store • Access control • Tracking object position (Surie et al., 2013)
ToF Sensor / Laser distance measurement	Measures distance by calculating the time laser pulses take to reflect off an object. It provides precise real-time distance measurements.		• Limited by walls. • Max range depends on brightness (e.g., 0.7 m to 4 m for VL53L1X (STMicroelectronics, 2024)). • Detects movement direction (toward/away). • Works in both stationary and dynamic settings.	• Robots measuring distance (Brancalião et al., 2023) • Indoor navigation (Niculescu et al., 2022)
Ultrasonic Sensor	Uses high-frequency sound waves to detect objects by measuring the time it takes for the sound to reflect back, offering accurate distance readings.		• Limited by walls. • Detects distances from around 0.02 m to 6 m • Senses movement direction (toward/away). • Suitable for stationary or dynamic settings, with distance readings every 20 ms.	• Obstacle avoidance (Adarsh et al., 2016) • Same as ToF sensor, but with less accuracy

Presence / Distance / Orientation / Movement & Motion / Identity / Location
Not Supported / Partially Supported / Supported

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Name	Description	Dimensions	Comment	Example Applications
UWB	Employs short radio-frequency pulses to measure distance and detect objects with high accuracy using time-of-flight calculations.		• Each communication partner requires a UWB tag. • Dual-UWB tags enable orientation recognition.	• Apple AirTag[6] • Indoor positioning system (Grasso et al., 2022) • Proxemic cross-device interactions (Li et al., 2023)
WiFi	Estimates proximity by measuring the signal strength of WiFi transmissions. As the object approaches, the signal becomes stronger, indicating closer proximity.		• Movement is detected by analyzing changes in WiFi signal strength. • Issues: high attenuation from water molecules and reflections in enclosed spaces.	• WiFi positioning system (Ismail et al., 2022)

Presence / Distance / Orientation / Movement & Motion / Identity / Location

Not Supported / Partially Supported / Supported

Table 14.1: List of sensors for detecting proxemic dimensions.

[6] https://www.apple.com/newsroom/2021/04/apple-introduces-airtag/

14.2.2 How to Read the Sensor List

The sensor list provides a practical reference for selecting appropriate sensors based on the specific proxemic dimensions relevant to a project. By examining the capabilities of different sensors, readers can find technologies that meet their requirements for detecting identity, distance, orientation, movement, presence, and location. In many cases, combining multiple sensors can overcome individual limitations, ensuring more accurate and comprehensive detection.

We present the following scenarios with real-world use cases where proxemic dimensions are crucial to illustrate how to use the sensor list. These examples demonstrate how to identify suitable sensors and, where necessary, combine them to enhance detection capabilities.

1. Scenario: Tracking movement and orientation of museum visitors
Goal: Track the movement and orientation of each visitor to determine which exhibit they are viewing.

Solution: Since visitors will likely carry a smartphone, UWB technology, available in many phones, can track their movement and location when combined with stationary UWB transceivers in the museum. Gyroscope data from the smartphone can detect orientation, assuming the visitor is looking at the screen and aligning their orientation with the phone.

2. Scenario: Automatic connection between tablet and whiteboard
Goal: Establish a connection between a user's tablet and a whiteboard as the user approaches.

Solution: This interaction requires detecting presence, distance, and identity. Bluetooth is a suitable technology, as it detects presence when a signal is received and determines identity through the device's unique identifier. Distance can be estimated based on signal strength, which is sufficient to distinguish between proximity zones.

3. Scenario: Adjusting zoom levels for a digital painting based on viewer distance
Goal: Control the zoom of a digital painting based on the viewer's proximity.

Solution: Presence, distance, and basic movement detection are needed. A combination of pressure sensors embedded in floor tiles and an ultrasonic sensor offers a simple but effective solution. The pressure sensors recognize discrete distance zones based on the viewer's position, while the ultrasonic sensor provides fine distance measurement when the viewer is close to the painting.

4. Scenario: A robot following a person while avoiding obstacles

Goal: Enable a robot to autonomously follow a person through a building and avoid collisions with objects.

Solution: The robot needs to detect distance and identity to follow the correct person and track its surroundings to avoid obstacles. While a camera could be used, a combination of UWB technology and a LiDAR sensor offers an alternative solution. UWB helps identify and track the person carrying a UWB responder, and LiDAR detects surrounding objects, allowing the robot to navigate even in low-light conditions.

This structured introduction and the scenario examples offer a straightforward way to guide users through the sensor list, helping them understand how to select and combine sensors for different proxemic sensing needs.

15. A Deep Dive Into Orientation Detection

Orientation is critical to proxemic interactions, influencing how devices understand and interact with users in spatial contexts. Detecting presence and distance in a space can be straightforward using various sensors, but orientation detection presents a more complex challenge. The precise identification of orientation – whether a person or object is facing a specific direction or has shifted – requires more nuanced sensor data and advanced processing techniques.

In this chapter, we will explore how different types of embedded sensors can be utilized to detect orientation effectively. From the list of sensors, we can see that the gyroscope, LiDAR, camera, and UWB offer the ability to detect orientation.

Gyroscopes are a natural candidate for orientation detection due to their ability to measure angular rotation. However, they have significant limitations: without prior knowledge of the device's initial orientation, the sensor's output can be incomplete or misleading. In contrast, more complex systems such as LiDAR depend on sophisticated software implementations, which make them less ideal for embedded systems and beyond the scope of our study.

Camera-based solutions also rely heavily on computational models, but advances in embedded machine learning have shown that simple models can effectively work even on resource-constrained devices. This makes cameras a viable option, and our experiments will show how well this works. UWB technology appears particularly promising. Its precise distance measurement capability opens the door for presence detection and robust orientation estimation, which we aim to validate through experiments. Finally, while Bluetooth can measure distance, it lacks the precision necessary for reliable orientation detection, and we will demonstrate why this is the case.

Throughout this chapter, we will systematically evaluate these technologies. Starting with Bluetooth, followed by UWB, and finally, camera-based solutions, we will assess each sensor's ability to detect orientation by detailing the experimental setups, discussing how orientation can or can not be detected, and presenting the results of our findings. Finally, we will conclude with a summary of the results.

15.1 Bluetooth / BLE

BLE, introduced in 2010, is a low-power wireless communication protocol widely available in modern devices such as smartphones and laptops. Due to its prevalence and minimal hardware requirements, BLE is an interesting option for distance estimation. However, one of its primary limitations is its susceptibility to environmental interference, particularly from metallic objects, walls, and water, including the human body (Afaneh, 2018).

To estimate distance with BLE, the received signal strength indicator (RSSI) is used. RSSI measures the signal strength between a BLE transmitter and receiver, where a stronger signal (higher RSSI) indicates closer proximity and a weaker signal (lower RSSI) suggests greater distance (Giovanelli & Farella, 2018).

A key challenge with RSSI-based estimation is the effect of environmental factors, which can distort signal strength and make it difficult to distinguish whether changes in RSSI are due to actual distance or obstructions. This sensitivity complicates reliable distance measurements, particularly in real-world settings.

In the next section, we will describe our experimental setup and analyze the results of BLE's performance in distance measurement.

15.1.1 Experimental Setup

The purpose of the BLE experiments is to demonstrate that BLE is not suitable for accurate orientation detection due to the limitations of RSSI-based measurements. These experiments are conducted in three different test setups, each simulating a common scenario encountered during orientation detection and addressing specific challenges. The setups are illustrated in Figure 15.2, $a) - c)$. The used BLE module can be seen in Figure 15.1.

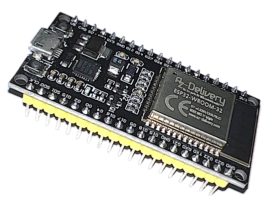


Figure 15.1: BLE module

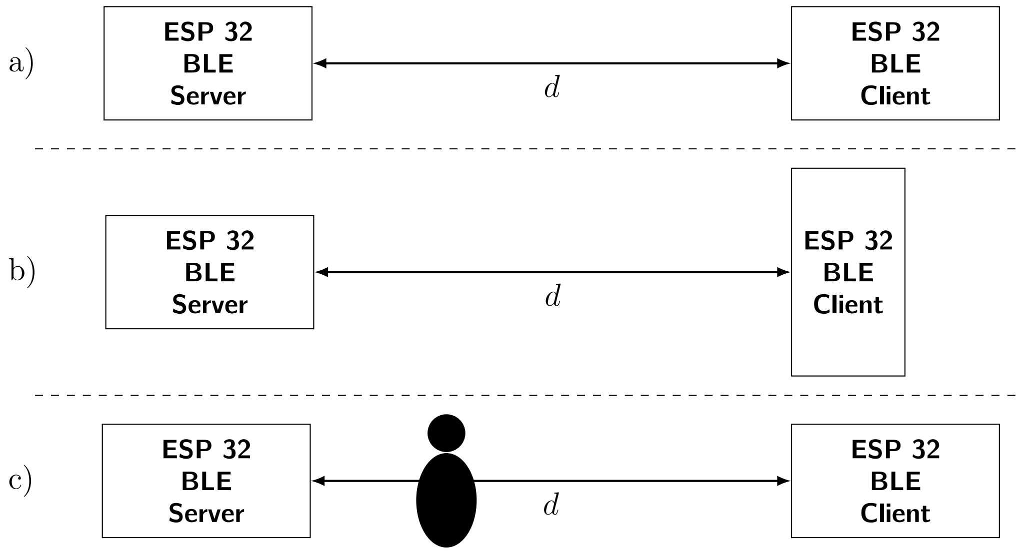


Figure 15.2: The three evaluated test setups for BLE: *a*) no obstacle, *b*) module rotated 90°, and *c*) human within the modules.

In the first setup (*a*), ideal conditions are represented, with a direct, unobstructed transmission path between the BLE modules. This setup is expected to produce the strongest and most stable signal readings.

The second setup (*b*) examines the impact of antenna direction by rotating the module 90 degrees while maintaining the same distance. In this scenario, the signal strength is anticipated to be comparable to or slightly weaker than that of the first setup.

The third setup (*c*) explores the effect of a human body as an obstacle. A person stands between the two BLE modules, introducing water into the transmission path, which is expected to degrade the signal strength significantly.

In these experiments, the distance d between the modules is measured in meters, and the received RSSI is recorded in decibels (dB). One BLE module runs the server code, while the other operates as the client, requesting signal strength measurements. The code is based on Arduino library examples provided by Neil Kolban[1].

Results 15.1.2

The RSSI values obtained from the experiments are summarized in Table 15.1, with each column corresponding to the test setups illustrated in Figure 15.2.

[1] https://github.com/nkolban/ESP32_BLE_Arduino/tree/master/examples

The experiments involved positioning the two BLE modules according to each setup and recording the RSSI values. The values shown in Table 15.1 represent the rounded average of five measurements. Fluctuations were typically within ± 3 dB, so the averages provide a reliable summary of the results.

Distance in m	*a*) RSSI in *dB*	*b*) RSSI in *dB*	*c*) RSSI in dB
0.1	−45	−49	−79
0.3	−49	−56	−90
0.5	−55	−61	−75
1.0	−69	−72	−79
1.5	−72	−76	−83
2.0	−78	−80	−92
4.0	−80	−82	−90

Table 15.1: BLE measured RSSI values with *a*) no obstacle, *b*) antenna rotated 90°, and *c*) human between transceivers.

As expected, the RSSI values worsen (more negative) with increasing distance and from setup *a* to setup *c*. While this suggests that RSSI can be used for basic distance measurement, closer inspection reveals inconsistencies. For example, it is not easy to differentiate between distances in setups *a* and *b*. Specifically, the RSSI value at 2.0 m with the module rotated by 90° (setup *b*) is nearly identical to the value at 4.0 m with the straight alignment (setup *a*), making precise distance estimation unreliable.

The logarithmic nature of the dB unit also limits its accuracy over longer distances. For instance, in setup *a*, the difference between 2.0 m and 4.0 m is only 2 dB, while the difference at shorter distances, such as 0.4 m (between 0.1 m and 0.5 m), is 10 dB. This lack of fine granularity at greater distances necessitates mapping RSSI values to broad intervals (e.g., $-79\,\mathrm{dB} \rightarrow [3.0, 5.0]$ m).

In setup *b*, we observe that antenna direction impacts signal strength more at shorter distances than anticipated. The difference between straight and rotated antennas diminishes at greater distances, partly due to the logarithmic scaling of dB values.

An anomaly appears in setup *c*, where signal strength improves unexpectedly despite the increasing distance. The behavior of radio waves can explain this: at certain distances, reflected signals become stronger than the direct ones. At shorter distances, such as 0.1 m and 0.3 m, the human body fully obstructs the signal. However, the obstacle becomes less significant beyond 0.5 m, allowing the signal to travel more easily.

In conclusion, the results confirm that BLE and RSSI are unsuitable for precise distance measurement and, therefore not viable for accurate orientation detection.

15.2 Ultrawideband

UWB is a wireless communication technology designed for short-range, high-precision applications. It transmits short-duration radio pulses across various frequencies, allowing for highly accurate distance and positioning measurements, efficient energy usage, and low power consumption. UWB technology can typically achieve distance measurement accuracy within the range of 2 cm to 50 cm and a communication range of up to 15 m to 50 m (Elsanhoury et al., 2022).

One key advantage of UWB, particularly relevant to this work, is its ability to measure distance with exceptional precision using just two modules – one for each entity. This accuracy is made possible through ToF-based ranging. The distance d between the modules is calculated using Equation (15.1), which depends on the round-trip time of the signal between the two devices:

$$d = \frac{t_{round_1} \cdot t_{round_2} - t_{delay_1} \cdot t_{delay_2}}{2 \cdot (t_{round_1} + t_{round_2})} \cdot c \tag{15.1}$$

ToF-based ranging involves measuring the time a signal travels from a transmitter to a receiver. The accuracy of this process requires synchronized clocks on both devices. Once the travel time is obtained, it is multiplied by the propagation speed of the signal in the given medium to calculate the exact distance between the two entities (Ravindra & Jagadeesha, 2014).

In addition to precise distance measurement, UWB can be used to calculate continuous orientation data. More UWB modules (tags) are required per entity. The relative positioning and orientation (RPO) technique enables relative orientation detection without a stationary anchor network. This method uses two UWB modules per object, and in the case of larger entities (such as shipping containers), it provides highly accurate results (Theussl et al., 2019). RPO is beneficial for measuring the relative orientation between objects, but it can also be adapted for absolute orientation measurements, which is a focus of this work.

15.2.1 Experimental Setup

The module used for the experiment is the ESP32-UWB v1.0 by Makerfabs[2], as shown in Figure 15.3. This module is based on the DWM3000 chip and includes an ESP32-WROVER-B, which offers 8 MB of external PSRAM, compared to the standard ESP32-WROOM (Espressif Systems, 2019).

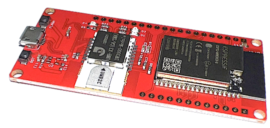


Figure 15.3: UWB module

In the UWB orientation detection setup, continuous angle measurement is achieved using four UWB modules: two anchors (a_1, a_2) and two tags (t_1, t_2). The tags are positioned equidistantly from the vertical axis of rotation, specifically attached to the left (t_1) and right (t_2) sides of the hips, with a distance of approximately $l_t = 35\,\text{cm}$ between them.

The stationary anchors are mounted at the same fixed height[3] as the tags. This setup defines the zone in which the orientation can be determined. The six measurable distances are illustrated in Figure 15.4: the distance between the anchors l_a, the distance between the tags l_t, and the distances from each anchor to each tag l_{at} with $a, t \in \{1, 2\}$. All modules must remain in the same horizontal plane to prevent significant measurement inaccuracies.

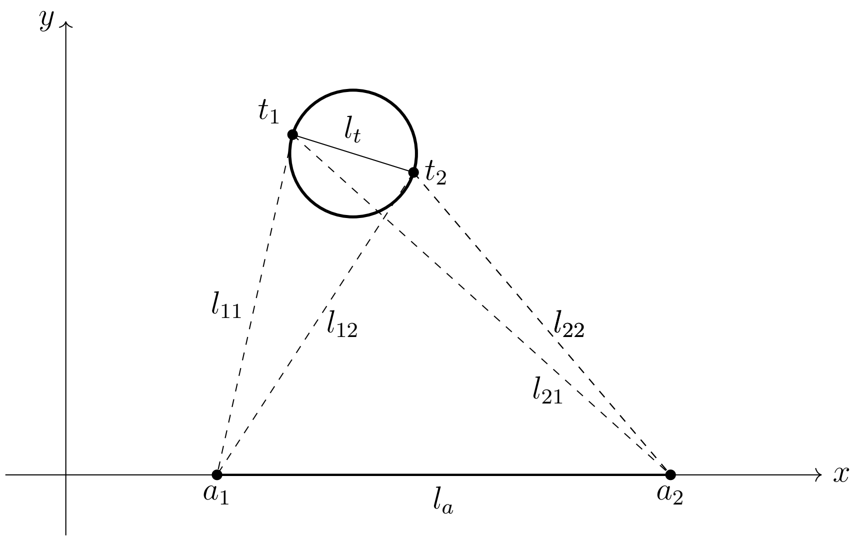


Figure 15.4: Schematic relationships between tags and anchors with the measured distances between them.

[2] https://www.makerfabs.com/esp32-uwb-ultra-wideband.html

[3] The height must remain constant throughout the experiment to avoid measurement inaccuracies. Height adjustments would require projection of the distances to the tag level using the Pythagorean theorem, which is beyond the scope of this experiment.

Once the distances shown in Figure 15.4 are obtained, the rotation angle (illustrated in Figure 15.6) is calculated using the following procedure:

1. Measure the Euclidean distances between the anchors l_a and the tags l_t. These distances remain constant until the system is restarted.[4]
2. Measure the distances l_{11}, l_{12}, l_{21}, and l_{22}.
3. Use l_{11} and l_{21} to calculate two possible intersection points for tag t_1 using the radii of two circles centered on the anchors.
4. Eliminate the intersection point with a negative y-coordinate, as it falls outside the valid area.
5. Repeat the previous steps for l_{12} and l_{22} to determine the position of tag t_2.
6. Identify the applicable case from Figure 15.5 and compute the orientation angle.
7. Repeat from Step 2.

For the calculation in Step 3, the Pythagorean theorem is used (Johansson & Wassénius, 2019):

$$t_1.x = \frac{l_{11}^2 - l_{21}^2 + l_a^2}{2l_a} \qquad \text{and} \qquad t_1.y = \pm\sqrt{|l_{11}^2 - (t_1.x)^2|} \tag{15.2}$$

The negative value for $t_1.y$ is discarded, simplifying the calculations and ensuring that only two anchors are required for accurate orientation detection.

In Step 6, the angle α is computed using the function F, which is based on basic trigonometry:

$$\alpha = F\left((f, \Delta, o), l_t\right) = f\left(\frac{\Delta}{l_t}\right) + o$$

The function F accepts a tuple (f, Δ, o) and the distance l_t as inputs, where $f \in \{sin^{-1}, cos^{-1}\}$ is a trigonometric function, Δ is a distance between points, and $o \in \{0, 90, 180, 270\}$ is an offset based on the case (A, B, C, or D) depicted in Figure 15.5. For cases A and B, the sin^{-1} function is used, while cos^{-1} is used for cases C and D:

[4] In these experiments, l_a and l_t are hardcoded rather than dynamically measured.

$$with\ (f, \Delta, o) = \begin{cases} (sin^{-1}, t_2.y - t_1.y,\ 0), & \text{if } t_1.x > t_2.x \land t_1.y \leq t_2.y\ (A) \\ (sin^{-1}, t_2.x - t_1.x,\ 90), & \text{if } t_1.x \leq t_2.x \land t_1.y < t_2.y\ (B) \\ (cos^{-1}, t_2.x - t_1.x,\ 180), & \text{if } t_1.x < t_2.x \land t_1.y \geq t_2.y\ (C) \\ (cos^{-1}, t_1.y - t_2.y,\ 270), & \text{if } t_1.x \geq t_2.x \land t_1.y > t_2.y\ (D) \end{cases}$$

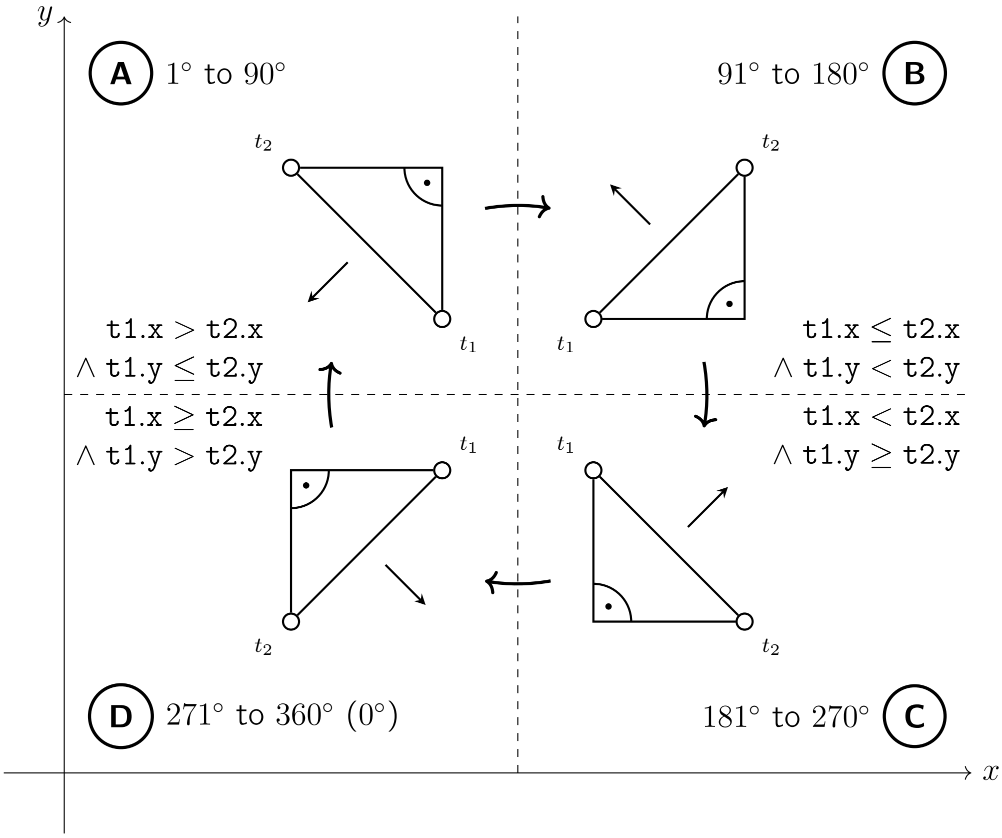


Figure 15.5: The four possible rotation cases detectable with two anchors.

Figure 15.6 illustrates the measurement of the angle α, with an example where a 45° angle is calculated relative to the reference axis r. The orientation is always measured in a clockwise direction.

In the experiment, the measured distances are transmitted to a computer via WiFi using the MQTT protocol[5]. A Python program running on the computer handles the orientation calculation. This external computer is used primarily for visualization purposes, though the calculations could alternatively be performed directly on the ESP32 module itself.

[5]https://randomnerdtutorials.com/esp32-mqtt-publish-subscribe-arduino-ide/

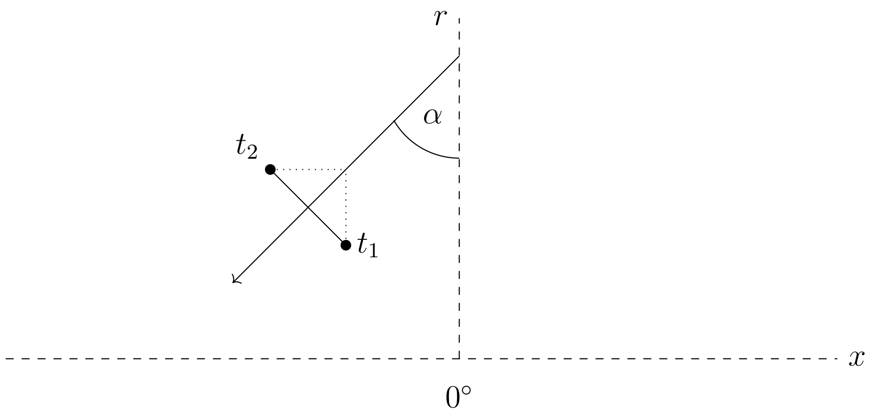


Figure 15.6: Illustration of the calculated orientation with the reference axis r and the rotation angle $\alpha = 45°$.

Results 15.2.2

For the UWB orientation measurement experiment, initial calibration of the tags and anchors was required. Each module needed custom calibration of the antenna delay, performed manually for the DW3000 modules used in this setup. Despite careful calibration, an error margin of approximately ± 5 cm was consistently observed, and this increased to as much as 30 cm when a human body was present between the tags (Johansson & Wassénius, 2019).

After calibration, the anchors were placed at fixed positions with a distance of $l_a = 3.00$ m between them and a height of 0.90 m. The tags, placed on the left and right sides of the hips with a separation of $l_t = 0.35$ m, were battery-powered. The test person stood about 1 m away from the anchors. Figure 15.7 shows the system's output as visualized on the computer, where the blue arrow represents the calculated facing direction, and the red dots mark the positions of the UWB modules. Anchor a_1 is set as the origin of the coordinate system, and the x-axis is defined by the line between a_1 and a_2.

Initially, the setup exhibited significant inaccuracies during the orientation detection. To address this, a distance smoothing filter was implemented. This filter maintains an array of the last n measurements and calculates their mean value to reduce noise. A history length of $n = 3$ was chosen, as it provided a good balance between responsiveness and accuracy. Using a larger value of n, such as 5, introduced noticeable delays during rotations.

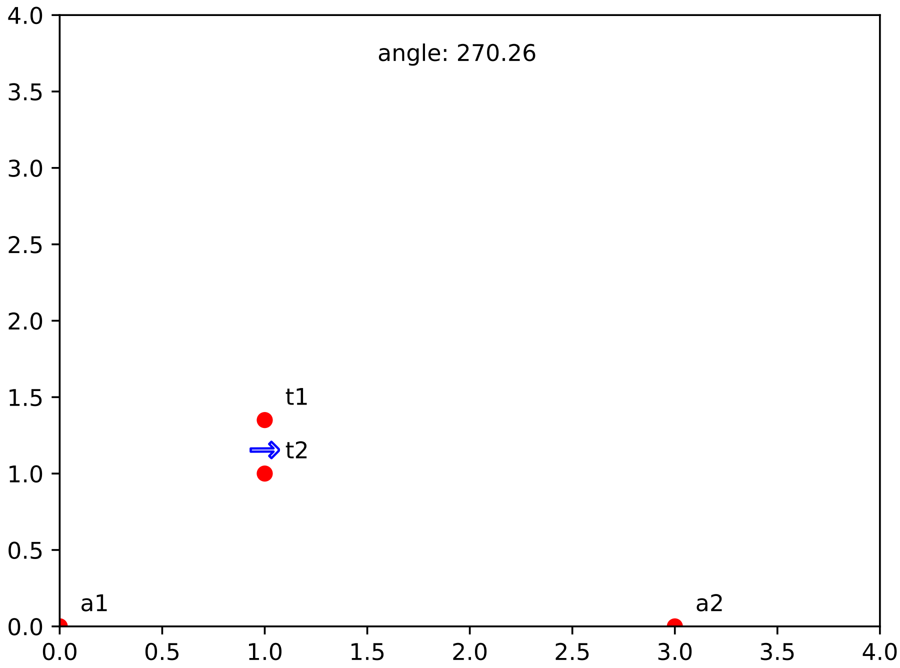


Figure 15.7: Plot of the UWB module positions with the anchors on the x-axis, the tags and the calculated orientation.

In the experiment, the x- and y-coordinates of the tags were successfully determined, with updates occurring approximately every fifteen to thirty seconds. Figure 15.8 displays two additional plots obtained during the test, showing different orientations.

To verify the accuracy of the measured orientation, the output was visually compared to the actual position of the test subject in the room. This validation was performed ten times with random orientations. Since an accuracy level within $\pm 10°$ was deemed acceptable for this test, precise reference measurements were unnecessary. The results showed that the calculated angles were correct when the subject remained within the zone between a_1 and a_2. However, areas outside this zone were not tested.

One notable challenge occurred when a person stood between the modules, which caused the system to overestimate the distances to the tag in the shadow of the signal. The process was slow and imprecise, while orientation information could still be determined. Further optimization of the UWB library and potential integration of additional modules could improve the speed and accuracy of future measurements.

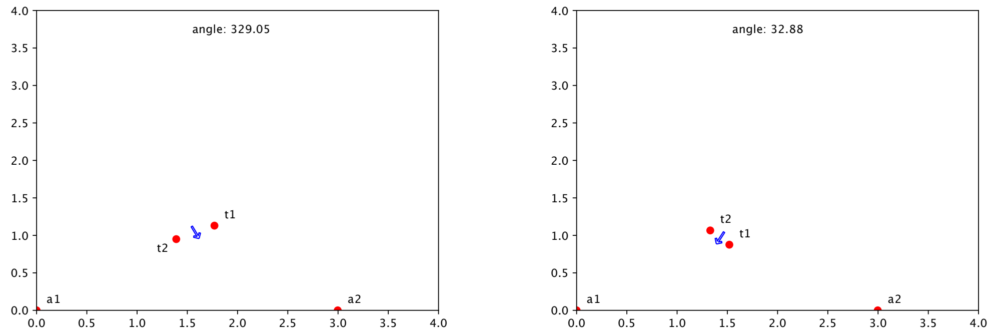


Figure 15.8: Two UWB test output plots with different orientations.

Camera 15.3

A camera is a versatile input device for orientation detection, but its use requires extensive software integration and imposes significant computational demands, especially when paired with machine learning algorithms. Given the focus on embedded orientation recognition, the challenge is to ensure that all necessary calculations can be performed on a small System on a Chip without relying on external hardware like a GPU.

For this purpose, an ESP32 camera module is used, which combines an ESP32 chip with a 2.4 GHz transceiver and an OV2640 camera. The ESP32 itself provides 520 kB of internal SRAM, 8 MB of external PSRAM, and operates at a clock frequency of up to 240 MHz (Espressif Systems, 2023).

The module can capture images with a resolution of up to two megapixels. These images are processed using a neural network, allowing orientation detection within an embedded system context. While this may initially seem beyond the scope of embedded sensors, it is achievable through using TinyML[6], a framework for deploying machine learning models on low-power devices. By downscaling images to a resolution of 96×96 pixels, the ESP32's computational resources are efficiently utilized, enabling classification tasks without exceeding the capabilities of embedded systems.

In this setup, the camera detects orientation relative to its viewpoint, classifying orientation into discrete categories. The concept of "front" is extended to include well-defined sides or orientations, as dictated by the structure and labels within the dataset used to train the neural network. The following sec-

[6]https://www.tinyml.org

tion provides a more detailed explanation of the machine-learning algorithm and the data sets employed.

15.3.1 Experimental Setup

The ESP32 camera setup for orientation detection is the only setup involving additional hardware, compared to the other independent sensor systems. The extra hardware is used to visualize the neural network's evaluation results, as shown in the wiring diagram in Figure 15.10. Power is supplied by an Arduino Uno, which also handles serial communication with a peripheral laptop. Communication with the ESP32 camera module is additionally possible through a web interface (see Figure 15.9 for a picture of the camera module).

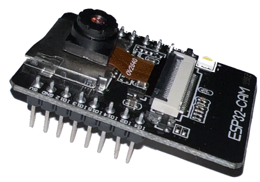


Figure 15.9: ESP32 camera module

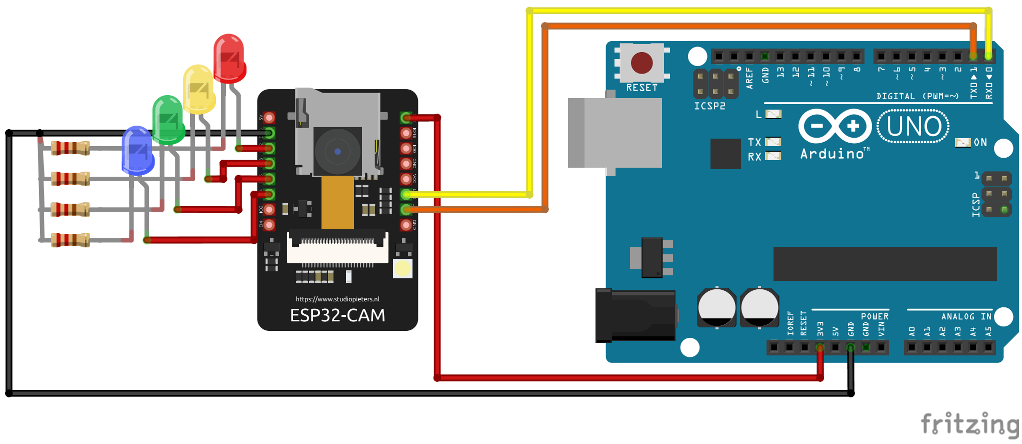
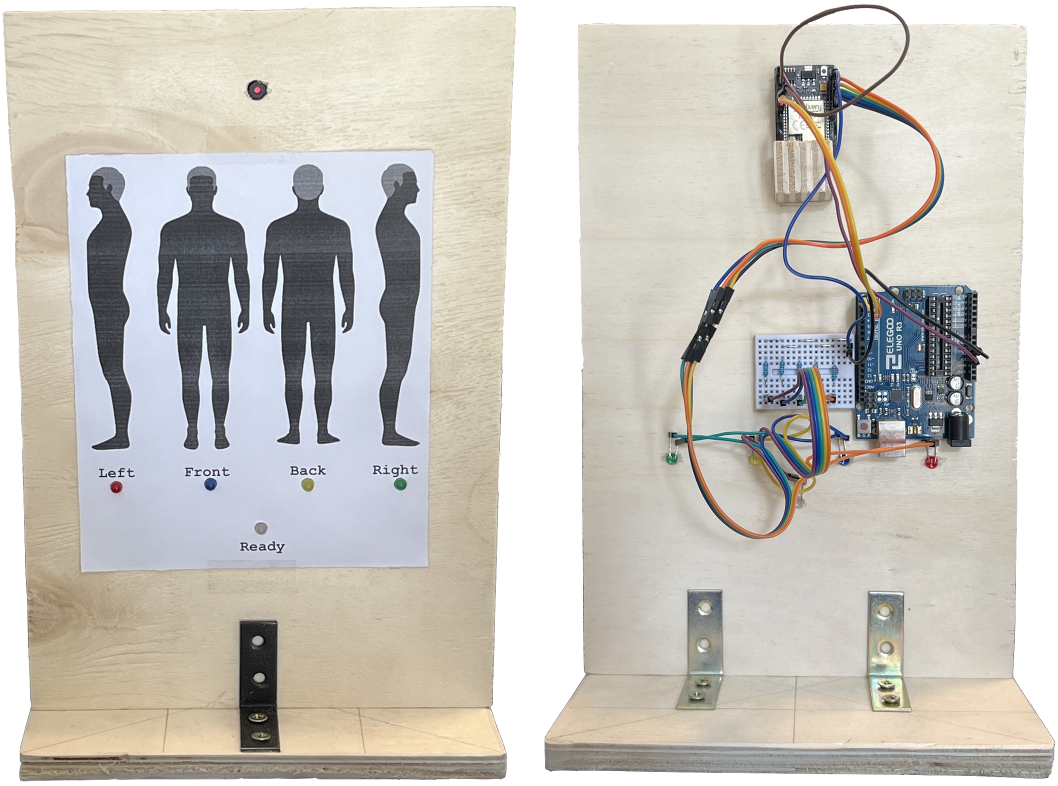


Figure 15.10: Wiring diagram for the camera orientation detection setup.

The camera is mounted on a stand and positioned at an average eye level of 1.57 m[7], with the test subject standing one meter away. The setup is equipped with LEDs that indicate the current classified orientation of the person standing in front of the camera (Figure 15.11a). Each LED color corresponds to a specific orientation class, and if no orientation is detected, all LEDs light up. The hardware setup is depicted in Figure 15.11.

A machine learning approach is used for orientation detection, leveraging TinyML to address the ESP32's limited computational power. The setup fol-

[7]DIN CEN ISO/TR 7250-2



(a) Front view of the setup. **(b)** Hardware (back) of the setup.

Figure 15.11: Camera orientation detection hardware setup.

lows an image classification guide[8], and the model training is performed in Edge Impulse Studio. Transfer learning is employed to reduce the size of the training dataset, with a pretrained MobileNetV2 model (Zhuang et al., 2021) serving as the base. This model features a 16-neuron dense layer and processes 96×96 grayscale images, significantly reducing the memory required.

The algorithm captures images via the ESP32 camera, crops and converts them to grayscale, and resizes them to 96×96 pixels to reduce the input feature size. These features are then passed through the neural network model for classification. Based on the output, hardware actions, such as lighting up the corresponding LED, are triggered.

The model is trained twice to assess the impact of dataset size and image variety. The first training set consists of 250 images per class (*front*, *back*, *right*, *left*, and a *junk* class), all taken of a single male subject (Figure 15.12 $a) - e)$). In the second approach, an additional 250 images per class were

[8] https://www.hackster.io/mjrobot/esp32-cam-tinyml-image-classification-fruits-vs-veggies-4ab970

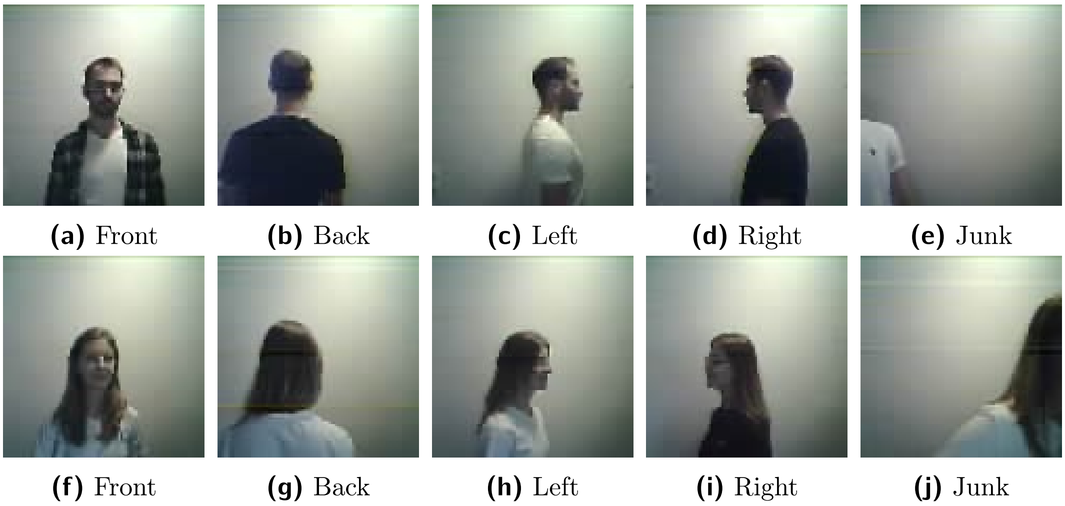


Figure 15.12: Sample images from the training dataset.

First training approach:

Output Class \ Target Class	junk	back	front	left	right
junk	46 98%	0 0%	2 5%	0 0%	2 4%
back	0 0%	50 100%	0 0%	0 0%	3 6%
front	1 2%	0 0%	40 93%	0 0%	0 0%
left	0 0%	0 0%	1 2%	50 98%	1 2%
right	0 0%	0 0%	0 0%	1 2%	42 88%

Second training approach:

Output Class \ Target Class	junk	back	front	left	right
junk	79 99%	1 1%	0 0%	0 0%	3 4%
back	0 0%	69 93%	1 1%	0 0%	6 8%
front	0 0%	0 0%	83 91%	0 0%	1 1%
left	1 1%	2 3%	5 5%	78 100%	14 18%
right	0 0%	2 3%	2 2%	0 0%	54 69%

Figure 15.13: Confusion matrices of the camera test setup models.

added, featuring a second female subject (Figure 15.12 $f) - j)$), to increase diversity and improve model performance.

15.3.2 Results

The initial setup aimed to verify the functionality of orientation detection using the ESP32 camera. The model was trained with a dataset of 1000 images and tested on a separate set of 250 images. The performance for 50 evaluation images per class is represented in the confusion matrix on the left in Figure 15.13, showing an overall accuracy of 95.53 %.

Despite the relatively small dataset, the results from the camera tests show strong performance in real-world scenarios, as illustrated in Figure 15.14. In a live test, separate from the confusion matrix results, the model was evaluated on its real-time performance with unseen individuals. The model correctly classified 21 out of 25 orientations for a previously unseen female subject, while for a male subject, it achieved 23 out of 25 correct classifications. The subjects stood in front of the camera and randomly changed positions while an observer documented the outcomes. Misclassifications occurred primarily in the right and left orientation classes, with four incorrect classifications. The best results were obtained when the subjects were in front of a neutral, monochromatic background, indicating that such conditions help the model perform optimally in distinguishing and classifying orientations.

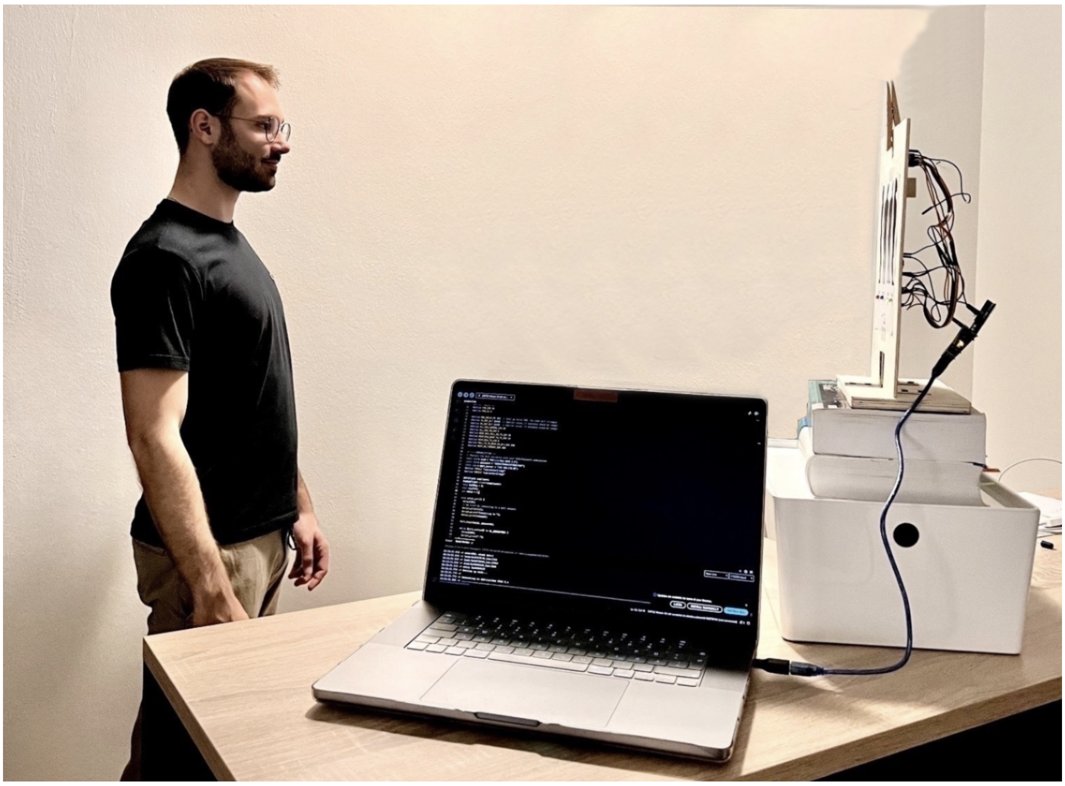
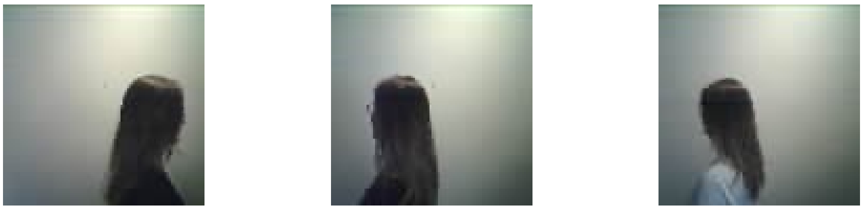


Figure 15.14: ESP32 camera during classification with a camera height of 1.57 m and a distance of approximately 1 m.

The training dataset size doubled in the second test phase, and improved performance was anticipated. However, the overall accuracy decreased to 90.50 %. The confusion matrix on the right side of Figure 15.13 shows that the model frequently misclassified images from the "facing-right" class as "facing-left". This issue is suspected to be due to the subject's hair obscuring parts of the face, making it harder for the model to differentiate between the two orientations, as illustrated in Figure 15.15.

In the live test of this second model, the accuracy decreased further. Out of 25 test orientations, the model correctly classified 19 for the female and 21 for the male subjects. These results suggest that increasing the dataset size alone does not necessarily enhance model performance and that the quality and clarity of the training images play a crucial role.



(a) Facing right. **(b)** Facing left. **(c)** Facing left.

Figure 15.15: Suspected difficulty in differentiating between orientations due to occlusion.

15.4 Summary

This chapter explored using different embedded sensor technologies – BLE, UWB, and camera-based systems – for orientation detection in embedded environments. Each technology was evaluated based on its capability to measure distance and determine orientation and its practicality for use in small, resource-constrained devices like the ESP32.

BLE was found to be insufficient for reliable orientation detection, primarily due to the imprecision of its RSSI-based distance measurements, which are highly susceptible to environmental factors such as obstacles and interference. This limitation makes it impractical for accurate orientation tracking in real-world scenarios.

In contrast, UWB provided far more precise distance measurements thanks to its Time of Flight (ToF) methodology, which allowed for a more accurate determination of relative orientation. However, the system still encountered limitations, including signal distortion, when objects, particularly humans, obstructed the path between the modules. While UWB shows promise for embedded orientation detection, issues with speed and accuracy, particularly in dynamic environments, suggest further optimization is needed.

Using an ESP32 camera module, the camera-based solution demonstrated strong potential for embedded orientation detection through machine learning. By leveraging TinyML and neural networks, the camera could accurately classify orientations in controlled conditions. However, challenges arose when scaling up the dataset or dealing with occlusions (such as hair or clothing), indicating the need for more refined datasets and potential improvements in model robustness.

In conclusion, while each technology has strengths, UWB and camera-based methods are the most viable options for orientation detection in embedded systems. BLE is unsuitable due to its inherent limitations, whereas UWB offers higher precision but requires further refinement. Though computationally demanding, the camera-based approach showed promising results, especially when used with machine learning techniques like TinyML.

16. Conclusion

In this part of the work, we aimed to fulfill the second research objective:

Composing a Sensor Toolkit for Proxemics Detection
Compose a practical sensor toolkit for proxemics, providing designers and engineers with a consolidated resource to simplify sensor selection and advance the development of proxemic interactive systems.

2

We first compiled a catalog of various sensor types capable of detecting proxemic dimensions to achieve this. Then, we explored the specific challenges and solutions for detecting orientation, a complex yet crucial dimension in proxemic detection.

To start, we provided a comprehensive list of 14 sensor types, ranging from basic sensors like ultrasonic sensors, which are straightforward and reliable for distance measurement, to more specialized sensors, such as microphones, which serve niche applications within proxemic sensing. This catalog offers developers a foundational resource that accelerates the process of building proxemic-aware systems, meeting the core goal outlined in our research objective.

However, we extended our efforts by addressing orientation detection – an incredibly challenging dimension due to the limited sensor options available. In the second half of this part, we demonstrated effective techniques for sensing orientation, utilizing an embedded camera paired with a lightweight machine-learning model capable of running on a microcontroller to classify a user's facing direction (e.g., towards, away, or side-to-side relative to the camera). Additionally, we showed how UWB chips can be employed to measure orientation angles continuously. While both methods revealed some limitations in our experiments, they nonetheless offer developers valuable tools for tackling orientation detection alongside the broader sensor toolkit.

In summary, this part successfully meets the objective by providing a versatile list of sensors for general proxemic detection and offering practical solutions for orientation detection. Together, these contributions simplify the process for others developing proxemic-aware systems, equipping them with a strong starting point and making the complex task of proxemic detection more approachable.

Comment by Prof. Bearingtons

Splendid work, absolutely top-notch! This sensor toolkit is just what I need for my upcoming project – a proxemic-aware berry dispenser that senses when I'm near and offers just the right mix of berries fresh from the forest. Orientation detection will be perfect too! It'll make sure it only dispenses when I'm facing it – no more accidental berry spills when I'm rummaging around for honey. It's truly groundbreaking stuff!

V Novel Approaches to Amplify Proxemic Interactions in HRI

17. Overview

In this third and final main part of the work, we address the remaining research objective, namely objective 3:

Explore Novel Approaches to Amplify HRI Proxemics
Expand the scope of proxemic interactions in HRI by integrating additional proxemic dimensions, such as orientation, and shift the focus from finding a 'good' interaction distance to human perception of the robot's proxemic behavior.

3

We conducted three studies exploring novel approaches to proxemic interactions in HRI to address the third research objective, moving beyond identifying a singular "good" distance. Instead, we focus on how a robot's use of various proxemic cues influences human perception and interaction quality. These studies integrate a HCI perspective by applying dimensions from PIF to the HRI context and focusing on how the human perceives and rates the proxemic interaction by the robot.

In the first study, presented in Chapter 18: *Proxemic-Aware vs. Non-Aware Robot*, we employed a virtual reality (VR) experiment to introduce the robot VIVA in a "robot in a new home" scenario. This study bridged knowledge from HCI to HRI by incorporating PIF dimensions into the design of the robot's behavior. Participants interacted with either a proxemic-aware robot that adapted its behavior based on their actions or a non-aware robot. This allowed us to explore how proxemic awareness affected user perception of the robot's social proxemic behavior.

The second study, described in Chapter 19: *Robot's Traversing Behavior*, involved a video-based experiment where participants observed a robot navigating a narrow corridor between two individuals. Instead of focusing solely on the distance, the robot altered other proxemic dimensions, such as speed (movement and motion) and orientation, to better fit the social context. This study examined how these alternative cues impacted participants' perceptions of the robot's behavior, highlighting the role of nuanced proxemic adjustments in enhancing interaction quality.

In the third study, outlined in Chapter 20: *Robot's Reaction To Emotions*, we explored the role of dynamic distance adjustments in response to human emotional expressions. This video-based experiment tested how a robot that changes its distance based on a person's emotional state influenced user perception. By shifting focus from an "optimal" static distance to dynamic, context-sensitive adjustments, we investigated the potential of proxemic variations to communicate meaning and enrich the interaction.

The findings from these studies are summarized in Chapter 21: *Conclusion*, where we discuss how incorporating a broader range of proxemic cues and focusing on user's perception can enhance HRI. These insights pave the way for future research on proxemics in HRI, emphasizing the importance of flexibility and contextual sensitivity in designing robot behaviors.

The studies described in this part are based on the research and findings published in the following three papers:

- **Petrak, B.**, Weitz, K., Aslan, I., & Andre, E. (2019). Let Me Show You Your New Home: Studying the Effect of Proxemic-awareness of Robots on Users' First Impressions. *2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, 1–7. https://doi.org/10.1109/RO-MAN46459.2019.8956463
- **Petrak, B.**, Sopper, G., Weitz, K., & André, E. (2021). Do You Mind if I Pass Through? Studying the Appropriate Robot Behavior when Traversing two Conversing People in a Hallway Setting. *2021 30th IEEE International Conference on Robot & Human Interactive Communication (RO-MAN)*, 369–375. https://doi.org/10.1109/RO-MAN50785.2021.9515430
- **Petrak, B.**, Stapels, J. G., Weitz, K., Eyssel, F., & André, E. (2021). To Move or Not to Move? Social Acceptability of Robot Proxemics Behavior Depending on User Emotion. *2021 30th IEEE International Conference on Robot & Human Interactive Communication (RO-MAN)*, 975–982. https://doi.org/10.1109/RO-MAN50785.2021.9515502

18. Comparative Study of Proxemic-Aware and Non-Aware Robots in Domestic Settings

Introduction 18.1

The field of personal service robotics, in particular, is seen as having growth potential for the future (Bartneck & Forlizzi, 2004). Here, robots can enrich people's lives by providing physical support (e.g., as support for housework) or address psychological aspects (attention & caring, support for social behavior, coaching) (Bartneck & Forlizzi, 2004). A robot can cover varying levels of complexity with these tasks. The spectrum ranges from very mechanical and seemingly not very lively machines that perform a specific task (e.g., vacuum cleaner robots) to robots that are perceived as living entities. With these living entities, the scope of action covers simple, non-verbal, and intuitive ways of acting, as one would ascribe them to pets. However, also very complex robots, which express themselves through language and appear at least human-like, can be in focus (e.g., Sophia[1]). In order to be able to use social robots for tasks in the private environment, technically challenging requirements such as cognition (planning and decision making), perception (navigation and environment sensing), and action (e.g., mobility & manipulation) (Fong et al., 2003) have to be solved. In addition to these technical challenges, human trust in the robot must also be included in the design of these systems. The first contact between humans and robots is a unique situation in which technical aspects must prove themselves. This first contact is also important in the trust-based relationship between robots and human beings. After purchasing a new social robot and unpacking it at your home, the robot is in an unknown location in an unknown environment. Therefore, one of the robot's first tasks will be to discover its environment and create a map of it so that it can navigate autonomously around your home (Dissanayake et al., 2001). This work is about the consideration of this first contact. The focus is on the technical implementation of the perception aspect, especially the navigation aspect. In the following study, we compared participants' evaluation of two different behav-

[1]https://www.hansonrobotics.com/sophia/

iors of robots in virtual reality (VR) as a prototyping method while exploring an unknown room. One robot's behavior is proxemic-aware (i.e., looking after the user during the exploration) while the other robot is exploring the room independently as a baseline condition. The two robots are kept simple and pet-like in their behavior and communication skills.

We argue that the proxemic-aware behavior of the robot results in people perceiving the robot to be more anthropomorphic (H1a) as it copies the natural spatial behavior of humans and leads to higher ratings in animacy (H1b). In addition, we expect that the robot's behavior increases likability (H1c) and that the robot is perceived as more intelligent (H1d). Furthermore, we address the aspect of human-robot trust in this situation. We expect participants to have more trust in a robot (H2a) when it explores the room with the user, and users will be more interested in interacting again (H2b) with the robot in the future.

Before we describe the VR setting and the user study and present all results in detail, we provide a brief background of proxemic interactions and trust in a human-robot relationship.

18.2 Background and Related Work

An introduction to the proxemics theory by Hall can be found in Chapter 2: *Hall's Proxemics*. This study also makes use of the concept of f-formations, which is described in Chapter 3: *F-Formations* and uses the PIF, which is described in Section 4.1: *The Proxemic Interactions Framework*. A general overview of related work for proxemics in HRI can be found in Chapter 5: *Proxemics in Human-Robot Interaction*. This section briefly overviews the most relevant work for this study.

18.2.1 Proxemics

Researchers have adopted a reactive and proxemic interaction design approach in diverse fields and explored, for example, proximity-sensitive actuated and shape-changing mobile phones (e.g., Hemmert et al., 2013; Pedersen et al., 2014) and proxemic touch screen targets (e.g., Aslan and André, 2017; Aslan et al., 2015, 2018). Common to the aforementioned examples is that the research did not focus specifically on anthropomorphism but still reported that proxemic behavior resulted in users referring to interfaces and interface elements as if they were living organisms and animals with agency and a consequent increase in perceived hedonic qualities (e.g., fun). While stationary computer systems, e.g., in smart homes, are only able to react to the proxemic behavior of users (e.g., **Bittner** et al., 2019), virtual agents can at least use their body orientation and gaze behavior (e.g., Peters et al., 2010) to show proxemic behavior. Bee et al. (2009) used only the orientation dimension utilizing gaze in a “first impression scenario” to get into interaction with a human. However, mobile robots are enabled to use this one dimension and move in a room by themselves. They can, therefore, not only react to the proxemic behavior of humans, but they can also show active spatial behavior in multiple dimensions and thus enable a broader range of interaction possibilities. In a recent work Li et al. (2019), the authors have taken inspiration from improv theater and studied how a non-anthropomorphic robot can use locomotion only for social expression (i.e., dominance). In sum, related work strongly indicates that a mobile companion robot, which acts in a proxemic-aware manner, will result in users perceiving them as more alive, experience more hedonic qualities, and ultimately, the robot will leave a better first impression than a version that is mobile and autonomous but not proxemic.

Social Interaction & Trust 18.2.2

Trust is a fundamental basis for developing socially interactive robots in the private environment (e.g., Gaudiello et al., 2016; Salem et al., 2015). When talking about (social-) interaction in robotics, it has to be differentiated between two kinds of interactions: robots as collective interactors (Beckers et al., 1994; Deneubourg et al., 1991) or as individual interactors (Dautenhahn & Billard, 1999). Collective interactors describe societies characterized by anonymous, homogeneous groups (Fong et al., 2003). Dautenhahn and Billard (1999) defined social robots as individual interactors who are part of a heterogeneous group and are perceived as individuals. To model and develop social robots, social learning and imitation, gesture and natural language communication, emotion, and recognition of the interacting partners have to be considered (Fong et al., 2003). Coeckelbergh (2012) points out that the robot’s appearance influences people’s trust. It has been shown that people tend to interpret active body movements as a sign of sympathy for others (Maxwell et al., 1985). Therefore, the robot’s perception as trustworthy is influenced by its movement behaviour (MacArthur et al., 2017). For example, investigating the proxemic behavior of robots in the household environment in the work of Walters et al. (2011) showed that proxemics could influence the user’s trust. Likewise, people’s trust in the robot impacts how they evaluate its proxemic behavior (Honig et al., 2018). The perception of the movement behavior of the robot is part of an affective component that is involved in evaluating the robot as trusting. This corresponds to the definition of Lewis and Weigert (1985), which divides trust into cognitive and affective aspects. In human-robot trust, cognitive trust can be seen as a person's mental attributes, reasons, and arguments towards an agent. In contrast, affective trust describes a person's feeling towards an agent (Castelfranchi & Falcone, 2010).

18.3 Virtual Reality Prototype/Environment

To test our hypotheses, we created a virtual setting in which to conduct a user study. In the following, we describe the environment (i.e., the room) in which the user is placed and the robots the user interacts with.

18.3.1 Room

When users put on the VR headset, they are in a room that looks like a living room. The room measures approx. $2.5\,\mathrm{m} * 5.5\,\mathrm{m}$ and users can move around freely, as the dimensions correspond to the room in which the user physically is. The virtual room is filled with some furniture (e.g., tables, shelves) and several objects (e.g., TV, flowers) as shown in Figure 18.1. So that both the robot and the user can move quickly in the room, we have positioned the interior only at the sides of the room.

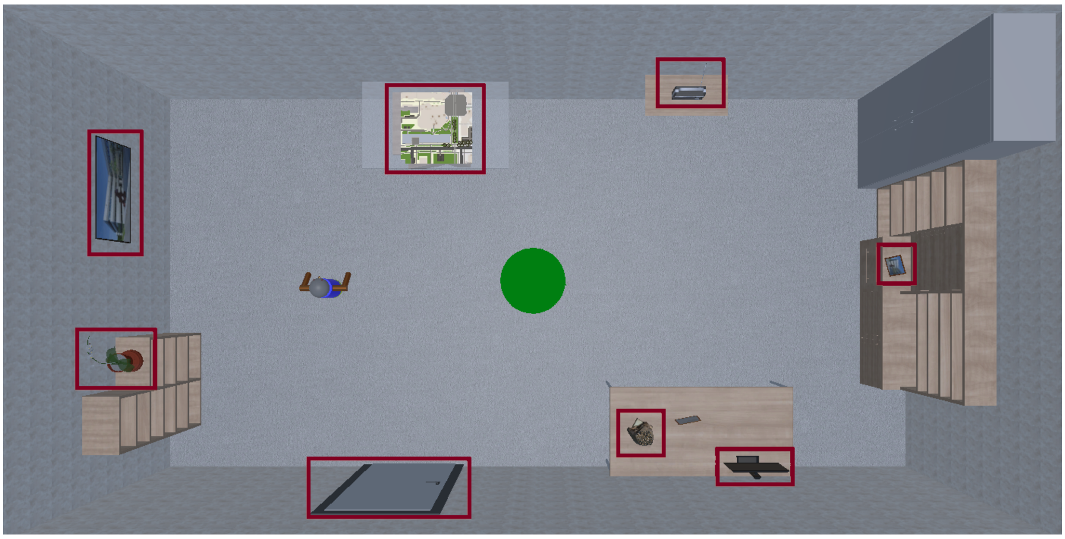


Figure 18.1: Top view of the room in which the interaction with the robot takes place. The green dot shows the user's entry point. The red outline highlights intractable objects, clockwise from the bottom left: flower, TV, map, radio, picture, monitor, statue, door.

Robots 18.3.2

Together with the user, one of two robots is in the room. Both robots have the same design but differ in their behavior. The robots have a simple structure and consist of a torso, a head with eyes and nose, and arms. The primary purpose of the arms is to help the user see in which direction the robot is oriented. The robots are about 1 m tall and "glide" over the floor as if they were moving on wheels, similar to the robot Pepper[2]. We decided to keep the robots simple so that the users always know where the robot is looking and in which direction its body is oriented, and we gave him a smaller height to give him a pet/companion look.

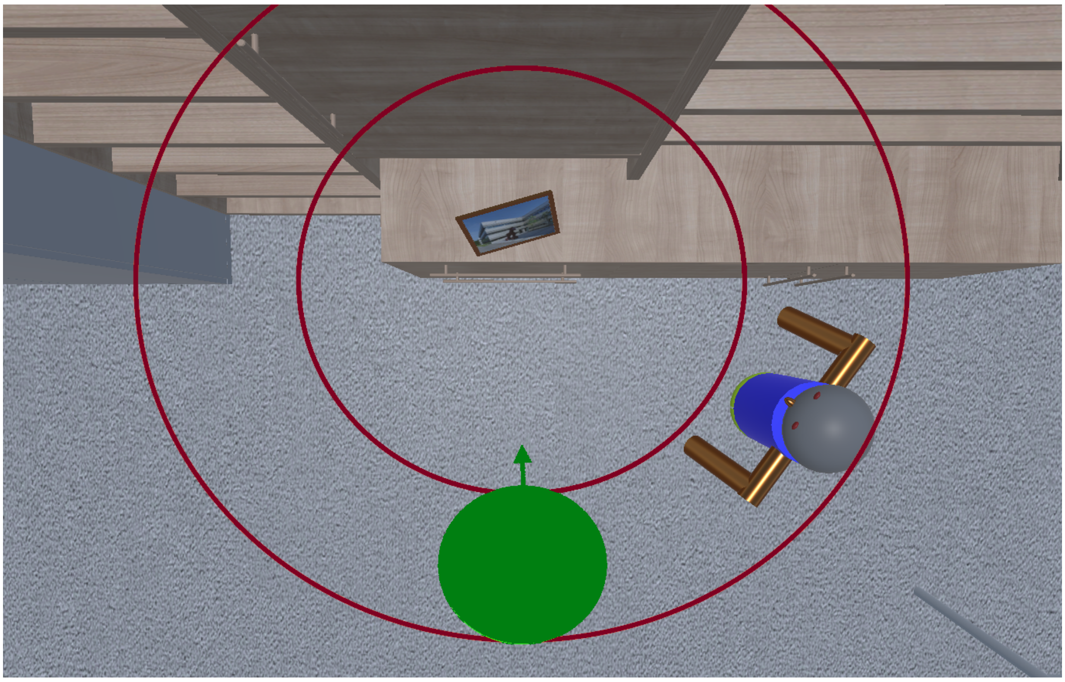


Figure 18.2: The robot's positioning in the f-formation while the user looks at an object in the room. The object (i.e., the picture) is in the o-space (inner red circle), while the person (green circle) and robot are in the p-space (between the two red circles).

The behavior of the two robots is guided by the goal of exploring the objects in the room. The proxemic-aware robot tries to explore the objects together with the user, while the other robot explores the room autonomously. The behavior has been defined using the PIF (Marquardt & Greenberg, 2015). We manipulate the spatial behavior of the robots in the proxemic dimensions, such as location (i.e., where in the room the robot is positioned) and orientation (i.e., body and head orientation).

[2]https://www.softbankrobotics.com/emea/en/pepper

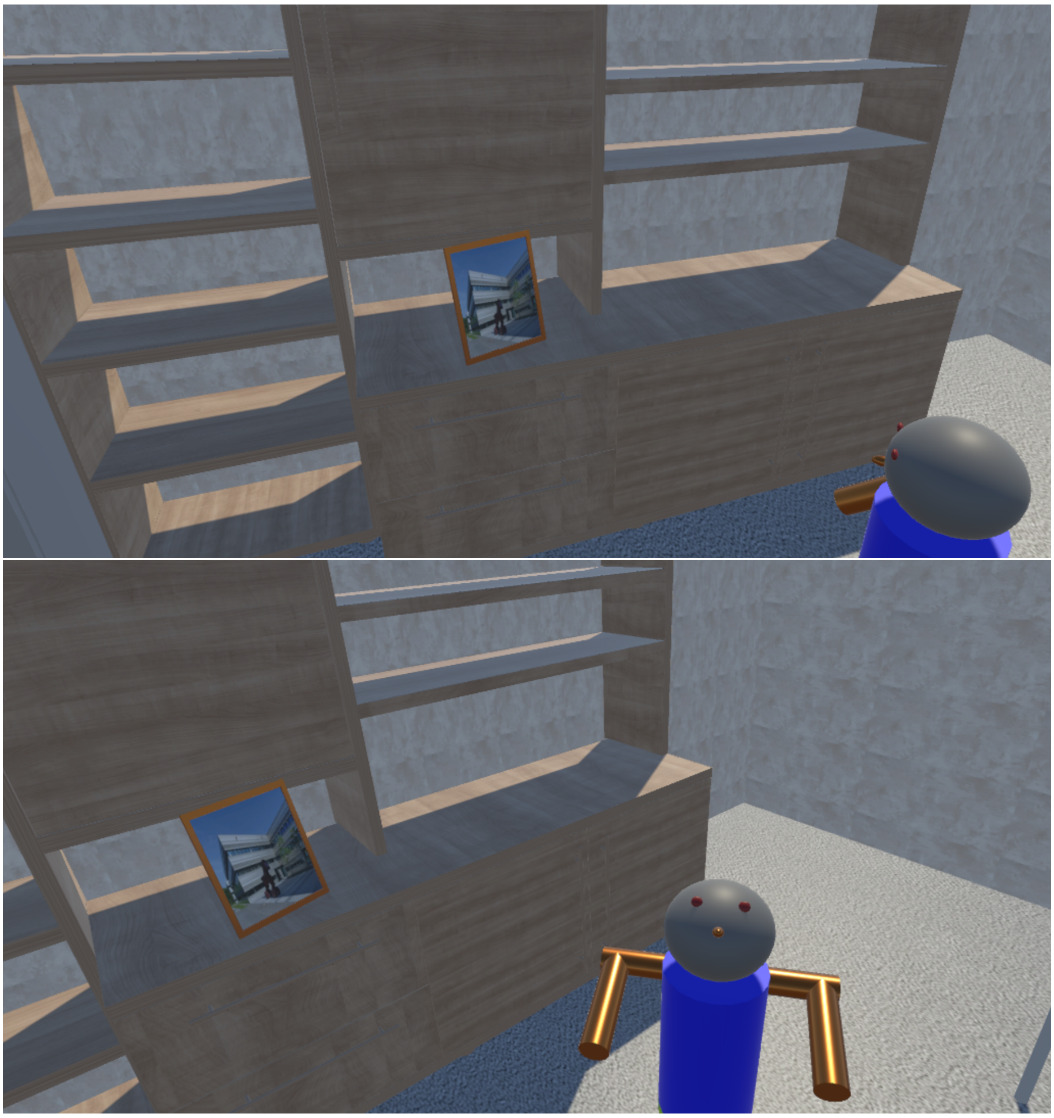


Figure 18.3: Robot orientation behavior. Top: When the user looks at an object. Bottom: When the user looks at the robot.

When the user approaches and orientates towards an object, the robot positions itself in an "corner-to-corner" f-formation together with the user in the p-space, while the object is in the o-space so that they look at the object together (see Figure 18.2). Depending on where there is more space, the robot can position itself to the right or left of the user. When the user faces the robot, the robot faces the user and looks at him. The robot adjusts its body orientation and head direction to look at the object or the user's eyes (i.e., in the direction of the camera). Figure 18.3 shows the robot's orientation behavior from the user's point of view when looking at an object or the robot. As soon as the user moves on to the next object, the robot follows and repositions itself according to the same rule for the new object.

The behavior of the autonomous robot is defined as randomly selecting an object in the room, approaching it, and orientating itself toward the object. The robot then looks at the object for a few seconds before randomly selecting a new one. The robot 'ignores' the user completely.

Study 18.4

Design and Participants 18.4.1

A total of 16 participants took part in the within-subjects study, most of them without any experience interacting with robots. Half of the participants were female, the other half male and the majority were between 20 and 30 years old.

Procedure 18.4.2

The participants were mainly German students recruited at a university. We told the participants that the study is about interaction with two robots that have different ways of interaction. They were tasked with looking around the room and searching for objects (e.g., pictures and statues) so that the robot could learn where the objects were.

Initially, the participants read the instructions and then explored the room with both robots in a counterbalanced order in the virtual environment. We helped the participants correctly put the VR headset (HTC Vive Pro[3]) on so the image was clearly visible and the headset comfortably fitted. When the participants put the headset on correctly, they explored the room, with each run taking about four to six minutes. We let the participants interact with the robot as long as they wanted. After taking the headset off again, they rated the robot (see Section 18.4.3: *Dependent Measures*) and then repeated the procedure with the other robot. Once they interacted with both robots and finished the rating, they selected which robot they preferred to interact with and gave reasons for their choice.

Dependent Measures 18.4.3

The German version of the Godspeed questionnaire series (Bartneck et al., 2009) was used to evaluate the impact of the two robots on the user. This questionnaire is a validated tool for measuring HRI. It comprises five core con-

[3] https://www.vive.com/us/product/vive-pro/

cepts of HRI: anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety that are queried using different semantic differentials. Participants must evaluate each semantic differential on a scale from 1 to 5 (e.g., for the concept of animacy: dead vs. alive). Due to the research questions described in Section 18.1: *Introduction*, only four of the five concepts queried in the Godspeed questionnaire series were used for the evaluation. The evaluation of perceived safety was not part of the research questions and, therefore, was not included in the evaluation, as our study was conducted in a VR environment. Given the inherent differences between VR simulations and real-world interactions with physical robots, we determined that perceived safety in a VR setting is not directly comparable to a real robot experiment. Consequently, it was not considered within the scope of our research questions.

To get an impression of the two robots' effects, the participants were also asked how trustworthy they considered the respective robot to be and whether they would interact with it again. These two questions were asked using a 5-point Likert scale (-2=disagree, 2=fully agree).

To gain even more information about what played a role in the participants' evaluation of the robot, open questions were also asked about what the participants found to be particularly good and particularly bad about the respective robot. At the end of the study, the participants also had to re-evaluate which robot they preferred and justify their answers.

18.5 Results

First, we analyzed the general trends in the quantitative data collected with the Godspeed questionnaire series and the two items evaluating the robot's trustworthiness and desire for re-interaction. Afterward, we describe the results of the qualitative data (open questions) analysis, aiming to provide reasons for specific results and observations.

18.5.1 General Trends

Figure 18.4 and Figure 18.5 graphically present the mean values of the dependent variables measured. When looking at the plots, it is noticeable that the proxemic-aware robot is rated higher in all areas than the autonomous robot. Furthermore, all ratings of the proxemic-aware robot are in the positive range of the scale $(0-2)$, while all ratings of the other robot are in the negative range

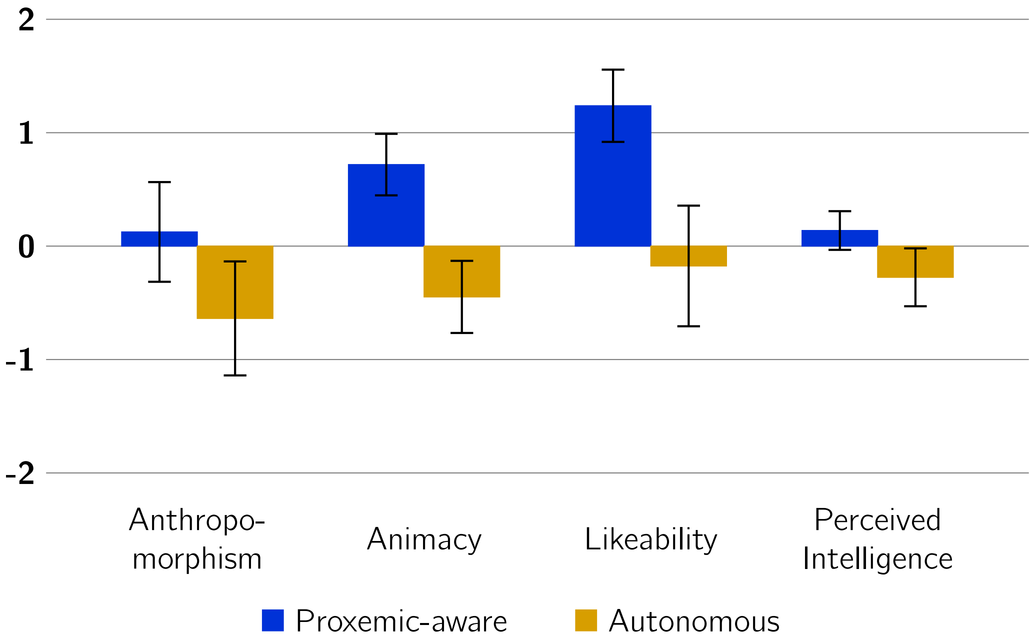


Figure 18.4: Overview of mean values for each condition and dependent variable measured by the Godspeed questionnaire series. Error bars denote 95% confidence intervals. Scale ranges from -2 to 2.

(-2 – 0). The biggest differences in the rating are on the scales of likeability, trustworthiness, and whether users would interact with the robot again.

Statistical Analysis 18.5.2

A paired-sample t-test was conducted to test the differences between the two robots (i.e., proxemic-aware, autonomous) across the dependent variables measured by the Godspeed questionnaire series (i.e., anthropomorphism, animacy, likability, perceived intelligence) and the two additional questions regarding trust and if the people would interact again with the robot. Table 18.1 shows the mean values and the standard deviation of the dependent variables and the results of the t-tests with corrected p-values for multiple testing using the Holm correction (Holm, 1979). The t-tests showed significant effects for the four relevant concepts of the Godspeed questionnaire series. In order to estimate the size of the effect, hedges g^* were calculated in which the variances are not only pooled but also corrected with the Bessel correction, thus reducing the error of estimating the effect strength, especially in small sample (Hedges, 1981). In addition, using g^* corrects the positive approximation error when calculating g (Hedges & Olkin, 1985). According to Cohen's (Cohen, 1988) recommendation, the effect strengths can be interpreted as follows: Values

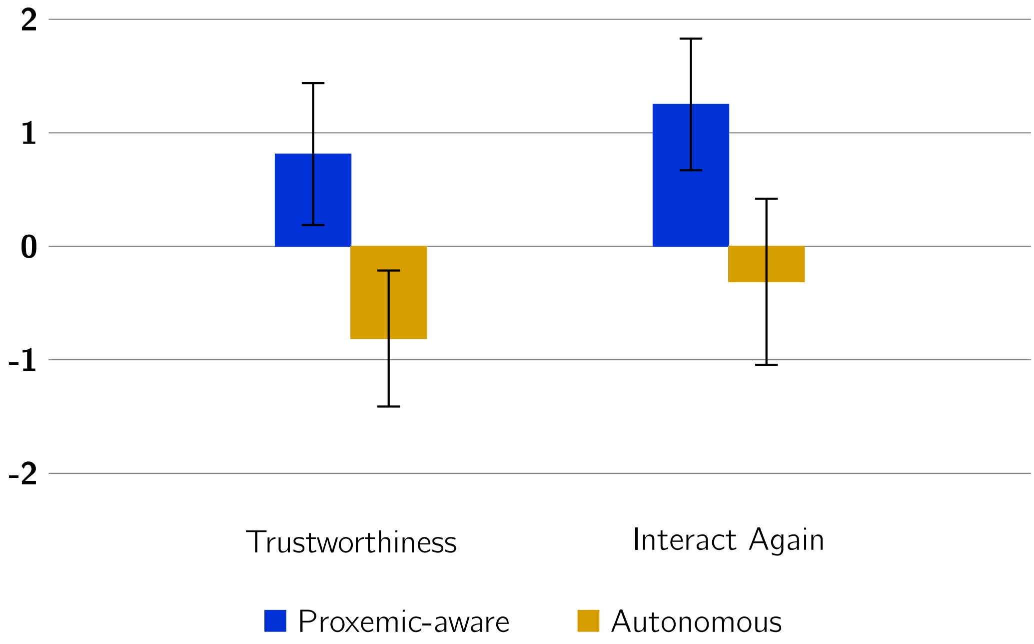


Figure 18.5: Overview of mean values for each condition and dependent variable measured by the questions whether participants trusted the robot and if they wanted to interact again with the robot. Error bars denote 95% confidence intervals. Scale ranges from -2 to 2.

above 0.2 speak for a small effect, values above 0.5 for a medium effect, and values above 0.8 for a large effect.

It was found that the proxemic-aware robot was perceived as more anthropomorphic ($g = 0.77$ – medium effect), more animalistic ($g = 1.89$ – large effect), more likable ($g = 1.54$ – large effect), and more intelligent ($g = 0.87$ – large effect) than the autonomous robot. Additionally, the participants rated the proxemic-aware robot as significantly more trustworthy than the autonomous robot ($g = 1.26$ – large effect). There was also a significant difference in whether the participants would interact again with the robot, where the participants would rather interact again with the proxemic-aware robot than with the autonomous robot ($g = 0.90$ – large effect).

18.5.3 Analysis of Qualitative Data

13 of the 16 participants (81 %) said they preferred the proxemic-aware robot. They preferred this robot because it was "polite", "respectful", "friendly", "courteous", "interested", and showed "intuitive behavior". Many participants highlighted in particular that the robot looked back when they looked at the robot and looked at the objects that the user found interesting. In addition, the experience of exploring "together" with the robot was perceived as positive.

Item	M_P	SD_P	M_A	SD_A	$t(15)$	p
Anthropomorphism	0.13	0.90	−0.64	1.03	3.09	$.007^{**}$
Animacy	0.72	0.55	−0.45	0.65	7.56	$< .001^{***}$
Likeability	1.24	0.65	−0.18	1.09	5.14	$< .001^{***}$
Perceived Intelligence	0.14	0.35	−0.26	0.52	2.55	$.011^{*}$
Trustworthiness	0.81	1.28	−0.81	1.22	4.61	$< .001^{***}$
Interact Again	1.25	1.18	−0.31	1.49	4.75	$< .001^{***}$

$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, *one-tailed*
M_P = proxemic-aware robot, M_A = autonomous robot

Table 18.1: Comparison of participants' ratings of the robots.

Also, participants perceived the behavior of the proxemic-aware robot as similar to that of a pet, and two of them said the robot was "like a faithful dog". In contrast, the behavior of the autonomous robot was described as "cat-like" negatively since the robot acts independently and ignores the user. The participants perceived the fact that the robot does not involve the user in the exploration as a very negative experience. Participants who preferred the autonomous robot argued that the proxemic-aware robot. However, they liked its behavior sometimes, but it was too intrusive in the long term, and one participant even found the behavior too intrusive right from the beginning.

18.6 Discussion

Overall, the motivation for improving social robots' interaction qualities is that users would benefit greatly if their robots could demonstrate social and affective skills, even if skill levels were at the level of a pet (Duffy, 2003). However, many pets, such as dogs or cats, use both appropriate explicit and implicit interaction capabilities and, indeed, can be socially very smart and foster healthy interactions and relationships with their owners. However, owning or caring for a pet is not an option for many people (e.g., due to allergies and job conditions), and for some people, the social attention they may receive from a pet may not be enough or not the right kind of attention for them. In contrast to pets, social robots have a great potential to address the needs of diverse users, and less ethical considerations need to be addressed (e.g., screaming at a robot may be ok).

We have motivated our research by emphasizing that for social robots, especially companion robots in homes, it is important to follow established social norms in interpersonal interaction (Kuipers, 2018). These are important to generate positive effects in the field of affective trust and thus to establish and maintain the acceptance of social robots in the private environment. The ongoing proliferation in robotics inspires us to explore interaction scenarios, which convey social norms in an increasingly multimodal and comprehensive manner.

Thus, when social companion robots turn mobile, they should follow the social conventions identified by proxemics, which describes a set of interrelated communication modalities in interpersonal interaction often utilized for implicit spatial interactions, including gaze, body orientation, and spatial positioning.

While it seems reasonable for a social mobile robot to obey the rules of proxemics, it is unclear how users would perceive such a non-human mobile agent with its potentially peculiar body features. But because many humans have functioning social relationships with their pets and social robots for homes are often imagined to fill in a similar role and even look and feel similar to a pet, we were optimistic to observe mainly positive effects. In retrospect, a socially intelligent and anthropomorphic moving robot could have triggered an uncanny valley effect.

In our study, we focused on an introduction and house tour scenario as a viable future situation in which a mobile companion robot has the opportunity to leave a positive first impression on its future human companions by utilizing and demonstrating proxemic awareness. We believe that the scenario was well suited to exploring the effect of proxemics.

Results of the self-reported data support all our hypotheses (H1a-d, and H2a-b) that a proxemic-aware robot is perceived superior, considering user experience factors, such as likability (see Table 18.1). Participants' reports also show that they found the proxemic-aware robot significantly more trustworthy and reported a significantly higher willingness to interact with it. The effects of proxemic-aware behavior on perceived anthropomorphism and animacy confirm our assumption that participants would perceive the proxemic-aware robot due to its behavior as more human-like, animal-like, and thus, as more "alive".

Although the results seem to demonstrate a clear preference (i.e., 13 of 16 participants) towards the proxemic-aware robot, the comments of some participants (especially those who did not prefer the proxemic-aware robot) suggest that there is still space for improvements, which we believe is ultimately due to individual differences in how people perceive proxemic behavior. As aforementioned in the analysis of the interview data, some participants stated that they could imagine that the proxemic robot's behavior may become too intrusive or annoying over time. We believe that such individual differences and an adaptation over time can only be addressed by advanced programming approaches, such as reinforcement learning approaches (e.g., Ritschel et al., 2017, 2018; Weber et al., 2018).

Overall, the main effect of proxemic-aware behavior on all relevant items of the Godspeed questionnaire strongly implies that robot creators should implement proxemic awareness in their future mobile home companion robots and that by doing so, they will create more trustworthy robots with which inhabitants are willing to interact significantly more often.

18.7 Limitations and Future Work

Our research has some limitations, which fellow researchers should consider when reusing it or applying it to other setups. First, we utilized virtual reality and applied an experience prototyping approach since building the required behavior recognition and reactivity with a physical robot would have been difficult. Participants may perceive both robot behaviors, which we analyzed in the virtual reality setting in reality, as stronger than the materiality of physical robots and safety concerns that exist in reality but do not apply to virtual reality. In our future work, we intend to replicate some of the interaction aspects that we studied solely in virtual reality with the physical Pepper robot. Furthermore, motivated by the results of the study at hand, an important focus of our future work will be the research of how proxemic-aware behavior can be taught to mobile companion robots using interactive machine learning and especially reinforcement learning approaches.

19. Robot's Proxemic Behavior When Traversing Two People

Introduction 19.1

In recent years, a lot has happened in the field of robotics, and a future in which humans and robots live together no longer seems far away but relatively imminent. Much work in the field of HRI shows that we expect robots to follow specific social rules to be tolerated and accepted by people (Złotowski et al., 2012). However, while we humans grow up with social rules from an early age and learn these rules during interaction with others, we need to program them into robots or allow the robots to learn them, for example, through socially-aware reinforcement learning, where a robot learns appropriate behaviors by integrating social signals from humans into its reward function (Ritschel et al., 2019).

Our social rules influence how we move through the world. They lead us to respect other people's personal spaces and, for example, do not walk between two conversing people. When we want robots to follow these social rules, we have to move from only purely technical navigation and obstacle avoidance to socially-aware navigation. Various works have already investigated how robots can implement this navigation, for example, to avoid people who interact with other people or objects (Rios-Martinez et al., 2011) (a good overview of various works can be found in the work by Rios-Martinez et al. (2015)). However, there may always be situations where avoidance is impossible, and the robot will have to violate people's personal space if it is not supposed to stop.

This work investigates how a robot should behave in such situations. As an example, we use a situation in a narrow corridor. Here, two people are standing facing each other, and the only possible path for the robot is to pass through them. In an online study, participants were presented with three videos where a robot crosses two talking people in different ways (no interaction, nonverbal interaction, and nonverbal and verbal interaction) and were then asked to evaluate the robot's behavior. The robot we use in the videos is a social robot created as part of a research project and is expected to perform appropriate verbal and nonverbal behavior in daily interactions. The robot can move autonomously and should, therefore, also follow spatial social rules and respect the personal space of others.

In the scope of our study, we aim to answer the following research questions:

- **Behavior of the robot:** What influence does the particular behavior of the robot have on the user's perception of the robot in terms of the following attributes: *social adequacy*, *comprehensibility*, *anticipation*, *disturbance*, *whether the behavior facilitates the interaction*, *likeability*, *uncanniness*
- **Impact of human attributes:** How is the perception of robot behavior related to user attributes (i.e., experience with robots, technical affinity, and age)?

19.2 Background and Related Work

An introduction to the proxemics theory by Hall can be found in Chapter 2: *Hall's Proxemics*. An overview of related work for proxemics in HRI can be found in Chapter 5: *Proxemics in Human-Robot Interaction*. This section briefly overviews the most relevant work for this study.

19.2.1 Proxemics & Socially-Aware Navigation

Several works highlight that proxemic interactions also play an important role in HRI (e.g., **Petrak** et al., 2019) and demonstrated that the zones defined by Hall also hold true (Syrdal et al., 2007; Walters et al., 2011). Many other works investigate which characteristics of humans and robots influence these distances. Of particular interest for this work is the influence of prior experience with robots (Walters et al., 2008) and the influence of the robot's gaze direction (Takayama & Pantofaru, 2009). The aforementioned work addresses proxemics in a direct interaction with the robot. However, proxemics also affects how we move around others and respect each other's personal spaces. This part of proxemics is called socially-aware navigation (see Section 5.3: *Socially-Aware Navigation*).

However, there is a gap in the research that we want to fill with this work. Most of the research on socially-aware navigation only focuses on cases when the robot respects the personal space of humans and, therefore, avoids it. However, as argued in the beginning, it may happen that the robot has to enter this space in order to continue its path, especially in narrow environments such as hallways. Another work examines how a robot can best approach a group of people. For example, studies include which direction is best for the robot to approach (Karreman et al., 2014). Some concepts use machine learning to generate an appropriate path for approaching a group (Gao et al., 2019; Yang & Peters, 2019). However, this usually considers how the robot can join the group interaction rather than avoiding the interaction if possible. In work by Pacchierotti et al. (2006), the distance a robot should keep when avoiding a person was investigated in a narrow hallway setting. However, only one person was considered, and the robot had enough space to dodge. The results showed that most participants felt more comfortable with a larger lateral distance to the robot. This demonstrates that our question is relevant when a large distance cannot be maintained. Nevertheless, to the best of our knowledge, no work addresses how robots should behave when they need to invade people's personal space to continue on their path.

19.3 Preliminary Study

19.3.1 Procedure

We conducted a preliminary study to decide which behavioral variants the robot would perform in the main study. We investigated how humans would behave in a narrow situation to get past two people talking to each other. We were particularly interested in whether and how people would make contact and how the walking person would pass the talking people. To do this, we created three videos showing three different scenarios. Each shows a first-person perspective of approaching two people in a narrow hallway who are having a conversation and end shortly before the people are reached. The videos differ in how the two people are positioned in the hallway, but they always face each other and talk to each other. In the first video, the two people are each standing on one side of the hallway, so there is space between them. In video two, they stand in the middle of the hallway, so there is not enough space between the people to walk between them. In video three, they stand on one side of the hallway so that there is room on the other side, but not between the people. See Figure 19.1 for an overview of the different positions of the persons. By varying the people's positions, we wanted to find out to what extent this impacted the behavior of the person walking and their expectations for the behavior of the people standing.

(a) First video: The two persons are standing on each side of the hallway.

(b) Second video: The persons are standing in the center of the hallway.

(c) Third video: The persons are standing at the right side of the hallway.

Figure 19.1: Overview of the videos we showed participants in the preliminary study.

Evaluation Methods 19.3.2

In the study, which was conducted as an online survey, participants were presented with all the videos in random order and asked questions after each video so that they could respond textually. First, we let the participants describe how they would act in the situation. We then asked more specific questions, namely whether they would make contact verbally or nonverbally. If they made contact verbally, we additionally asked what they would say. Furthermore, we asked if they would wait for a reaction from the other people and how their reaction should look. Finally, we asked how much they would adjust their speed when passing.

Results 19.3.3

For clarity, we report only those results that informed the design of the main study. This preliminary study involved 14 people. Nine were male and five female between 15 and 56 years old ($M = 24.38$, $SD = 13.39$). For the setting in the first video (people standing on the sides of the hallway with space to walk through between them only), participants described very different approaches to how they would act in this situation. Some described walking between the persons without making contact to disturb the conversation as little as possible. Some also described that they would make contact non-verbally or verbally and reduce speed until they received a signal from the individuals. All who would verbally initiate contact wrote that they would either say "Excuse me" or "Excuse me, may I get through". Most indicated they would increase their speed as they walked between the persons. Compared to the other videos, participants indicated an expectation for people to move out of the way (video 2, in which they stand in the way) or walk past people on the empty side (video 3, in which they stand on one side).

Main Study 19.4

Setup 19.4.1

We have again created three videos for the main study, all showing the same setting. In the setting, two people are standing in a corridor, each on one side with their backs to the wall, and the robot VIVA can only pass between them. The corridor is about 2 m wide. There is about 1.15 m of space between the persons such that if the robot passes centrally between the persons, it will enter the personal space of both persons (see Figure 19.2).

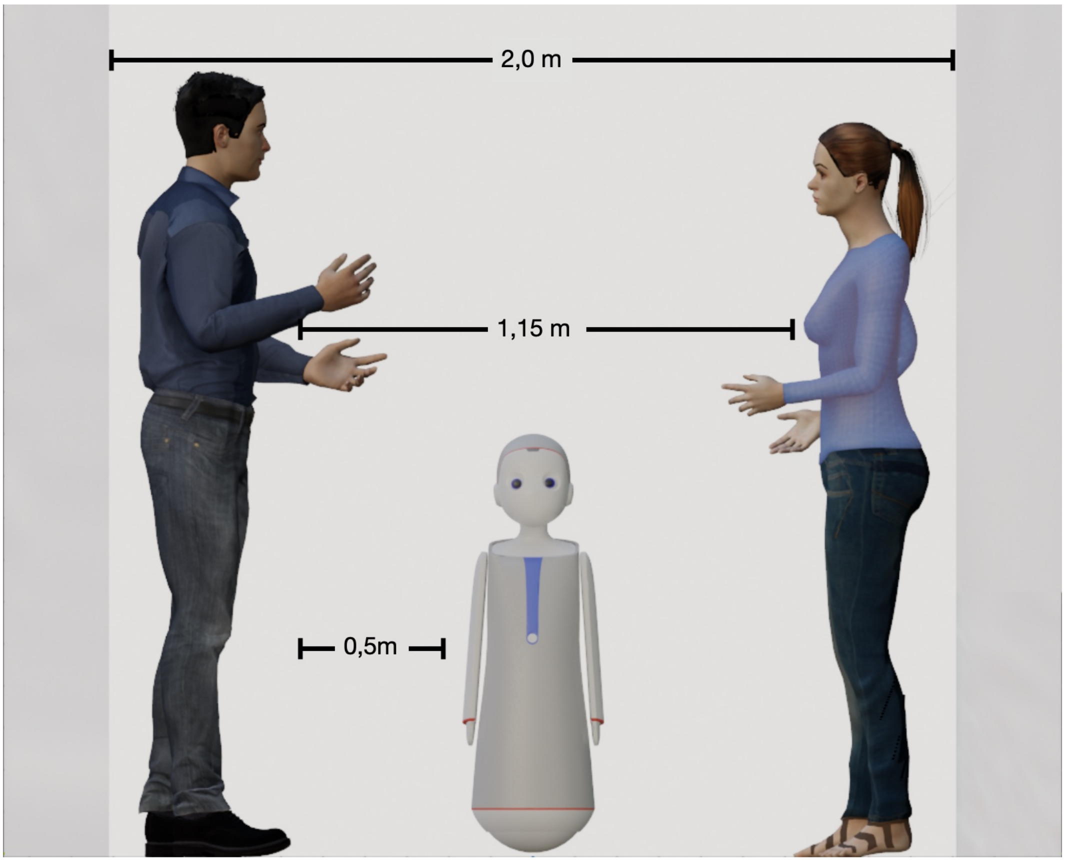


Figure 19.2: Overview of the distances in the hallway setting in the videos. The hallway's width, the distance between the persons, and between persons and the robot.

The videos differ in the robot's behavior when passing between the people. The results of the preliminary study informed the behaviors. Here, video a) acts as a baseline, in which the robot passes between the people without making contact. In video b), the robot makes contact non-verbally; in video c), it makes contact verbally and waits for a reaction from the person. The exact behavior sequence of the three variants can be found in Figure 19.4. Figure 20.2 further shows the camera perspective of the videos and the different stages of the robot's path.

The videos were created and animated by the software Blender[1]. The people in the videos were modeled using Make Human[2] software. To reduce gender effects, one person is presented as a man and one as a woman. In this way, most participants would associate themselves with one of the two. The woman is

[1] https://www.blender.org/
[2] http://www.makehumancommunity.org/

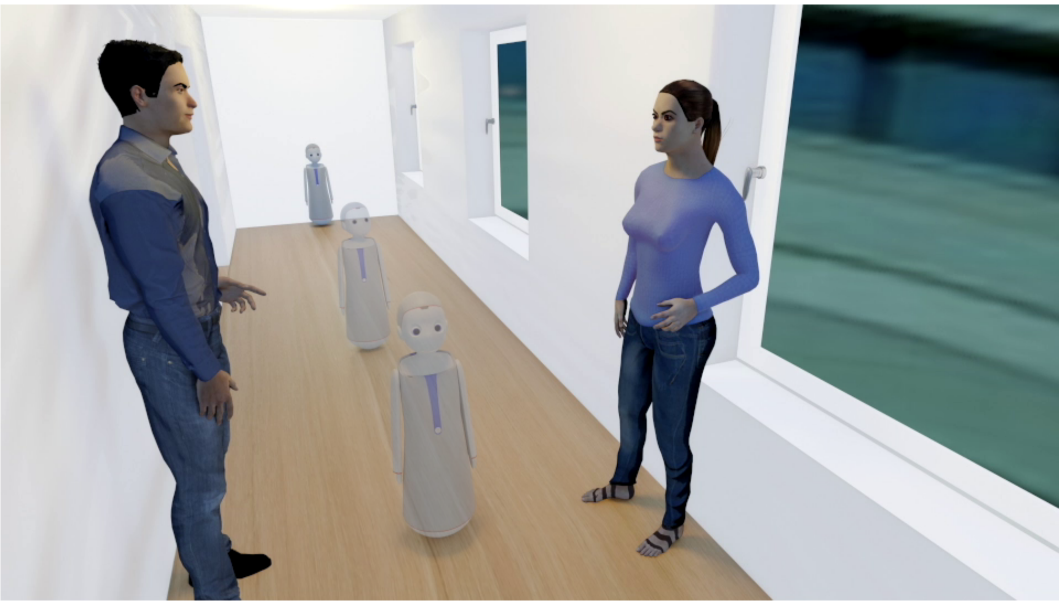


Figure 19.3: The image shows the perspective in the videos. The transparent robots show the path that the robot takes between the persons.

modeled after one of the authors - Gundula Sopper, while the man is a generic male. The size of the persons was chosen according to the average sizes of the respective gender in Germany (163.5 m for women, 177.0 m for men) (Mensink et al., 2013). A 3D model of the VIVA prototype was used to represent the robot in the videos. The robot is approx. 1 m high.

Evaluation Methods 19.4.2

We measured the following variables using different items in our online questionnaire to answer our research questions. Unless otherwise specified, all items were assessed on a scale from 1 (not at all) to 7 (very).

Nonverbal and Verbal Behavior: Participants were told to base their ratings solely on nonverbal behavior for the following five items. Subsequently, the five items were asked again for the verbal behavior (or absence of verbal behavior). In other words, participants rated social adequacy, for example, for nonverbal and verbal behavior separately. For each item, participants could also provide textual explanations for their rating. The items were asked after each video.

Social Adequacy: We measured the perceived social adequacy of the robot's behavior using one self-generated item: "How socially appropriate do you find VIVA's behavior in the situation shown in the video?"

Comprehensibility: The question about comprehensibility is modeled after the aspect "Perceived Ease of Use" of the Technology Acceptance Model (TAM)

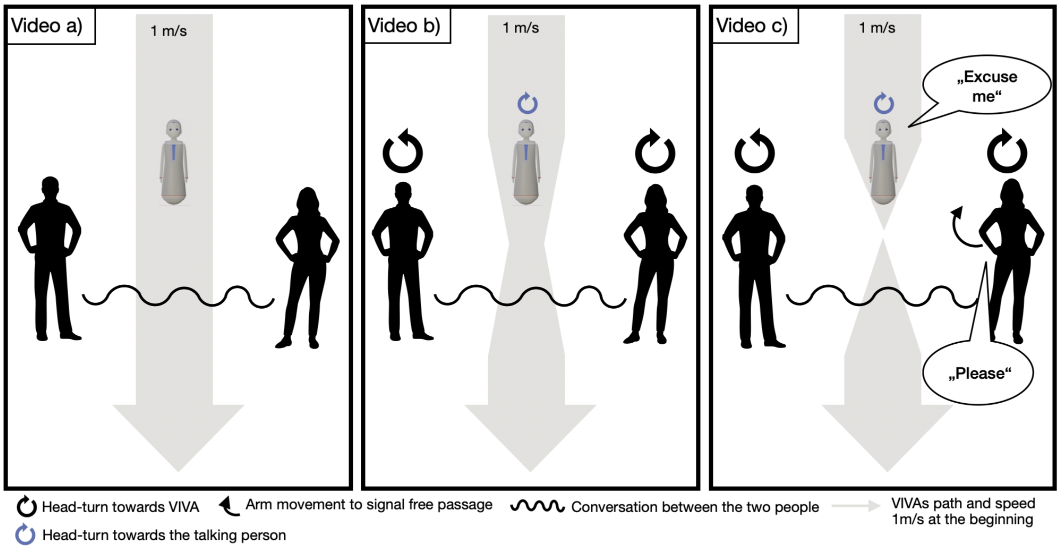


Figure 19.4: Overview of the three different forms of interaction used during the online study.

(Qingxiong & Liping, 2004). The question was: "How comprehensible do you find VIVA's behavior in the situation shown in the video?".

Anticipation: The question "How anticipatable do you find VIVA's behavior in the situation shown in the video?" addresses the perceived anthropomorphism of the robot and is modeled after Heafner and Epley (2014).

Disturbance: We measured the disturbance of the robot's behavior using one self-generated item: "How much do you feel disturbed by VIVA's behavior in the situation shown in the video?"

Facilitation: To measure the degree to which the behavior facilitates interaction, we adapted another question from TAM (Qingxiong & Liping, 2004): 'How much does VIVA's behavior in the situation shown in the video facilitate your social interactions with her?"

Likeability: To measure the likeability, we used the items of Salem et al. (2013) and Rau et al. (2009): endearing, friendly, likable, warm-hearted, and approachable. Asked after each video.

Uncanniness: To measure participants' impression of the robot's uncanniness, we used items from Bernotat and Eyssel (2017b), asking participants to rate the degree to which they felt uncomfortable, frightened, and insecure – asked after each video.

Technical Affinity: As the attitude towards the robot plays an important role in reacting to it and accepting different behaviors, we asked about the general attitude towards technology at the end of the survey. For this, we used the *Kurzskala zur Erfassung von Technikbereitschaft* that tests on technology acceptance, technology competence, and technology control (Neyer et al., 2012). The questions we used were: "Modern technology pleases me fast", "Modern technology makes me curious", "I am afraid to not use new technology properly and rather destroy it.", "I find the handling of modern technology difficult", "I like to use the newest technological devices", "When handling modern technology I am afraid to fail.", "I am often overwhelmed when using new technology", and "If I could, I would use modern technology more often than I do now."

Other: At the end of the survey, we asked whether they had ever had contact with a robot before (Reich-Stiebert & Eyssel, 2015). Finally, we asked about age, gender, and the highest level of formal education.

Procedure 19.4.3

After informed consent, participants were instructed to evaluate the social robot's behavior in the videos. We used a within-subject design so that each participant could see all three videos randomly. Participants watched the HRI videos and evaluated verbal and nonverbal social adequacy, comprehensibility, anticipation, disturbance, facilitation, and the robot's perceived likeability and perceived uncanniness concerning the interaction each time. After evaluating all three scenarios, we asked for their technical affinity, previous robot contact, and demographics.

Participants 19.4.4

Participants were recruited through personal connections and social media. 135 participants from Germany between 15 and 90 years ($M = 32.17$, $SD = 17.38$) took part in the study. Forty-five participants stated they had already interacted with a robot before, and 90 participants did not. Sixty-one participants had an academic background, 57 finished high school, five were still in school, 10 had vocational training, and two did not provide information about their educational background. Participants averaged a score of $M = 4.10$ ($SD = 1.20$) on technology affinity (items ranged from 1 to 7).

Results 19.5

Overall, we found that 18 participants (13.3 %) stated that they liked the robot's behavior in video a) most, 54 participants (40 %) liked the robot's

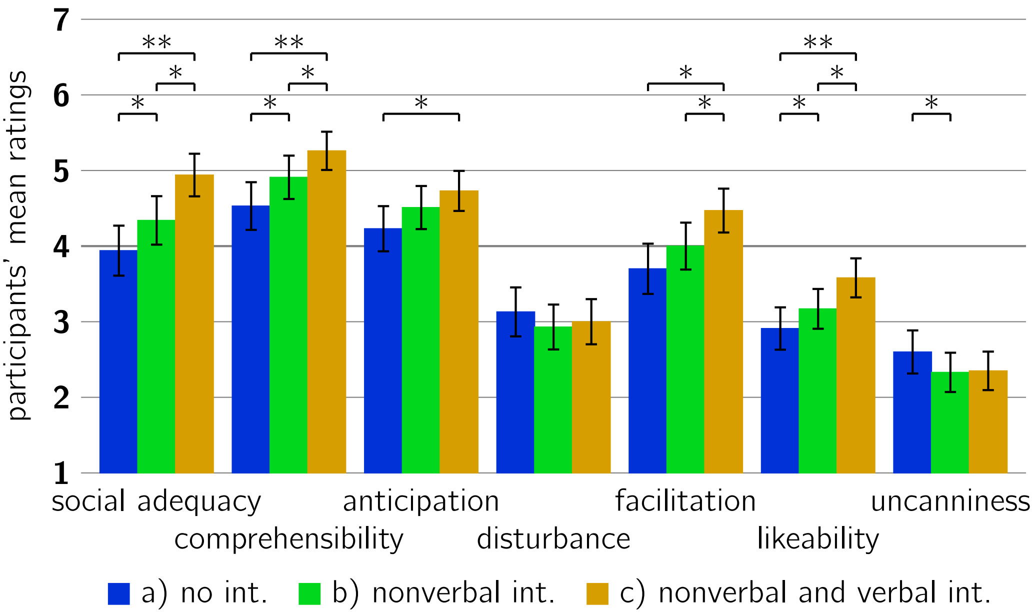


Figure 19.5: Overview of mean values for each condition and dependent variable asked during the online survey. Error bars denote 95 % confidence intervals. Scale ranges from 1 to 7. Higher rating is better, except for uncanniness. $^{*}p < .05$, $^{**}p < .001$

behavior in video b) most, and 63 participants (46.7 %) said that they liked the robot's behavior in video c) most. In the next step, we investigated what influence the robot behavior in the three presented videos had on participants' ratings of the robot.

19.5.1 Impact of the Robot's Behavior User's Perception

To determine the direction of the differences between the three robot videos (a = no interaction, b = nonverbal interaction, c = verbal interaction, see Figure 19.4 for details) regarding social adequacy, comprehensibility, anticipation, disturbance, facilitation, likeability, and uncanniness, we used paired t-tests. In Figure 19.5 is an overview of the participants' ratings on the measured constructs. Detailed statistics results are in Table 19.1. To calculate effect sizes for significant results, we report Cohens' d[3].

When looking at the results, it is immediately noticeable that video c) was rated best in most categories. Regarding the scales of social adequacy, comprehensibility, facilitation of interaction, and likeability, the ratings are significantly higher than video a) and video b). For anticipation, the ratings of video c) are only significantly higher than video a). For disturbance, there are no

[3]For the interpretation, we use the recommendations from Gignac and Szodorai (2016): .10 for small, .20 for medium, and .30 for large effects

significant differences between the robot behaviors. For uncanniness (lower is better), only video a) is rated significantly higher than video b), while there are no significant differences between a) and b) and b) and c). Video b) is also rated significantly higher than video a on social adequacy, comprehensibility, and likeability scales.

Impact of Human Attributes 19.5.2

To investigate the significant variables of the paired t-tests, we calculated Pearson product-moment correlation coefficients. We examined the dependent variables *social adequacy*, *comprehensibility*, *facilitation*, and *likeability*. These variables were tested with: *age*, *technical affinity*, and *previous experience with robots*.

Social Adequacy: We found a significant negative correlation between age and the social acceptability of video b), $r_p = -.18$, $p = .042$. The older the subjects were, the less socially acceptable they considered the robot to be. No further significant correlations were found for other videos and dependent variables.

Comprehensibility: We found a significant negative correlation between the participant's technical affinity and their comprehensibility rating in video c). People with higher scores in technical affinity rate the robot's actions as less comprehensible ($r_p = .20$, $p = .022$). No further significant correlations were found for other videos and dependent variables.

Facilitation and Likeability: We found no significant correlations regarding the likeability and facilitation of the videos b) and c) with technical affinity, age, or previous experiences with robots.

Qualitative Data 19.5.3

When completing the questionnaire, participants had the opportunity to comment on their rating for each of the scales. They could state why they gave this particular rating or what would improve the rating. This provided interesting insights into the participants' thoughts and added further evidence.

For example, when rating the robot's disturbance in the situations in video c), participants commented that they did not like that VIVA interrupted their conversation. On the other hand, some also felt that they were disturbed by VIVA simply passing by without communicating, as in the robot's behavior in video a). One participant expressed that the robot should wait until the conversation is over before passing since a robot is never in a hurry. Some also said that a robot should only contact humans when it needs something specific. However, some also wrote that the robot could have greeted, especially on video a). Many comments also referred to the robot's size, mainly that it was not disturbing because it was so small, but that this also made it easy to overlook. It was also frequently mentioned that collision could occur if it were unclear that VIVA would choose the path between people or, due to its size, would not be noticed. Many participants expressed these concerns for video a), a few for video b), and for video c). It was mainly mentioned that here, compared to the other videos, a collision was improbable because the robot waits until it gets a signal.

Several comments highlighted how the behavior could be improved, such as having VIVA look at the person talking and wait for their verbal response. In contrast, some suggested that VIVA should also be able to read nonverbal responses, be more gestural, or show friendlier facial expressions. Some also mentioned that this extended interaction could help anticipate that the robot wants to cross the people, thereby avoiding a collision. A few comments also indicated that there were sometimes problems in understanding the videos. However, overall, the number of problems described is very low.

19.6 Discussion

The results show that video c) (nonverbal and verbal interaction) was rated significantly better than video a) (no interaction) on most scales and video b) (nonverbal interaction) on some. In addition, the explicit question about which behaviors is preferred showed that most people chose video c) here as well. So is the robot behavior in video c) (i.e., stopping and waiting until one gets permission to pass) the best way for a social robot to cross two conversing people? While it seems so initially, a closer look at the ratings and comments proves this is not necessarily the case. First of all, it is exciting that when asked about the preferred behavior, while most selected video c), a large proportion of participants also preferred video b) (63 vs 54), whereas video a) was barely selected. Thus, the difference here is not as large as the significantly different scale scores suggest. Looking at the comments written by the participants, there are several clues about possible causes for this discrepancy.

One thing often mentioned in the comments is the risk of collision with the robot if the robot's behavior is unpredictable. In the case of the behavior in

Scale	Condition	$t(134)$	p	Cohens d
social adequacy	a) vs. b)	−2.08	.039*	.18[s]
	b) vs. c)	−3.16	.002*	.27[m]
	c) vs. a)	4.49	< .001**	.39[l]
comprehensibility	a) vs. b)	−2.07	.04*	.18[s]
	b) vs. c)	−2.12	.036*	.18[s]
	c) vs. a)	3.62	< .001**	.31[l]
anticipation	a) vs. b)	−1.54	.126	–
	b) vs. c)	−1.25	.212	–
	c) vs. a)	2.51	.013*	.22[m]
disturbance	a) vs. b)	−1.08	.283	–
	b) vs. c)	−0.39	.695	–
	c) vs. a)	−0.70	.488	–
facilitation	a) vs. b)	1.45	.149	–
	b) vs. c)	−2.49	.014*	.21[m]
	c) vs. a)	3.29	.001*	.28[m]
likeability	a) vs. b)	−2.22	.028*	.19[s]
	b) vs. c)	−2.84	.005*	.24[m]
	c) vs. a)	4.40	< .001**	.38[l]
uncanniness	a) vs. b)	−2.27	.025*	.19[s]
	b) vs. c)	−0.25	.804	–
	c) vs. a)	−1.97	.051	–

$^{**}p < .001$, $^{*}p < .05$, [s] small effect, [m] medium effect, [l] large effect

Table 19.1: Results of the paired t-tests to compare the three different robot behaviors in the videos (conditions). Cohens d effect sizes are reported only for significant results.

video c), according to the comments, this collision is prevented because the robot only continues after it has received the permission of the people, i.e., the robot has also been noticed, and the people are thus prepared for the crossing. Lower ratings for comprehensibility, anticipation, and facilitation of interaction on the other videos also suggest that the risk of collision is higher in that case, which is also underlined by further participants' comments. The need for safety plays a significant role and presumably leads to higher ratings for video c). In contrast to the need for safety, the need to be disturbed as little as possible. While the quantitative data showed no significant differences between the three videos, the qualitative data shows a somewhat different picture. Here, variant c) is especially perceived as disturbing since the robot interrupts the conversation with its behavior. In contrast, in variants a) and b), it hardly disturbs at all and is mainly perceived as disturbing by people who generally find a crossing disturbing. These contrasting needs may lead to the discrepancy described earlier. In the qualitative data between the videos, no significant differences could be found in how much the robot disturbs, whereas in the comments, version c) is perceived as disturbing compared to the other two alternatives.

The perception of many participants that a collision could occur could be because none of them have yet experienced an interaction with the VIVA robot, and most have not even experienced an interaction with robots in general. Thus, if humans interact with robots more frequently, the problem could resolve itself if the robot's behavior is always the same and, therefore, easily predictable, as some comments also indicated. Results from Walters et al. support these, showing that more experience with robots resulted in people allowing a lower distance to the robot (Walters et al., 2008). Furthermore, the statistical correlations showed that people with higher technical affinity found the robot's behavior in video c) less comprehensible. These findings align with the work of Pacchierotti et al. (2006), where people with higher technical affinity found a too-wide evasion as exaggerated. The robot's stopping may also have been perceived as exaggerated and thus not comprehensible. This also suggests that more experience with robots could lead to further tendencies toward the behavior in video b). However, minor adjustments in the behavior of video b) or c), or a robot behavior that combines parts of both behaviors, could also lead to a better result. Also, as noted by some participants, enhanced facial expressions and gestures could make the behavior easier to anticipate and thus also reduce the fear of collisions. Which behavior will help specifically needs to be explored in further studies.

19.6.1 Limitations and Future Work

Since the study was conducted online, the participants had to put themselves in the situation. Since most had never had contact with a robot, this might have been difficult for some participants. As also pointed out in some comments, the robot's size plays a role in the evaluation, so the results should not be generalized to all different-sized robots. We also designed the behavior variants based on the preliminary study results and the capabilities of the robot prototype VIVA. Therefore, the behaviors are limited to nonverbal communication via orientation, gaze direction, and speed. However, extended facial expressions and gestures could further influence the evaluations of the behaviors.

Future work should take the findings of this work and focus on a variation between the versions in video b) and video c). In particular, an adaptation of the experiment with a real-world setting should be attempted. One possible research question is how the robot's behavior can be further adapted so that people can clearly anticipate its behavior without disturbing it too much and interrupting people's conversation. For example, extended facial expressions and gestures may be utilized for this purpose. In addition, variables that impact the robot's behavior should ideally be investigated – for example, the robot's size, voice, or appearance.

19.7 Conclusion

In this work, we reported on a study in which we compared three ways a robot traverses two people in conversation in a hallway in an online survey. In doing so, we address a gap in social navigation research, in which mostly only avoidance is an option for the robot. However, situations may arise in which the robot cannot find an alternative path and thus has to traverse, for example, two people. We investigated how three different behaviors affected various constructs: social adequacy, how much the behavior disturbs, or the robot's likeability. The results show that it is important to the participants that the behavior is as little disruptive as possible but that the robot's behavior must be anticipatable for the people. Hence, they are not concerned about a collision. Nonverbal cues play an important role here, as they are less likely to interrupt the subjects' conversation. None of our three variants presented in the videos emerged as a clear favorite. Therefore, further studies should be conducted to gain additional insights into how the behavior can be improved to satisfy the desired criteria.

20. Robot's Proxemic Response to Expressed Human Emotions

Introduction 20.1

Do you have a smart speaker at home with a virtual assistant like Google Assistant, Alexa, or Siri? Then, you live in a growing number of households where such smart speakers are being used. Their applications range from processing easy voice commands to supporting everyday tasks (e.g., playing music, reminders, or timers) or providing social services that might reduce people's loneliness (Pradhan et al., 2019). Due to how smart speakers work, they are often limited to auditive interactions and are fixed to a location where they have been positioned. These are disadvantages that robots do not have due to their stronger embodied presence. Physically embodied social robots enable interactive social communication using various communication channels, e.g., verbal and nonverbal communication or proxemics.

These capabilities enable robots to impact many areas of our daily lives in the future, just as smart speakers do today. However, for that to happen, social robots must be designed so that users not only tolerate but also accept them. To achieve this ultimate goal, robots must be able to engage in socially and emotionally adequate interactions. A robot's capability to move in physical space can facilitate or hinder this, as such movement transports meaning (**Petrak** et al., 2019). In addition to purely technical aspects such as navigation, questions such as what a spatial interaction between humans and robots looks like must be well-researched. This is linked to the idea that movement in physical space represents a form of nonverbal communication. Hall (1966) coined this proxemics.

In this work, we investigate the relationship between an emotion expressed by a human and the subsequent spatial interaction (i.e., approaching, no movement, or moving away) of a social robot and how this robot behavior affects perceived social adequacy of the behavior, the robot's perceived likeability, and uncanniness. To test this, we use the robot platform "VIVA", a humanoid robot specifically designed to interact with humans socially.

20.2 Related Work

An introduction to the proxemics theory by Hall can be found in Chapter 2: *Hall's Proxemics*. An overview of related work for proxemics in HRI can be found in Chapter 5: *Proxemics in Human-Robot Interaction*. This section briefly overviews the most relevant work for this study.

20.2.1 Proxemics

What represents an adequate social distance between humans and robots? Previous research has tried to gain insights into this empirical issue. A standard paradigm investigates human responses to robot approach behavior, i.e., researchers monitor when precisely a human stops the robot or if and when the human moves towards the robot. Moreover, previous research has explored determinants of proxemics behaviors in HRI. Among these are characteristics of the robot such as voice (Walters et al., 2008), body pose (Obaid et al., 2016), expressed emotion (Bhagya et al., 2019), or gaze direction (Takayama & Pantofaru, 2009), but also characteristics of the human such as previous experience with robots (Walters et al., 2008), ownership of pets (Takayama & Pantofaru, 2009), personality traits (Walters, Dautenhahn, te Boekhorst, et al., 2005), body pose (Obaid et al., 2016), and also culture (Khaliq et al., 2018). For a detailed overview of relevant factors for proxemics, refer to Section 5.4: *Factors Influencing Proxemics in HRI*. The work by Narayanan et al. (2020) has also considered user emotion for their socially-aware navigation. However, this is not done directly between a person and a robot; instead, it is used to avoid other persons.

Many existing studies studied proxemics in isolation, primarily focusing on the "right" physical distance depending on various factors. However, in everyday interactions, proxemic behaviors merely represent one among other means of indirect, nonverbal communication, complementing other communication channels. For example, verbal encouragement has a much stronger effect on a person if you simultaneously approach that person than if you remain standing. For such an interaction, it is necessary to recognize the emotional state of one's interaction partner. With the help of modern approaches such as machine learning-based methods, the existing sensory technology of robots can be extended. Consequently, the robot may process spatial information and interpret the emotional expression of the human interaction partners (Schiller et al., 2019; Wanner et al., 2017). Accordingly, the robot can adapt its spatial behaviors to the emotional status of the interactant.

It is an open research issue to construct such a constellation. That is, what such an interaction should ideally look like and how this impacts the acceptance of robots in society need to be investigated.

Affective Human-Robot Interaction 20.2.2

Non-verbal emotional feedback such as emotional facial expressions or movements play an important role in the interaction between humans (Van Breemen et al., 2003). Based on this information, one can quickly and reliably assess the state of the interaction (e.g., whether a person is interested, scared, or hostile). In addition, nonverbal emotion displays also affect our interaction with others. For example, the extent to which we sympathize with others depends on their ability to resonate with us and to respond with empathy (Seidel, 2009; Thimm et al., 2019).

Nonverbal communication likewise represents an important source of information in HRI. To illustrate, a vast amount of existing literature has focused on (1) the robots' facial expression of emotions (for a review, consult Van Breemen (2004) and Van Breemen et al. (2003)) and (2) the robots' ability to recognize facial emotions of humans (e.g., Chen et al., 2018; Liu et al., 2017). Humans prefer robots that can recognize and express human emotions (Reich-Stiebert et al., 2019). Currently, however, there are only a few robots that can indeed perceive or express emotions. For instance, the KAPPA (Fukuda et al., 2001) can recognize emotions based on facial expressions and express six basic emotions. The Minotaur robot (Röning et al., 2014) can interact with humans using gestures, speech, and facial expressions. Tsiourti et al. (2019) investigated the influence of a robot's multimodal emotional reactions (i.e., body language and voice) on user perception. They found that users perceived the robot as less empathetic when it showed incongruent behaviors. This affected their liking of the robot. The authors point out that robots must use multimodal, congruent behaviors when interacting with humans.

Therefore, in addition to using facial expressions, the robot could use proximity behavior to show congruent and, therefore, appropriate behavior toward humans. Due to the reciprocity nature of social interactions, the robot's proximity behavior should be related to the emotional state of the human counterpart (e.g., forward movement when the user is happy, distancing when the user is angry).

However, what proximity behavior is an appropriate reaction? Our study contributes to answering this question. We investigate which proximity behavior of a robot (i.e., approaching, no movement, or moving away) is appropriate depending on the emotional expression of the human counterpart.

20.3 The Present Experiment

In the present experiment, we investigated the role of robot proxemics behaviors in response to specific user emotions. Concretely, we explored the perceived social adequacy of the robot's reaction. We showed participants six animated videos of interactions between a human and a robot. In each video, the human protagonist verbally expressed one of the basic emotions (i.e., anger, fear, disgust, surprise, sadness, or joy), and the robot VIVA randomly showed one of three proximity-related behaviors (a=approaching, b=no movement, c=moving away). The following hypotheses were tested:

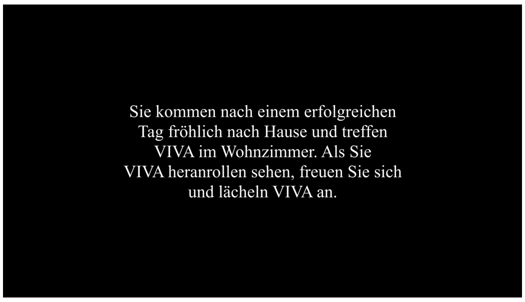
- **H1a-6a**: When the protagonist expresses *[emotion]*(emotion: anger = 1a, fear = 2a, disgust = 3a, surprise = 4a, sadness = 5a, joy = 6a) and the robot approaches the user, this behavior is evaluated as appropriate.
- **H1b-6b**: When the protagonist expresses *[emotion]*(emotion: anger = 1b, fear = 2b, disgust = 3b, surprise = 4b, sadness = 5b, joy = 6b) and the robot does not move, this behavior is evaluated as appropriate.
- **H1c-6c**: When the protagonist expresses *[emotion]*(emotion: anger = 1c, fear = 2c, disgust = 3c, surprise = 4c, sadness = 5c, joy = 6c) and the robot moves away, this behavior is evaluated as appropriate.

As preregistered[1], we operationalized *appropriate* using three criteria: (1) The mean social acceptability is significantly higher than four, (2) the mean likeability is significantly higher than four, and (3) the perceived uncanniness is significantly lower than four.

Using G*Power, we estimated a required sample size of $n = 27$ for a t-test against a constant with 80 % power and an alpha of 5 %. The calculation of correlations requires larger sample sizes: To be able to calculate exploratory correlations; we will stop data collection at 82 complete responses (calculation for two-tailed correlations with 80 % power, alpha = 5 %, medium-size effect).

[1] https://aspredicted.org/i8xn2.pdf

Method 20.4



(a) The introduction text is displayed to the viewer.

(b) The protagonist verbally expressing his emotion.

(c) The VIVA robot answering 'I understand'.

(d) The VIVA robot after moving away from the protagonist.

Figure 20.1: Sequence of screenshots from the video presented to male participants in the study. The video depicts the emotion 'joy', with the robot VIVA responding by moving away after the protagonist's emotional expression. All text in the video is in German.

Participants and Design 20.4.1

As preregistered, 82 participants were recruited online to participate in a study concerning the design of the newly developed social robot VIVA. We intended to exclude participants who indicated not having participated meticulously, but this criterion did not apply to any participant. The data of 82 participants were included in the analysis (24 female, 58 male; $M_{age} = 26.67$, $SD_{age} = 7.32$). All participants were students (55 Psychology, 22 other). Participants rated six HRI scenarios, that is, one scenario per emotion (IV1 (within): anger, fear, disgust, surprise, sadness, joy), while the robot behavior was randomized (IV2 (between): approaching, no movement, moving away), respectively.

Experimental Manipulation 20.4.2

We provided a series of animated videos to manipulate robot proxemics behavior and user emotion. The manipulation consisted of three videos depicting

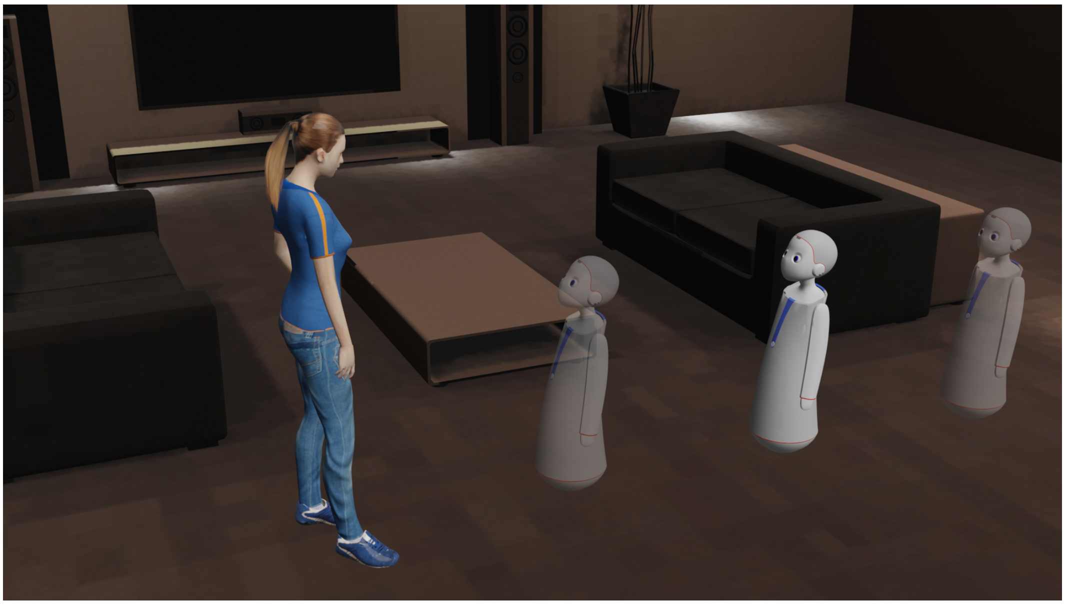


Figure 20.2: The image shows the perspective in the videos (example for female participants) and the positioning of the robot to the person. The transparent robots in the image show the positions after approaching or moving away from the person.

HRI, with the robot approaching, not moving, or moving away from the human protagonist (see Figure 20.2). For each emotion condition, we presented an introductory text describing the protagonist's interaction and emotional reaction. Each participant saw one video per emotion (six videos), while the respective robot behavior (approaching, no movement, or moving away) was chosen randomly. All the scenarios described in the videos and the protagonist's emotional reaction to the robot can be found in Table 20.1. An overview of the content of the videos is provided in Figure 20.1.

Subsequently, in every interaction, the robot responded "I understand". This was done to keep the verbal level constant across all conditions.

Further, the protagonist's gender was matched to the participant's gender. Participants indicating a non-binary gender identity would have been shown a random protagonist; however, in this sample, all participants identified as either male or female.

20.4.3 Measures

Attitudes towards robots are not always clearly positive or negative but somewhat ambivalent, calling for a multi-method approach in analyzing user feedback (Stapels & Eyssel, 2021). We therefore measured the social appropriateness of the robot's behavior, robot likeability, and uncanniness as the main variables of interest. Social appropriateness is defined as the degree to which

Emotion	Introduction	Quote
Anger	You walk into the living room after a long day and want to watch a movie. When you press 'play', your streaming service freezes, and you snort angrily and frown.	"This thing makes me angry!"
Fear	You are at home going over a very important presentation that is scheduled for the next day. Thinking about the upcoming situation, you get scared and draw your eyebrows together in worry.	"I'm afraid of the presentation tomorrow."
Disgust	You are in the kitchen and want to cook. When you take the cheese out of the fridge and see that it's moldy, you frown and pucker your mouth in disgust. You walk into the living room and say to VIVA:	"The cheese is moldy, how disgusting."
Surprise	You are at home and listening to the radio. When you hear a rumble from another room, you make a surprised face and look around.	"I heard something and I was frightened."
Sadness	You are at home and want to take your old favorite mug out of the cupboard. When you accidentally drop the mug, you sigh in dismay.	"I dropped my favorite mug and I'm sad because now it's broken."
Joy	You come home happy after a successful day and meet VIVA in the living room. When you see VIVA rolling up, you are happy and smile at VIVA.	"I am cheerful, I had a successful day."

Table 20.1: Translated introduction of the situation and what the protagonist said in the video for each of the expressed emotions in the experiment.

users understand a robot's behavior and perceive it as predictable (Gockley et al., 2007). Further, robot likeability is the degree to which the robot appears sympathetic and well-meaning (Reysen, 2005). In order to account for the multidimensional nature of attitudes, we further assessed perceived robot uncanniness (Bernotat & Eyssel, 2017a). Considering the ambivalent and multidimensional nature of attitudes by utilizing multiple measures provides a comprehensive look at attitudes and potential attitudinal conflict (subjective ambivalence. cf. Priester and Petty, 1996). Unless otherwise specified, all items were assessed on a scale from 1 (not at all) to 7 (very).

20.4.3.1 Social Adequacy

We measured the perceived social adequacy of the robot's behavior using one self-generated item: "How socially appropriate do you find VIVA's nonverbal behavior (here: VIVA's movement) in the situation depicted in the video?".

20.4.3.2 Likeability

We measured the robot's likeability using six items (five items adapted from Reysen (2005) and one item from Salem et al. (2013)), e.g., "VIVA is likable".

20.4.3.3 Uncanniness

We measured the perceived uncanniness of the robot using three items from Bernotat and Eyssel (2017a) (i.e., uncomfortable, insecure, frightened), with which participants indicated to what degree the robot evoked certain feelings while watching the interaction in the video.

20.4.3.4 Exploratory Variables

After each scenario, we additionally measured perceived robot agency and experience using four items adapted from Eyssel and Loughnan (2013), e.g., "VIVA can understand how other people feel". Further, to assess attitudinal conflict, which is a prevalent characteristic of attitudes towards robots (Stapels & Eyssel, 2021), we employed a measure of subjective ambivalence (i.e., perceived attitudinal conflict) concerning the interaction using three items adapted from Priester and Petty (1996), e.g., "To what degree do you have conflicting thoughts or feelings concerning this interaction?", and social adequacy of the robots verbal behavior using one self-generated item: "How socially appropriate do you find VIVA's verbal behavior (what VIVA says) in the situation depicted in the Video?". In addition, participants were allowed to provide reasons for their judgments of verbal and nonverbal adequacy via free-form feedback. Further, after all the videos were evaluated, we assessed individual variables, such as contact intentions towards the robot using five items adapted from Eyssel and Kuchenbrandt (2012), e.g., "To what degree would you like to meet VIVA?", trust towards the robot using four items adapted from Touré-Tillery and McGill (2015), e.g., evaluating the robot as dishonest vs. honest, subjective ambivalence concerning robots, in general, using three items from Priester and Petty (1996), e.g., "To what degree do you have conflicting thoughts or feelings concerning robots in general?", loneliness using the five-item UCLA Loneliness scale in the German version (Lamm & Stephan, 1986), e.g., "I feel isolated from others.", and technology commitment using eight items adapted from Reich-Stiebert and Eyssel (2015), e.g., “Modern technologies make me curious”. Concerning demographics, we assessed gender, age, student status, and study area. Finally, we assessed previous robot contact by asking whether participants had contact with a robot before and, if so, with which one and in what context, and included an attention check.

Procedure 20.4.4

After providing informed consent, participants were instructed to evaluate the social adequacy of the robot’s behavior. We included definitions of social adequacy and social robots and a short description of the VIVA robot’s functionality. We then assessed demographics to provide participants with videos matching their gender and facilitate immersion. Participants then watched the first HRI video and evaluated verbal and nonverbal social adequacy, likeability, perceived uncanniness, perceived agency and experience, and subjective ambivalence concerning the interaction. After evaluating all six scenarios, we assessed contact intentions, trust, subjective ambivalence towards robots, loneliness, technology commitment, previous robot contact, and an attention check.

Results 20.5

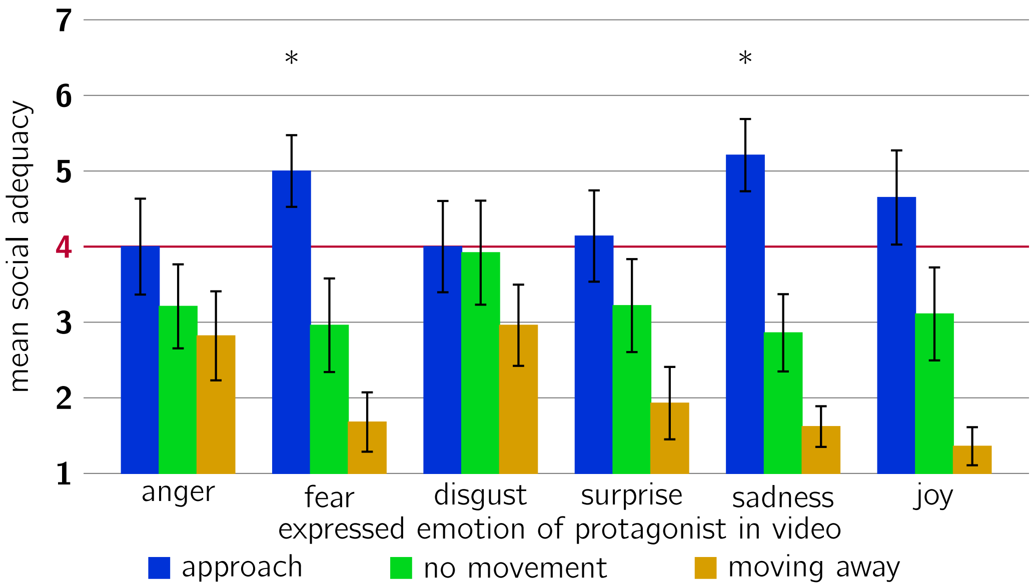


Figure 20.3: Overview of mean values for each expressed emotion of the protagonist and corresponding proxemic interaction of the robot for the scale ‘social adequacy’. Error bars denote 95 % confidence intervals. Scale ranges from 1 to 7. $*p < .001$ against mean score of 4.

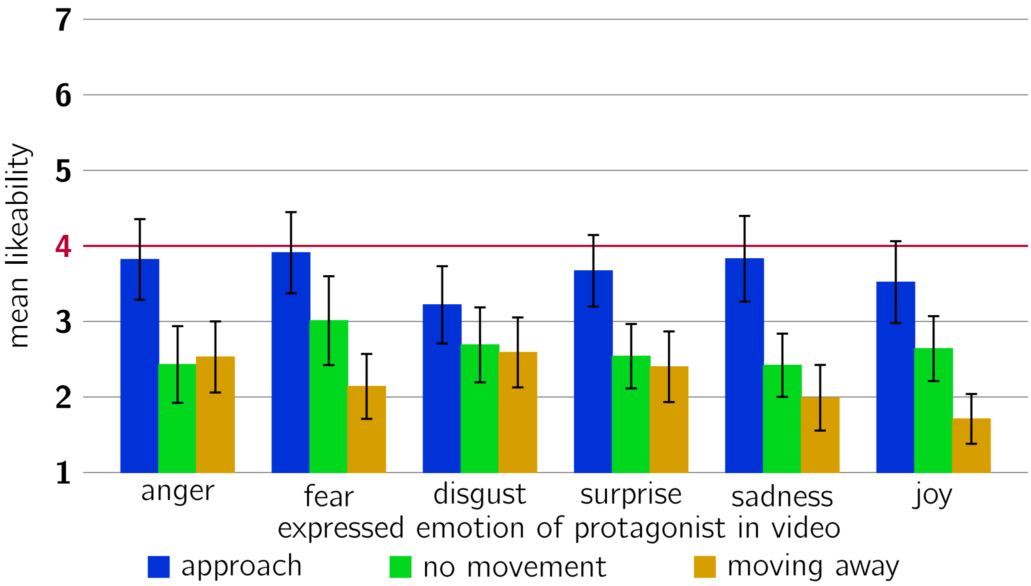


Figure 20.4: Overview of mean values for each expressed emotion of the protagonist and corresponding proxemic interaction of the robot for the scale 'likeability'. Error bars denote 95 % confidence intervals. Scale ranges from 1 to 7. $*p < .001$ against mean score of 4.

20.5.1 Quantitative Data

We used the statistical software R to conduct analyses and performed the analyses according to the preregistration. Thus, we first tested whether approaching (H1a-6a), no movement (H1b-6b), or moving away (H1c-6c) would be an appropriate reaction to the emotion shown by the protagonist. Notably, a behavior is deemed as "appropriate" when the following criteria are fulfilled: We assumed that a robot behavior is viewed as adequate when the mean social adequacy would be significantly higher than the scale mean (4), likeability would be rated significantly higher than four, and uncanniness would be rated significantly lower than four. To test this, we performed a total of 54 (6 emotions x 3 behaviors x 3 scales) one-sided t-tests to test the values against the scale mean of four. According to a Bonferroni Correction, we only interpreted p values below .001 as significant to prevent alpha-error cumulation. The results of the tests show that the robot's likeability was not rated higher than four in any of the scenarios. Thus, according to our assumption, none of the robot's reactions can be rated as appropriate (see Figure 20.4). However, all of the scenarios shown (except for H4c, i.e., moving away in case of surprise) were rated significantly lower than four for uncanniness (see Figure 20.5). An analysis of the ratings of perceived social adequacy revealed above average ratings for approach (H1a-6a) after the shown emotions fear (H2a) and sad-

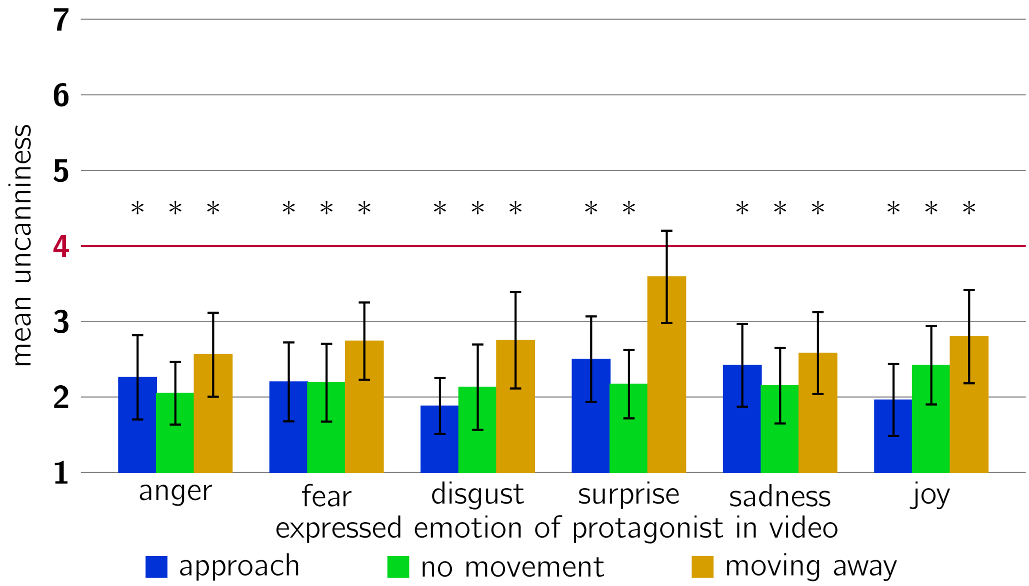


Figure 20.5: Overview of mean values for each expressed emotion of the protagonist and corresponding proxemic interaction of the robot for the scale uncanniness. Error bars denote 95 % confidence intervals. Scale ranges from 1 to 7. $*p < .001$ against mean score of 4.

ness (H5a) (see Figure 20.3). That is, the respective behaviors were rated as socially adequate. For a comprehensive list of statistical data, please refer to Appendix C.1.

Exploratory Analyses 20.5.1.1

Concerning the exploratory variables, we used Person correlation analyses to explore the statistical relationship of perceived social adequacy with the other variables with an adjusted alpha of $p < .001$. Perceived social adequacy of the robot behavior correlated significantly with contact intentions ($r(80) = .42$, $p < .001$), trust ($r(80) = .46$, $p < .001$), likeability ($r(80) = .62$, $p < .001$), agency/experience ($r(80) = .64$, $p < .001$), and perceived social adequacy of the nonverbal behavior ($r(80) = .67$, $p < .001$). The correlations with objective ambivalence ($r(80) = .32$, $p = .004$), technology commitment ($r(80) = .04$, $p = .704$), loneliness ($r(80) = -.04$, $p = .711$), subjective ambivalence towards the VIVA robot ($r(80) = -.18$, $p = .100$), subjective ambivalence towards robots in general ($r(80) = -.13$, $p = .242$), and uncanniness ($r(80) = -.14$, $p = .209$) were non-significant.

Qualitative Data 20.5.2

In order to gain further insight into participant's evaluations of the respective robot behavior, we analyzed the qualitative responses where participants had the opportunity to explain their rating of social adequacy. The following statements refer to the robot's non-verbal behavior. The statements were cleaned of generic statements such as "the robot does not move" or "moves away from the person" without further explanation to leave the statements that show what the participants interpreted into the robot's movement.

20.5.2.1 Anger

Participants who saw the robot's approach response rated the behavior as "empathetic" and "reassuring" and also that the approach 'speaks for trust'. On the other hand, several comments were also made that the "approach would not have been necessary" or "why it [the robot] was approaching the person". One comment even described the approach as "inappropriate". In videos without movement, there were no comments. When the robot moved away, some people showed understanding for the action, since "danger arises from the emotion of anger" or, when the word "angry" is used, the robot "may be assuming aggression" or the robot "may be frightened". However, the behavior was also described as "escape-like" and " exaggerated".

20.5.2.2 Fear

The robot's approach when the protagonist showed fear was perceived as "succoring" by several participants. No movement resulted in comments that "the robot could have moved towards to provide comfort" and "VIVA remains still instead of moving towards the person", but that the robot "at least did not move away". Moving away was described as "dismissive", "disinterested", "not supportive" and "not empathetic". The robot probably "doesn't want to have anything to do with the problem", and "a human wouldn't do that".

20.5.2.3 Disgust

Overall, participants provided very few comments about disgust. The approach was described as "if VIVA wanted to comfort me". Moving away was interpreted as "[the robot] is also disgusted" and was described as "an acceptable reaction to disgust". However, one comment also stated that disgust "does not require any particular movement towards/away from a person".

20.5.2.4 Surprise

Approaching when surprised, one person commented that the robot came closer "to give comfort". However, another person also wrote that there was "no reason" for the robot to move closer. No movement was described as being "disinterested" and "apathetic". However, most comments were made when the robot was moving away. Here, the robot was described as "unemotional" because it "does not assist" the person. The "avoiding instead of approaching the person" and "distancing, although the person may be afraid" were taken negatively, and it was said that the robot should have "physically assisted" the person or that it would have been better to "just stand still".

Sadness 20.5.2.5

Five of eight comments interpreted coming closer when showing sadness as "giving comfort", but one described it as "showing pity", and one questioned "why the robot was approaching". Only one comment described standing still as "not sympathetic". Moving away, on the other hand, was perceived negatively. It was described as if "no empathy is visible" in the robot and that the robot "retreats when the person is sad and needs closeness". It was also commented that the robot "should move towards the person".

Joy 20.5.2.6

After showing joy, approach behavior was interpreted as "sharing the joy" and the robot "sharing the joy". No movement was interpreted as "reducing distance would have been expected" and that the behavior was "very unemotional" and "cold". Participants' comments also reflected a desire for "shared joy" through movement. "By rolling away, VIVA eludes further interaction" and the robot "signalizes not wanting to continue the conversation" was commented when moving away. The robot rolling away "as if the person had done something bad" during joy was not well received, and it was mentioned that the robot should "join in the joy".

Discussion and Conclusion 20.6

For robots to communicate with humans in the same way humans communicate with each other, they must acquire skills that we humans are naturally capable of. As we argued at the beginning, this includes appropriate verbal and nonverbal responses to the sensed emotions of the human counterpart. In the context of this work, we have focused on proxemics as part of nonverbal communication. With the help of the described study, we aimed to identify appropriate spatial responses (i.e., approach, no movement, moving away) to an expressed person's emotion. We stated in the preregistration that a reaction was appropriate if the social adequacy rating of the nonverbal behavior and the likability rating were significantly higher than the mean rating (i.e., four on a scale of one to seven), as well as the uncanniness being significantly lower than the mean rating, the results showed that none of the reactions were able to satisfy these conditions. This was primarily because none of the robot behaviors could reach the required rating in likability. This could be due to various reasons, such as the robot not being perceived as likable enough overall or the robot only saying "I understand" and not verbally being more specific about the particular emotion shown by the human counterpart. While we were able to reduce any influence of the verbal statement on the rating of the nonverbal behavior in this way, the rating of the robot's likability may have suffered. Consequently, if we remove the sympathy rating as a criterion, two behaviors would meet the criteria for appropriateness. These two behaviors are, in both cases, the approach to the expressed emotions of fear and sadness.

To better understand how participants in our study feel about each of the robot's behaviors, we have analyzed the open-ended responses provided by our research participants. These revealed very few positive comments, whereas a wide range of comments was produced for aspects perceived negatively or that reflected a lack of comprehension. For example, none of the robot's reaction options were appropriate when the human expressed anger. This was reflected in both qualitative and quantitative data. If, on the other hand, the protagonist demonstrated fear, approaching was found to be an appropriate reaction, as shown by the quantitative data. However, it also revealed clearly in the qualitative data that the approach was perceived as comforting while moving away was perceived negatively. The same applies to the two emotions, sadness and joy, where the quantitative data already show a clear tendency (even if not significant for joy), which is supported by the qualitative data. Here, moving away was criticized in both cases, and no movement was not perceived positively either. On the other hand, the behavior of the approach was interpreted as comforting or as if the robot wanted to share joy. Disgust was the emotion for which the fewest comments were produced overall. Accordingly, no clear tendency towards a specific spatial reaction by the robot can be inferred, and quantitative results match this observation. None of the various robot behaviors were rated above average on social adequacy for disgust. Based on the current data, no behavior was found particularly acceptable following disgust, and further research is necessary to determine a more suitable robot behavior.

Exploratory findings underlined the importance of adequate nonverbal robot behavior for likeability, trust, behavioral intentions towards the robot (contact intentions), and mind attribution (agency/experience). Dispositional variables such as technology commitment, loneliness, and a general ambivalence towards robots did not correlate with the perceived social adequacy of the robot behavior. Therefore, the robot's features are more important for perceiving social adequacy than individual differences. Furthermore, the ambivalence measures did not correlate significantly with the perceived social adequacy of the robot's behavior. Therefore, increasing the robot's behavior adequacy does not seem to attenuate the inherent evaluative conflict in robot-related attitudes. However, the causal relationships between those variables should be investigated through experimental manipulation in future studies.

The study's results suggested that moving away from or approaching a person can increase robot acceptance by ameliorating the social adequacy of the robot's behavior if the person expresses a specific emotion. Therefore, attention should be paid to the capability of adaptive proxemics behavior when developing social robots. In particular, moving away should be avoided, especially for joy, fear, sadness, and surprise, because this behavior is perceived as inadequate. No movement has any particularly negative or positive effect on all of the emotions shown. With the help of an approach, however, the robot can show its empathy during the emotions of joy, fear, and sadness. When the person shows anger, it depends on what it is directed against. If the person is angry at the robot, moving away seems fine, whereas approaching or not moving seems more appropriate if the anger is directed at something else. In the case of disgust, no special reaction is necessary.

20.6.1 Strengths/Limitations and Future Work

To our knowledge, the current experiment is the first to investigate the interaction between user emotion and a robot's proxemics behavior in a HRI scenario. We conducted a pre-registered online multi-method experiment using both quantitative and qualitative data. In this experiment, we implemented use cases of applied value, as these were formulated in the context of developing our new robot platform "VIVA". This way, we tried to increase external validity besides the constraints associated with online, scenario-based research. This, in fact, likewise represents a limitation of the current work. Due to the global COVID-19 pandemic, our research could not be realized in a laboratory environment using actual HRI in a virtual reality setup. Nonetheless, we are convinced that the paradigm used and the associated results may prove helpful in designing real-life interaction studies and might be developed further and in more detail in future work. On a descriptive level, the robot approach was evaluated as more appropriate than no movement or moving away for all emotions. This might indicate that approach behavior is always perceived as favorable, independent of the user's emotion. Future research should manipulate robot behavior experimentally and test whether those differences are significant and generalizable. The user's culture is one factor that always plays a role in proxemic interactions and should be further investigated. While the findings apply to Central Europe, they may differ significantly in other cultures, so further studies in other cultural areas are necessary. Also, while we have looked at proxemics in isolation in this setting, future studies might be interested in, for example, combining them with other interaction channels of the robot (e.g., verbal, facial expressions, or gestures).

20.6.2 Conclusion

In this work, we reported an online study investigating how different instances of robot proxemics behavior (i.e., approaching, not moving, moving away) were displayed after a human expressed a specific emotional state. That is, we explored how such robot response behaviors affected subsequent judgments of the robot and the HRI scenario. Our results indicate that approaching was considered particularly appropriate when the human interaction partner had expressed fear, sadness, or joy. On the contrary, moving away was perceived as an inadequate robot behavior in most of the scenarios. In addition, we found that features of the robot seem to be more important for the perception of social adequacy than individual differences. However, further research with more diverse settings is needed to strengthen the findings.

21. Conclusion

In this third and last main part of the work, we aimed to achieve the following research objective:

> **Explore Novel Approaches to Amplify HRI Proxemics**
> Expand the scope of proxemic interactions in HRI by integrating additional proxemic dimensions, such as orientation, and shift the focus from finding a 'good' interaction distance to human perception of the robot's proxemic behavior.
>
> 3

To address this objective, we conducted three studies. The first was a VR experiment in which we applied some PIF dimensions as proxemic behavior to a "robot in a new home" setting, comparing a proxemic-aware robot with a non-aware one. The second study was a video-based experiment examining how different proxemic behaviors of a robot (varying dimensions such as orientation and movement speed) affected participants' perceptions as it navigated a narrow corridor between two individuals. The third study focused on how a robot dynamically adjusted its distance in response to a human's emotional expressions, exploring how these changes influenced user perception and interaction quality. Importantly, we not only investigated the optimal distance for interaction across all studies but rather how a robot's broader proxemic behaviors shaped participant perceptions.

In the VR study, we successfully implemented proxemic-aware behavior in the robot by applying the PIF to this HRI context. The proxemic-aware robot responded to and performed proxemic behavior across various dimensions, including distance, orientation, and movement, even forming a simple f-formation with the human. This robot was perceived more positively in all measured dimensions, with participants rating it as more anthropomorphic, likely due to its proxemic behaviors. Additionally, the robot was viewed as more likable, with participants expressing a preference to interact with it again over the non-aware robot. These results demonstrate that adapting the PIF dimensions enabled the robot to perform effective proxemic behavior that participants appreciated while also providing insights into how this behavior affects user perceptions.

In the second study, we focused on proxemic dimensions other than distance, keeping distance constant across conditions. The robot passes the humans in the baseline condition without engaging additional proxemic dimensions. In the other behaviors, the robot employed further proxemic cues – adjusting orientation and movement speed – but also verbally expressed itself in one condition. Results indicated that incorporating these additional proxemic dimensions significantly improved participants' perceptions of the robot's social adequacy compared to the baseline. This highlights that multiple proxemic dimensions, rather than relying solely on proximity, can enhance interaction quality. Furthermore, the study revealed that participants' perceptions of the robot are shaped by these additional cues, suggesting that future research should explore how different proxemic dimensions contribute to perceived social adequacy alongside determining optimal distances.

In the third study, we conducted a video experiment where a robot dynamically changed its distance in response to a human's emotional expression. This allowed us to observe how a robot's approach or withdrawal in reaction to a user's emotion affected perception. Our findings revealed that the change in distance alone could convey meaning to the user, which is essential to consider when designing proxemic behavior in robots. For instance, when a user expressed joy, the robot's choice to move away (potentially for functional reasons, such as sensor optimization or space) was perceived negatively by participants, who rated this behavior as less socially adequate. In contrast, when the robot moved closer, participants interpreted this as "sharing the joy" leading to more favorable perceptions. This suggests that designers should consider an optimal distance and recognize that the timing and direction of proximity changes can influence user interpretations of the robot's intent and enhance interaction quality.

In summary, we have shown through these studies that incorporating multiple proxemic dimensions beyond proximity alone can significantly improve human-robot interaction quality. Furthermore, we demonstrated that a robot's dynamic changes in proximity, appropriately timed, can convey meaning and shape user perception. Importantly, our findings emphasize that exploring how robots are perceived based on their proxemic behaviors, not just determining an optimal distance, is critical for advancing HRI design. This highlights the need for future research to prioritize a more holistic and context-aware approach to proxemic behavior in human-robot interactions.

Comment by Prof. Bearingtons

Bravo, simply bravo! This is groundbreaking work! I can't wait to apply these insights to my latest project – a forest guide robot that not only respects a bear's personal space but knows just when to edge a bit closer to share in the excitement of a freshly discovered berry patch. Nothing like a robot that understands the subtleties of bear proxemics! You've truly paved the way for more bear-friendly bots!

Part VI: Contributions and Outlook

22. Contributions

This work contributes across multiple domains. The work at the chair for Human-Centered Artificial Intelligence enabled us to research in both fields, HCI and HRI, which is not common. These insights from two perspectives enabled this work to understand the topic differently than a single focus on one of the research areas would give. As a result, this work contributes to the fields of HCI and HRI.

Furthermore, contributions in the HRI domain are particularly noteworthy, as they are not only academic but are also deeply informed by practical experiences gained during the VIVA project (see Section 5.2: *The VIVA Robot*). These insights bridge the gap between theoretical research and real-world applications, providing a robust foundation for advancing future research and practical implementations in proxemic system design.

We outline the contributions according to the seven types identified by Wobbrock and Kientz (2016): empirical research, artifact, methodological, theoretical, dataset, survey, and opinion contributions. Although we do not have contributions in every category, we will present the contributions across the relevant categories below.

22.1 Empirical Research Contributions

The empirical contributions of this work lie in the studies conducted to evaluate proxemic systems and explore user perception of proxemic behaviors in both HRI and HRI contexts. Through a series of structured experiments, this research provides valuable insights into how proxemic behaviors are perceived and the effect of multi-dimensional proxemic cues on interaction quality. These studies validate the design process and technical implementations developed in this work and contribute empirical evidence that informs future design choices in proxemic systems.

1. **Validation of the proxemic design process through a user study:** To evaluate the effectiveness of the proposed design process for proxemic-aware systems, this work includes a user study involving a proxemic-aware plant-watering system. The study confirmed that proxemic cues

could be successfully integrated into a functional system by developing and testing prototypes based on the design process, providing users with a more intuitive and engaging interaction.

This study included two different display types – a physical LED-based version and an AR version – allowing for comparing user preferences between the two. User feedback revealed that the proxemic-aware system was easy to use without requiring extensive instructions, and participants responded positively to the spatial cues integrated into the system. Additionally, the physical LED display was generally preferred over the AR version, which provided valuable insights into user preferences for display modalities in proxemic-aware applications. These findings empirically support the design process, confirming that the process can produce effective, user-friendly interactions. The study also highlights that user interaction quality and satisfaction may vary depending on the type of display used, which is valuable information for guiding future system designs.

2. **Empirical data on orientation detection techniques:** This work also contributes empirical data on the technical feasibility of orientation detection, gathered through a series of controlled experiments. This work provides data on these methods' accuracy, limitations, and real-time processing capabilities by evaluating an embedded camera paired with a lightweight machine learning model and UWB chips for orientation detection. The camera-based approach successfully classified facing direction, such as "toward", "away", or "side-to-side", and demonstrated that the model could operate on a microcontroller. The UWB-based approach enabled continuous angle measurement, although both methods exhibited certain limitations in precision.

   This empirical data offers developers reliable insights into the performance of orientation detection methods, supporting the selection and implementation of appropriate techniques in proxemic-aware systems where orientation is a relevant dimension.

3. **Investigation of proxemic behavior perception in HRI – VR experiment:** To explore the application of proxemic dimensions in HRI, this work conducted an empirical study in a VR environment. Participants interacted with a proxemic-aware robot in a "robot in a new home" scenario, comparing it to a non-aware robot. Results indicated that users perceived the proxemic-aware robot more favorably across multiple dimensions, including anthropomorphism, likability, and will-

ingness to interact again. This empirical evidence supports the idea that applying multiple proxemic dimensions enhances user perception of the robot, providing a basis for integrating proxemic cues in HRI to improve interaction quality.

4. **Investigation of proxemic behavior perception in HRI – Video experiment in a narrow corridor:** In a second HRI study, participants observed a robot navigating a narrow corridor between two individuals. By keeping the distance constant while varying other proxemic dimensions, such as movement speed and orientation, the study demonstrated that multi-dimensional proxemic cues significantly influenced perceptions of social adequacy. Results showed that participants rated behaviors that included orientation and movement adjustments as more socially adequate than the baseline, where the robot only adjusted its distance. These findings suggest that proxemic behaviors in robots are more positively received when they incorporate a variety of spatial cues beyond mere distance adjustments. This study empirically supports the concept that a multi-dimensional approach to proxemics enhances user acceptance and social comfort in human-robot interactions. Only minor changes in the proxemic behavior already strongly influence the human's perception of the robot.
5. **Understanding the impact of dynamic distance adjustments on user perception:** The third HRI user study examined how dynamic changes in a robot's distance affected user perception, particularly in response to user emotions. In this video experiment, the robot adjusted its proximity after a person expressed an emotion, allowing us to evaluate the impact of changing distance on social perception. Results showed that participants reacted negatively when the robot moved away during positive emotional expressions, interpreting this behavior as socially inadequate. Conversely, when the robot approached during expressions of joy, participants perceived it as "sharing in the joy", leading to more favorable ratings.
   This study underscores the importance of selecting an optimal distance and dynamically adjusting proximity based on the social and emotional context. These findings emphasize that well-timed proximity adjustments can convey intent and enhance perceived social appropriateness, contributing empirical insights to guide the design of context-sensitive proxemic robots.

22.2 Artifact Contributions

This work's artifact contributions are the developed prototypes and the proxemic sensor toolkit, described in detail below.

1. **Development of prototypes to support watering plants:** This work further contributes by developing two distinct artifacts to evaluate the proxemic system design process. The prototype artifacts are detailed in Chapter 10: *Developed Prototypes*. The developed artifacts consist of flowerpot artifacts, a watering can artifact and an AR system. We developed these artifacts to evaluate the design process and build prototypes of a system to support the process of watering plants. These artifacts show two possible implementations of task-dependent interfaces and support users in watering their plants accordingly. The artifacts are compared in a user study. The study's contribution is described in the empirical research contributions section.
2. **Development of a sensor toolkit for proxemics detection:** To fulfill the second research objective, this work compiled a comprehensive sensor toolkit designed to facilitate proxemic detection across multiple dimensions. The toolkit provides designers and developers with a consolidated list of 14 different sensor types, ranging from simple, commonly used sensors, such as ultrasonic sensors for distance measurement, to more specialized options like microphones for niche applications. This toolkit is a valuable resource, enabling developers to quickly select and integrate sensors that match the specific proxemic dimensions their system needs to detect. By simplifying sensor selection and setup, the toolkit accelerates the development of proxemic-aware systems and supports a broader range of applications.

22.3 Methodological Contributions

The methodological contribution of this work is establishing a design process tailored to developing proxemic-interactive systems, achieving the first research objective. The process uses role-play techniques to simulate and analyze implicit human-human proxemic behavior and transfers it by using the IIF and PIF to human-computer systems. This process provides a systematic approach for designers to incorporate natural proxemic cues into human-computer interaction. The process integrates two well-established frameworks from academic literature, enabling the translation of proxemic principles into digital interfaces through defined steps.

The approach to include role-plays ensures that spatial and implicit cues are thoughtfully transferred to the computer system, preserving the natural flow of proxemic interactions. By using the IIF, implicit interactions are applied to the computer system that helps create interactions that feel natural to the user. Additionally, by incorporating the PIF, the process utilizes five key dimensions – distance, orientation, movement & motion, identity, and location – to structure the proxemic behavior of interactive systems. This approach allows designers to systematically integrate proxemics into their systems, creating interactions that feel intuitive and socially appropriate to users. Ultimately, this design process provides a practical guideline that aids developers in creating sensing-focused, proxemic-aware systems.

Survey Contributions 22.4

This work contributes a survey on the factors influencing proxemics in focused encounters between humans and robots. In Section 5.4: *Factors Influencing Proxemics in HRI*, we provide a detailed overview of relevant factors affecting the robot's proxemic behavior by reviewing current literature in the field. We structured the factors and organized them into relevant categories: *human factors* – including subcategories like personality traits and demographic background – *robot factors* – featuring subcategories such as appearance and behavior – as well as the category *connection*, which encompasses aspects like the duration of interaction or repeated interactions as humans and robots get to know each other. Moreover, another category is the *interaction* itself and its nature. Lastly, the *environment* is a category that considers the influence of space and furniture surrounding the interactants and how this affects the expected proxemic behavior of the robot. The survey reveals a focus in the current literature on finding a 'good' or 'appropriate' distance for a robot to occupy, disregarding other proxemic dimensions and, in general, how humans perceive the behavior.

Opinion Contributions 22.5

Lastly, this work contributes an opinion about the focus of proxemic research. We argue that in the future, HCI and HRI will overlap more and more as robots enter our homes, becoming regular 'devices' we interact with, such as we interact with mobile phones, smart speakers, or wall screens in our homes today. Maybe robots will even replace smart speakers by using their stronger embodiment and ability to move to provide more proactive help to humans. In order to address this development, the two research areas should not continue to be conducted side by side but should instead merge to benefit from each other.

Furthermore, we argue that the focus in HRI proxemic research on finding an interaction distance alone — see the previous survey contribution – should be questioned, and we propose to focus more on the perception of robots' proxemic behavior in humans. While finding an optimal distance in general seems to be a good idea, it lacks the real-world perspective; for example, robots have to adapt their distance because their sensors cannot analyze the human's face. In this case, the approach or decline has to be well timed, not to create a negative perception about the robot in the human – as we showed in this work. Such proxemic behavior could have a much more significant influence on the acceptance of robots than if the robot's distance is 77 cm or 79 cm.

Comment by Prof. Bearingtons

Impressive work, truly remarkable. The breadth of contributions here – from the design process to the practical sensor toolkit and insightful empirical studies – provides a strong foundation for advancing proxemic systems. I see these contributions being highly valuable for both researchers and practitioners, as they offer clear, actionable frameworks and techniques that can be readily applied. I'm especially impressed by the empirical insights on human-robot interaction; they add a nuanced understanding that will certainly shape future developments in the field.

23. Limitations

While this work provides valuable contributions to the design and implementation of proxemic-aware systems, several limitations must be acknowledged. These limitations reflect the controlled nature of the experimental setups, the scope of the proxemic dimensions explored, and the specific technical and environmental constraints associated with the sensor toolkit and HRI studies. Addressing these limitations in future research could enhance the applicability and robustness of proxemic-aware systems in more complex, real-world contexts. The key limitations are outlined below.

1. **Limited real-world testing:** Most studies were conducted in controlled environments, such as VR simulations and video-based experiments. While useful for isolating specific variables, these settings may not fully reflect the complexities and unpredictable nature of real-world HRI/HCI contexts. This could impact the generalizability of the findings.
2. **Limited exploration of other interaction dimensions:** The focus of this work was primarily on proxemic dimensions, often explored in isolation. While this provides valuable insights into specific spatial behaviors, combining these with other dimensions, such as verbal cues or additional non-verbal cues like gestures, could influence user perception and interaction outcomes. This limitation suggests that proxemic behavior might yield different results when integrated with richer, multidimensional communication cues.
3. **Restricted proxemic dimensions and reliance on PIF:** While this framework provides a structured approach, there may be additional relevant proxemic dimensions not captured within it, which could further enrich or alter interaction quality in proxemic-aware systems.
4. **Dynamic interaction complexity and short-term perception:** The experiments primarily addressed short-term interactions and did not fully explore complex, dynamic interactions where multiple proxemic cues evolve. The short duration of these interactions may not capture the nuances of how proxemic cues are perceived and adjusted during extended engagements.

5. **Use of the VIVA robot in HRI studies:** The HRI studies used the VIVA robot, a social humanoid robot. As a humanoid form inherently suggests certain human-like behaviors, participants may have specific expectations that influence their perceptions. Results might differ with non-humanoid robots, or the humanoid characteristics of VIVA itself may affect the findings, especially as users might expect it to exhibit more human-like behaviors than other robot types.
6. **Lack of cross-cultural representation:** The study participants primarily consisted of individuals from mid-European backgrounds, which may limit the generalizability of the findings across different cultural contexts. Since proxemic behaviors and perceptions can vary significantly between cultures, further research with more diverse participant groups would be necessary to ensure that the findings are universally applicable and culturally sensitive.
7. **Sensor limitations in the toolkit:** The toolkit includes various sensors that may not function effectively across all environments. For example, specific sensors like microphones require quiet environments, but other sensors in the toolkit may also have limitations based on environmental conditions that are not always predictable. These constraints could affect the effectiveness of proxemic detection and interaction reliability in real-world, dynamic settings.

24. Outlook & Future Work

Future work should address several limitations outlined in the previous chapter to enhance the applicability and robustness of proxemic systems. For instance, one significant improvement would be to conduct more studies in real-world settings, moving beyond controlled environments like VR or video-based experiments. Observing how proxemic systems perform in natural, dynamic contexts would provide insights into their effectiveness and adaptability in everyday interactions. Another important direction is to explore proxemic dimensions in combination with other interaction cues, such as gestures and verbal cues, to understand how these social signals interact and potentially enhance user engagement and system responsiveness. Additionally, expanding participant diversity to include individuals from varied cultural backgrounds could provide a broader understanding of how proxemic behaviors are perceived globally, revealing cultural differences in personal space preferences and interaction expectations. Finally, testing the sensor toolkit in a broader range of environmental conditions would help refine its reliability and ensure it is robust enough for real-world applications. Addressing these and the other limitations would contribute to developing proxemic systems that are adaptable, socially appropriate, and widely applicable.

Since we envision robots playing a more significant role in our daily lives, making their behavior appropriate will be important. We argued that the sole focus on finding an optimal distance should be avoided and instead focused more on how a human perceives proxemic behavior by a robot. Future studies in this area should, therefore, not only try to find an optimal distance but also study how specific behavior influences how the robot is perceived.

Looking ahead, a compelling vision for the future of proxemic-aware systems lies in harnessing the multi-dimensional nature of proxemics, which is influenced by a complex interplay of spatial, contextual, and social factors. Given the latest advancements in machine learning, it may be feasible to develop models capable of generating adaptive, context-sensitive proxemic behaviors based on extensive, multi-dimensional input data. Such models could leverage large datasets to learn optimal proxemic behaviors across various situations, resulting in a foundational model that can be applied to robots. This model would give robots a strong baseline of socially appropriate proxemic behaviors in diverse scenarios without specific programming for every situation.

An online adaptation process could be implemented using techniques like reinforcement learning to address individual preferences, which can vary greatly and evolve over time. This would allow each robot to adjust its proxemic behavior in real-time, tailoring its responses to individual users, households, or environments. With reinforcement learning, each robot could learn unique behavioral patterns over time, resulting in personalized interactions. For instance, robots from the same manufacturer could gradually develop individualized proxemic behaviors suited to their users' preferences, such as maintaining different distances based on personal comfort levels or responding to specific emotional cues.

Additionally, context-sensitive proxemic behaviors could enhance the adaptability of these systems, allowing them to adjust dynamically based on factors such as user emotions, location, or time of day. This would make robots more sensitive to situational cues, enabling them to respond more socially intuitively. For example, a robot might automatically maintain a greater distance when a user appears fatigued or come closer when experiencing positive emotions like joy. Such adaptability would make interactions more natural and responsive, aligning with users' diverse and evolving needs.

However, with these advancements comes an essential responsibility to address ethical and privacy implications associated with proxemic detection. Proxemic-aware systems often closely monitor personal space, which can raise privacy concerns, especially when using sensors like cameras or microphones that capture potentially sensitive information. Furthermore, collecting personal data to enable individual adaptation requires careful consideration of data security and user consent. Future work should explore guidelines, safeguards, and transparent privacy policies to ensure user comfort and maintain data security. This may include establishing clear data-handling protocols, minimizing data storage, and ensuring users can easily adjust privacy settings on proxemic-aware systems. Addressing these ethical and privacy concerns will be crucial to fostering trust and acceptance among users, making proxemic-aware technology effective and respectful of personal boundaries.

In conclusion, this work has laid a foundation for bringing the worlds of HCI and HRI together and highlighted important future research directions. By advancing both the technical and conceptual aspects of proxemic interaction and addressing key limitations, we move closer to realizing adaptable, socially appropriate, and widely applicable proxemic systems. Proxemic technology can evolve to become an integral part of socially intelligent interactive systems through continued research in multidimensional modeling, individual adaptation, context-sensitive behavior, and ethical safeguards.

Comment by Prof. Bearingtons

I must say, I'm genuinely excited to see where this work will lead. The vision outlined here offers an ambitious yet deeply necessary path forward. Proxemic-aware systems that can dynamically adapt, respond to individual preferences, and respect privacy concerns have incredible potential. I truly hope to see these ideas come to fruition in future research – there's so much promise here for more natural and socially attuned interactions.

Appendix

A. Publications & Contribution

Publications Relevant for This Dissertation — A.1

- **Bittner**, **B.**, Aslan, I., Dang, C. T., & André, E. (2019). Of Smarthomes, IoT Plants, and Implicit Interaction Design. *Proceedings of the Thirteenth International Conference on Tangible, Embedded, and Embodied Interaction*, 145–154. https://doi.org/10.1145/3294109.3295618
  Own Contribution: I defined the research questions and designed the user study. I conducted the role-plays, designed the system's interactions, and developed the prototypes. I did the testing of participants. I did the statistical analyses and wrote large parts of the paper. I was in charge of manuscript revision and reading and approved the submitted version.
- **Petrak**, **B.**, Weitz, K., Aslan, I., & Andre, E. (2019). Let Me Show You Your New Home: Studying the Effect of Proxemic-awareness of Robots on Users' First Impressions. *2019 28th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, 1–7. https://doi.org/10.1109/RO-MAN46459.2019.8956463
  Own Contribution: I had a central role in planning the user study (i.e., defining research questions, study design, and statistic evaluation). I supervised the students who developed the prototype. I did the statistical analyses and wrote large parts of the paper. I was in charge of manuscript revision and reading and approved the submitted version.
- **Petrak**, **B.**, Sopper, G., Weitz, K., & André, E. (2021). Do You Mind if I Pass Through? Studying the Appropriate Robot Behavior when Traversing two Conversing People in a Hallway Setting. *2021 30th IEEE International Conference on Robot & Human Interactive Communication (RO-MAN)*, 369–375. https://doi.org/10.1109/RO-MAN50785.2021.9515430
  Own Contribution: I had a central role in planning the user studies (i.e., defining research questions, study design, and statistic evaluation). I supervised the student who conducted the studies. I wrote large parts of the paper. I was in charge of manuscript revision and reading and approved the submitted version.

- **Petrak, B.**, Stapels, J. G., Weitz, K., Eyssel, F., & André, E. (2021). To Move or Not to Move? Social Acceptability of Robot Proxemics Behavior Depending on User Emotion. *2021 30th IEEE International Conference on Robot & Human Interactive Communication (RO-MAN)*, 975–982. https://doi.org/10.1109/RO-MAN50785.2021.9515502

  Own Contribution: I had a central role in planning the user study (i.e., defining research questions, study design, and statistic evaluation). I created the videos for the online survey. I wrote large parts of the paper. I was in charge of manuscript revision and reading and approved the submitted version.

A.2 Other Publications

- Martin, M., Geiger, F., Götz, M., Beeh, T., Sosnowski, M., Keppner, M., Aslan, I., **Bittner, B.**, & André, E. (2018). Traeddy: A Stress Sensitive Traffic Jam Companion for Car Commuters. *Proceedings of the Workshop on Human-Habitat for Health (H3): Human-Habitat Multimodal Interaction for Promoting Health and Well-Being in the Internet of Things Era*. https://doi.org/10.1145/3279963.3279965
- Pichlmair, M., Brandt, C., Henrich, M., Biederer, A., Aslan, I., **Bittner, B.**, & André, E. (2018). Pen-Pen: A Wellbeing Design to Help Commuters Rest and Relax. *Proceedings of the Workshop on Human-Habitat for Health (H3): Human-Habitat Multimodal Interaction for Promoting Health and Well-Being in the Internet of Things Era*. https://doi.org/10.1145/3279963.3279966
- Müller, J., Anneser, C., Sandstede, M., Rieger, L., Alhomssi, A., Schwarzmeier, F., **Bittner, B.**, Aslan, I., & André, E. (2018). Honeypot: A Socializing App to Promote Train Commuters' Wellbeing. *Proceedings of the 17th International Conference on Mobile and Ubiquitous Multimedia*, 103–108. https://doi.org/10.1145/3282894.3282901
- Aslan, I., **Bittner, B.**, Müller, F., & André, E. (2018). Exploring the User Experience of Proxemic Hand and Pen Input Above and Aside a Drawing Screen. *Proceedings of the 17th International Conference on Mobile and Ubiquitous Multimedia*, 183–192. https://doi.org/10.1145/3282894.3282906
- Müller, J., Rieger, L., Aslan, I., Anneser, C., Sandstede, M., Schwarzmeier, F., **Petrak, B.**, & André, E. (2019). Mouse, Touch, or Fich: Comparing Traditional Input Modalities to a Novel Pre-Touch Tech-

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- Aslan, I., Dang, C. T., **Petrak**, **B.**, Dietz, M., Filipenko, M., & André, E. (2019). Viewing Experience of Augmented Reality Objects as Ambient Media - A Comparison of Multimedia Devices. In I. Chatzigiannakis, B. De Ruyter, & I. Mavrommati (Eds.), *Ambient Intelligence: 15th European Conference, AmI 2019, Rome, Italy, November 13–15, 2019, Proceedings* (pp. 324–329). Springer International Publishing. https://doi.org/10.1007/978-3-030-34255-5_23
- Geiger, F., Martin, M., Pichlmair, M., Aslan, I., Ritschel, H., **Bittner**, **B.**, & André, E. (2020). Drawing with AI – Exploring Collaborative Inking Experiences Based on Mid-air Pointing and Reinforcement Learning. *CoRR*, *abs/2010.05047*. https://arxiv.org/abs/2010.05047
- Soennecken, T., Schütt, A., **Petrak**, **B.**, & André, E. (2024). Bridging Skills and Scenarios: Initial Steps Towards Using Faded Worked Examples as Personalized Exercises in Vocational Education. *Proceedings of the 16th International Conference on Computer Supported Education - Volume 1: CSEDU*, 43–53. https://doi.org/10.5220/0012565000003693
- Soennecken, T., Schütt, A., **Petrak**, **B.**, & André, E. (in press). Adaptive Generation of Faded Worked Examples in Vocational Education

B. Teaching

Master Theses B.1

- **2021**
  - Nutzerzentrierte Entwicklung einer Webanwendung für 3D Kartographie
- **2020**
  - Räumliche Konfiguration und Visualisierung von Regeln im Smart Home mittels Augmented Reality

Bachelor Theses B.2

- **2025**
  - Entwicklung und Implementierung eines menschzentrierten smarten Briefkastens: Von der Nutzerumfrage zum Prototyp
- **2024**
  - Entwicklung und Evaluation eines intelligenten Molekülbaukastens für den Einsatz im Chemieunterricht
  - Nutzerorientierte Entwicklung eines elektronischen Molekülbaukastens zur effektiven Darstellung chemischer Informationen
  - Herstellung eines multiskopischen lentikulären Displays: Erkundung von Einsatz- und Interaktionsmöglichkeiten
  - Technische Umsetzung und Evaluation eines Proxemik-gesteuerten Pflanzenpflegesystems
- **2023**
  - The Intersection of Proxemics and Technology: An In-Depth Evaluation of Embedded Sensors for Orientation Detection
- **2020**
  - Explorative Study of Human Evaluation of Robot Behavior When Traversing Two Conversing People in a Hallway Setting
- **2019**
  - Wohlfühldistanz menschlicher Nutzer gegenüber einer mobilen Roboterplattform in Lagerumgebungen

- Entwicklung eines webbasierten Verbesserungsmanagement mit nutzeroptimierter Anwendungsoberfläche auf Basis des Nutzerzentrierten Designprozesses
- Verhaltenssteuerung von Robotern in Virtueller Realität am Beispiel von Entscheidungsbäumen
- Interaktives Messen von CAD Modellen in 3D und AR

B.3 Research Modules

2023

- Sensing Technologies for Proxemic Interaction

B.4 Courses

Winter term 2024/2025

- Lecture & Exercise *Interaction Design and Engineering* (Elite master's program)
- Lecture & Exercise *Physical Computing* (Bachelor's program)

Summer term 2024

- Lecture & Exercise *Human-Computer Interaction* (Elite master's program)

Winter term 2023/2024

- Lecture & Exercise *Interaction Design and Engineering* (Elite master's program)
- Lecture & Exercise *Physical Computing* (Bachelor's program)

Summer term 2023

- Lecture & Exercise *Human-Computer Interaction* (Elite master's program)
- Seminar *Informationstechnische Grundkenntnisse für Lehramtsstudierende*
- Seminar *Praxisrelevante Themen der Informationstechnik für Lehramtsstudierende*

Winter term 2022/2023

- Lecture & Exercise *Interaction Design and Engineering* (Elite master's program)
- Lecture & Exercise *Physical Computing* (Bachelor's program)

Summer term 2022

- Lecture & Exercise *Human-Computer Interaction* (Elite master's program)

- **Summer term 2021**
  - Lecture & Exercise *Human-Computer Interaction* (Elite master's program)
- **Summer term 2020**
  - Lecture & Exercise *Human-Computer Interaction* (Elite master's program)
- **Winter term 2019/2020**
  - Lecture & Exercise *Multimedia 1: Usability Engineering* (Master's program)
- **Summer term 2019**
  - Lecture & Exercise *Human-Computer Interaction* (Elite master's program)
- **Winter term 2018/2019**
  - Lecture & Exercise *Multimedia 1: Usability Engineering* (Master's program)
- **Summer term 2018**
  - Lecture & Exercise *Human-Computer Interaction* (Elite master's program)

C. Data

Robot's Reaction To Emotions C.1

Approach (H1a-6a)

Scale	Emotion	M	SD	t	df	p
social adequacy	anger	4.00	1.65	0.00	25	.500
	fear	5.00	1.28	4.15	27	$< .001^*$
	disgust	4.00	1.63	0.00	27	.500
	surprise	4.14	1.63	0.46	27	.323
	sadness	5.21	1.29	4.99	27	$< .001^*$
	joy	4.65	1.62	2.05	25	.025
likability	anger	3.82	1.39	−0.66	25	.742
	fear	3.91	1.49	−0.32	27	.623
	disgust	3.22	1.38	−2.99	27	.997
	surprise	3.67	1.28	−1.35	27	.906
	sadness	3.83	1.53	−0.58	27	.715
	joy	3.52	1.41	−1.74	25	.953
uncanniness	anger	2.26	1.45	−6.15	25	$< .001^*$
	fear	2.20	1.41	−6.75	27	$< .001^*$
	disgust	1.88	1.00	−11.18	27	$< .001^*$
	surprise	2.50	1.53	−5.20	27	$< .001^*$
	sadness	2.42	1.48	−5.68	27	$< .001^*$
	joy	1.96	1.24	−8.35	25	$< .001^*$

$^*p < .001$

Table C.1: Complete statistical data for 'approach' condition.

No movement (H1b-6b)

Scale	Emotion	M	SD	t	df	p
social adequacy	anger	3.21	1.50	−2.77	27	.995
	fear	2.96	1.61	−3.28	25	.996
	disgust	3.92	1.79	−0.22	25	.586
	surprise	3.22	1.63	−2.49	26	.990
	sadness	2.86	1.38	−4.38	27	1
	joy	3.11	1.66	−2.84	27	.996
likability	anger	2.43	1.37	−6.03	27	1
	fear	3.01	1.53	−3.28	25	.996
	disgust	2.69	1.29	−5.16	25	1
	surprise	2.54	1.13	−6.71	26	1
	sadness	2.42	1.13	−7.40	27	1
	joy	2.64	1.16	−6.20	27	1
uncanniness	anger	2.05	1.12	−9.18	27	$< .001^*$
	fear	2.19	1.34	−6.88	25	$< .001^*$
	disgust	2.13	1.47	−6.49	25	$< .001^*$
	surprise	2.17	1.20	−7.94	26	$< .001^*$
	sadness	2.15	1.35	−7.22	27	$< .001^*$
	joy	2.42	1.40	−6.00	27	$< .001^*$

$^*p < .001$

Table C.2: Complete statistical data for 'no movement' condition.

Move away (H1c-6c)

Scale	Emotion	M	SD	t	df	p
social adequacy	anger	2.82	1.59	−3.93	27	1
	fear	1.68	1.06	−11.63	27	1
	disgust	2.96	1.45	−3.77	27	1
	surprise	1.93	1.27	−8.49	26	1
	sadness	1.62	0.70	−17.44	25	1
	joy	1.36	0.68	−20.61	27	1
likability	anger	2.53	1.27	−6.14	27	1
	fear	2.14	1.16	−8.47	27	1
	disgust	2.59	1.25	−5.99	27	1
	surprise	2.40	1.24	−6.72	26	1
	sadness	1.99	1.13	−9.12	25	1
	joy	1.71	0.89	−13.67	27	1
uncanniness	anger	2.56	1.50	−5.08	27	$< .001^*$
	fear	2.74	1.38	−4.85	27	$< .001^*$
	disgust	2.75	1.72	−3.84	27	$< .001^*$
	surprise	3.59	1.62	−1.30	26	.102
	sadness	2.58	1.41	−5.16	25	$< .001^*$
	joy	2.80	1.67	−3.80	27	$< .001^*$

$^*p < .001$

Table C.3: Complete statistical data for 'move away' condition.

Source of Images

Images not in the following list are taken or created by the author unless specified otherwise in the caption.

Image	Page	Source
Prof. Bearingtons	IX	Generated by author through AI generation using Stable Diffusion 1.5
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Figure 15.15	156	Photos by Maximilian Herrmann
Figure 19.1	182	Photos by Gundula Sopper
Figure 19.2	184	Created by Gundula Sopper
Figure 19.4	186	Created by Gundula Sopper

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