CREATING LIFELIKE ARTIFICIAL SOCIAL AGENTS

THE ROLE OF MOVEMENT STRATEGIES IN VIRTUAL REALISM

Jacob Michael Sharp

Doctor of Philosophy

ASTON UNIVERSITY

August 2024

Abstract

Creating Lifelike Artificial Social Agents
The Role of Movement Strategies in Virtual Realism
Jacob Michael Sharp
Doctor of Philosophy
2024

This thesis investigates the realism of human movement in Artificial Social Agents (ASAs) within virtual environments, aiming to enhance the authenticity and engagement of human-ASA interactions. Addressing a critical gap in existing literature, this research focuses on the nuanced micro-movement strategies and natural navigational behaviours essential for creating lifelike virtual agents. By integrating psychological theories, advanced technological developments, and various distance and orientation classifications, the study presents a comprehensive framework for improving ASA realism.

The methodologies employed include extensive recording and analysis of human locomotion data, which serve as the basis for developing sophisticated movement strategies for ASAs. This data-driven approach ensures that the proposed strategies closely mimic the subtle, unconscious micro-movements that characterize natural human behaviour. Additionally, the perceived realism of these movements is evaluated through rigorous user studies, providing empirical evidence on the effectiveness of the proposed movement strategies.

The findings underscore the significance of adaptive, context-aware behaviours in ASAs, demonstrating that the incorporation of sophisticated algorithms and machine learning techniques can substantially enhance the realism and engagement of virtual interactions. This research has broad implications across multiple domains, including education, healthcare, and social robotics, where the authenticity of virtual agents is pivotal in enhancing user experience and efficacy. The insights gained from this study pave the way for future advancements in the design and implementation of more lifelike and responsive ASAs, ultimately contributing to more realistic and effective virtual environments.

Keywords:
Artificial Social Agent (ASA), Micro-Movement Strategies, Human Locomotion, Realism, Virtual Environments, Human-Agent Interaction

To everyone who supported, guided and stuck with me, thank you.

Personal Acknowledgements

I would like to express my deepest gratitude to those who have supported me throughout this journey. First and foremost, I want to thank my mum and dad. Your unwavering emotional and financial support during the toughest times has been my anchor. Your belief in me has never wavered, and for that, I am eternally grateful.

To my amazing girlfriend, Eden, you have been my rock and my inspiration. Tackling and completing your own master's degree while standing by my side throughout my PhD journey is a testament to your incredible strength and dedication. You have been a shoulder to cry on, a voice of reason, and my biggest cheerleader. Your encouragement and unwavering support have pushed me forward even when I doubted myself at every stage. I couldn't have done this without you.

I am profoundly grateful to my supervisor, Ulysses. Thank you for sticking with me and pushing me to achieve my best, when I look back at my writing from even just a year ago, the difference is astounding. Your honest feedback and willingness to tell me the hard truths have been invaluable. From offering to bring food during COVID disasters to just offering your sympathy through family disasters, your guidance and mentorship have shaped this work, and for that, I am deeply appreciative.

I would also like to extend my gratitude to the University. Your support, especially during the challenging times of the COVID-19 pandemic and beyond, has been crucial in keeping me on track. The resources, guidance, and encouragement provided have been instrumental in the completion of this thesis.

To everyone who has played a part in this journey, whether through direct assistance or through their presence in my life, thank you. This accomplishment is as much yours as it is mine.

List of Publications

Sharp, J., & Bernardet, U. (2023). The missing tip: Lack of micro-movements impairs navigation realism in artificial social agents. *15th International Conference on Agents and Artificial Intelligence*, 380–386. https://doi.org/10.5220/0011798300003393

Contents

List of Figures

List of Tables

List of Acronyms

ASA Artificial Social Agent

IVE Immersive Virtual Environment

FSM Finite State Machine

ToM Theory of Mind

HCI Human-Computer Interaction

UX User Experience

Key Terminology

Artificial Social Agent (ASA): Autonomous entities designed to interact with humans in a socially meaningful way within virtual environments, using algorithms to simulate social behaviours and decisions without direct human control.

Movement: The basic action of changing position or orientation within a space. In the context of ASAs, movement refers to any physical or simulated motion, such as walking, turning, or gesturing, that an agent performs within its environment.

Micro-Movement Strategies: These are small, purposeful motor adjustments humans make during locomotion, contributing to the fluidity and naturalness of movement. Examples include backstepping, strafing, and curved walking. These strategies are critical for enhancing the realism of ASAs by mimicking the subtle, yet significant, behaviours observed in natural human movement.

Locomotion: The process of movement from one location to another. In the context of ASAs, locomotion refers to the simulation of walking, running, or other types of movement that replicate human behaviour in virtual environments.

Navigation: The broader process that encompasses both pathfinding and movement, involving the overall strategy and decision-making required for an ASA to move through an environment. Navigation includes determining the final destination, adapting to real-time changes, and making strategic decisions about the path and manner of movement.

Realism: The degree to which a virtual agent or environment convincingly replicates real-world appearance, behaviour, and interaction patterns. High realism in ASAs contributes to user immersion and engagement by making virtual interactions feel more authentic.

Presence: A psychological state where the user feels as though they are truly "present" in a virtual environment. High presence is achieved when the virtual environment and ASAs within it are perceived as realistic and immersive.

Proxemics: The study of personal space and the physical distance maintained between individuals during interaction. In virtual environments, proxemics influences how ASAs manage interpersonal distance to create realistic social interactions.

Finite State Machine (FSM): A computational model often used to design the behaviour of ASAs, where the system transitions between a finite number of states based on input.

Theory of Mind (ToM): The cognitive ability to attribute mental states—like beliefs, desires, and intentions—to oneself and others.

behavioural Realism: The extent to which an ASA's actions and reactions mimic those of a human. behavioural realism is critical for creating believable and engaging interactions between humans and virtual agents.

Human-Computer Interaction (HCI): The study of how humans interact with computers and digital systems, including virtual environments and ASAs. HCI principles guide the design of user-friendly and effective virtual agents.

Motion Capture: A technology used to record and analyse human movement, which is then used to inform the development of realistic movement strategies for ASAs. This data-driven approach helps in creating more lifelike virtual agents.

Immersion: The degree to which a user is absorbed and engaged in a virtual environment. High immersion is achieved when the virtual environment and the agents within it are sufficiently realistic to draw the user's attention and maintain their involvement.

Neural Networks: A type of artificial intelligence model inspired by the human brain's network of neurons.

Machine Learning: A subset of artificial intelligence focused on developing algorithms that allow computers to learn from and make predictions based on data.

Social Robotics: The field of robotics that focuses on the development of robots capable of engaging in social interactions with humans.

User Experience (UX): The overall experience a person has when interacting with a digital system, including ASAs. High UX is achieved when users find the interaction intuitive, engaging, and satisfying.

Proxemics in Human-Computer Interaction: The application of proxemic principles to the design of virtual environments and ASAs, ensuring that agents maintain appropriate interpersonal distances to enhance realism and comfort.

Navigation Strategies: The methods and algorithms used by ASAs to move through and interact with their environment. Effective navigation strategies are essential for maintaining the realism and functionality of virtual agents.

Chapter 1

Introduction

As technology continues to advance and embed itself into everyday life, interactions between humans and computer systems are becoming increasingly sophisticated. These interactions now extend beyond simple commands to complex engagements with artificial social agents (ASAs) and virtual environments. ASAs are designed to interact with both humans and other agents within these environments, making autonomous decisions to achieve specific objectives. This social and technical framework requires ASAs to operate in shared, dynamic environments where they can adapt to and influence each other.

A key factor in enhancing the functionality and realism of these systems is their ability to exhibit natural, human-like behaviours. While traditional research has primarily focused on pathfinding—the process of determining efficient routes—this approach often neglects the subtle, unconscious micro-movement strategies inherent in human navigation. These micro-movement strategies, such as orienting while walking, back-stepping, and minor adjustments during locomotion, are what we posit significantly contribute to the perceived realism of ASAs. When these nuances are absent, even well-designed agents risk appearing stiff or artificial, which can undermine user immersion and trust.

Despite their importance, there is a notable gap in current research regarding micro-movement strategies. Most studies emphasize broader aspects of navigation and visual fidelity, overlooking the detailed behaviours that enhance immersion and social presence. Immersion—defined as the subjective feeling of being in another world—is critical for effective virtual environments used in training, education, and therapy (Merchant et al., 2014). Moreover, realistic movement patterns not only enhance immersion but also improve the credibility and engagement of artificial social agents, as demonstrated by Latoschik et al. (Latoschik, Wienrich, and Botsch, 2017).

In addition to exploring the contribution of micro-movements to realism, this thesis discusses how an acceptable level of realism can be achieved. It considers the metrics and methodologies by which designers and developers can determine that their ASAs exhibit sufficient realism to enhance user experience while avoiding pitfalls such as the uncanny valley effect (Bailenson et al., 2003). This discussion covers both qualitative measures (e.g., user feedback, observational studies) and quantitative approaches (e.g., validated ASA questionnaires and performance metrics) to ensure that realism is both effectively implemented and appropriately balanced.

It is important to clarify at the outset that this work is not concerned with every facet of virtual agent behaviour. While topics such as avatar embodiment, complex emotional or conversational AI, and purely aesthetic enhancements are important in other contexts, they are beyond the scope of this thesis. Our focus is specifically on micro-movements—the fine-grained aspects of human locomotion—and their direct impact on the realism and social presence of ASAs.

This thesis aims to bridge the current research gap by investigating the role of micro-movement strategies in enhancing ASA realism. By recording and analysing human locomotion data, developing standardized descriptors for these movements, and evaluating their impact on perceived realism, this research proposes a comprehensive framework for realistic ASA navigation. Methodologies include advanced motion capture techniques, machine learning algorithms, and user studies to assess the effectiveness of the proposed movement strategies.

Additionally, this research explores the broader implications of realistic ASA movements in various applications, including social robotics, healthcare, and education. By integrating these micro-movement strategies into ASA navigation systems, we can significantly enhance their social presence and overall user experience in virtual environments.

In summary, this thesis addresses the critical need for realistic micro-movement strategies in ASAs to improve their functionality and user engagement. By focusing on the fine-grained aspects of human movement, this research not only enhances ASA realism but also paves the way for more lifelike and immersive virtual interactions. A clear roadmap follows in the subsequent sections, guiding the reader through the theoretical foundations, methodological approaches, and experimental validations that underpin this work.

While the field of virtual agents encompasses many closely related areas, it is important to delineate what is outside the scope of this work. In this thesis, we focus exclusively on Artificial Social Agents (ASAs)—autonomous, computational agents designed to interact with humans in dynamic environments by exhibiting lifelike movement behaviours. This work does not address:

User-Controlled Avatars: Unlike avatars, which are representations manipulated by users, ASAs operate independently and make autonomous decisions.

Complex Emotional or Conversational AI: Although emotional expression and dialogue management are important in other contexts, our focus is on the micro-movement strategies that contribute to the realism of ASAs.

Purely Aesthetic Enhancements: We concentrate on the behavioural and motion aspects that drive immersion, rather than on high-fidelity graphics or photorealistic rendering.

By establishing these boundaries, we clarify that our investigation centres on the subtle, yet critical, aspects of human locomotion—such as orientation adjustments, back-stepping, and other micro-movements—that are essential for creating lifelike and engaging ASAs.

1.1 Research Questions

This thesis aims to bridge critical gaps in the existing literature on human locomotion and its application in enhancing the realism of artificial social agents (ASAs) within virtual environments. The following research questions guide the investigation:

1. **What factors increase the realism of artificial social agent movements?**
   This question seeks to explore and formalize the fundamental components and behaviours that contribute to realistic human locomotion. By identifying and structuring these micro-movement strategies, the research aims to develop a comprehensive framework that can be applied to improve the navigational realism of artificial social agents.

2. **Which movement strategies are most commonly used by humans during navigation?**
   Understanding the frequency and context of different micro-movement strategies in

human locomotion is crucial for creating realistic artificial social agents. This question focuses on identifying and analysing the most prevalent movements humans use, providing empirical data that informs the design and implementation of these movements in ASAs.

3. **What is the effect of the identified micro-movement strategies on the perceived realism of artificial social agents?**
   Perceived realism is a critical factor in the effectiveness of artificial social agents. This question examines user feedback on the realism of the proposed micro-movement strategies, aiming to quantify their perceived authenticity through user studies. By evaluating the realism "score" of these movements, the research assesses the impact of the identified strategies on user experience and engagement.

Addressing these research questions will provide a robust understanding of human locomotion's nuances and their application in creating lifelike artificial social agents. The insights gained will contribute to the development of more immersive and effective virtual environments, enhancing the overall user experience.

1.2 Contributions of this Thesis

This thesis makes several contributions to the field of Artificial Social Agents (ASAs) with a specific focus on enhancing the realism of agent movement and interaction in virtual environments. The key contributions are as follows:

- We initially designed and implemented a controller for managing ASA locomotion and gaze control with the goal of exploring interpersonal distance regulation. However, the finite state machine (FSM) exposed significant shortcomings in replicating realistic movement, which ultimately led us to refocus our research on the fundamental elements of authentic, human-like motion.

- The formalization of micro-movement strategies, which are essential for achieving a higher level of realism in ASAs. This formalization serves as a basis for future research, enabling the development of autonomous systems capable of replicating these subtle behaviours.

- The collection and analysis of human movement data traditionally, providing critical insights into the dynamics of human locomotion. This empirical study informed the refinement of ASA control systems, and had some success with predicting movement based on other factors, ensuring that their movements more closely mimic human behaviour.

- The evaluation of perceived realism in ASAs, contributing valuable findings on the effectiveness of current ASA designs and identifying areas for improvement. This empirical evaluation advances the understanding of what constitutes realistic behaviour in artificial social agents.

Collectively, these contributions advance the understanding of ASA realism and provide a foundation for future research and development in the field.

1.3 Structure of this Thesis

The remainder of this thesis is organized into five chapters with the following structure:

Chapter 1 provides an overview of the field of artificial social agents (ASAs), highlighting their importance in various applications such as training, education, and therapy. The key research questions this thesis aims to address are outlined, and the main contributions of the research are summarized. Additionally, this chapter includes a comprehensive literature review, covering essential topics such as ASAs, presence in virtual environments, interpersonal distance, proxemics, and pathfinding. This review sets the groundwork by discussing the broader context and the significance of realism in ASAs.

Chapter 2 will delve into the critical challenges involved in developing a more believable and realistic Artificial Social Agent (ASA). The chapter begins by reviewing the technical background literature and will then explore the motivation behind this thesis, detailing the methodology and procedural framework designed to investigate how different interpersonal distances affect user interactions with ASAs. The chapter will also discuss the design and implementation of a Finite State Machine (FSM) to manage ASA locomotion and gaze control, highlighting its importance in creating realistic and responsive behaviours. Insights from initial investigations will underscore the necessity of authentic movement for accurately simulating human-ASA interactions. Finally, the chapter will outline future steps for refining ASA movement strategies, setting the stage for further sections of this work.

Chapter 3 focuses on the formalization of micro-movement strategies. This chapter provides a detailed analysis of human movement data, emphasizing the complexity of human navigational behaviour and the need for more nuanced data that captures orientation and micro-movements during locomotion. A comprehensive framework for categorizing and describing micro-movements is proposed, identifying six key micro-movement behaviours. This framework offers a structured approach to understanding and implementing these movements in ASAs. The chapter concludes with a discussion on potential future research directions, highlighting the necessity for further data collection and the development of autonomous systems capable of realistically replicating these micro-movements.

Chapter 4 delves into recording human locomotion data in the context of a waypoint-based task. The motivation behind this data collection is explained, particularly its relevance to tasks involving navigation to specific waypoints. The methodology for recording and analysing human locomotion data is described in detail, including experimental design, data collection techniques, and specific metrics used to evaluate movement patterns. Detailed analysis of the recorded data is presented, including differential and inferential analysis to identify patterns and correlations in human movement. The application of machine learning techniques to analyse and predict human locomotion patterns is explored, providing insights into the development of more sophisticated ASA control systems. The chapter concludes by summarizing the findings and discussing their implications for the development of realistic ASAs.

Chapter 5 empirically evaluates the perception of realism in micro-movement strategies identified and developed in the preceding chapters. Utilising a structured questionnaire, the study gathers participants' feedback on the human-likeness, naturalness, performance, and overall realism of these movements. The questionnaire items are adapted from the well-established Artificial-Social-Agent (ASA) Questionnaire, ensuring the reliability and relevance of the measures. Data collection is conducted via the Gorilla platform, enabling efficient and diverse participant recruitment. The findings from this chapter validate the effectiveness and believability of the micro-movement strategies, providing critical insights for refining these strategies and enhancing the realism of artificial social agents (ASAs).

Chapter 6 brings the thesis to a close by drawing conclusions from the results of the experimental studies conducted in the previous chapters. The research questions and contributions are revisited, concluding with a discussion of the implications of these findings for the field of ASA development. This chapter also emphasizes the importance of realism and immersion in virtual environments and how the integration of micro-movements in ASAs can significantly enhance user experience. Finally, the chapter suggests future avenues for research, underlining the potential for further advancements in the realism of artificial social agents.

Appendices include additional material that supports the main text, such as detailed data sets and supplementary analyses.

1.4 Introduction to Artificial Social Agents (ASAs)

As mentioned in the Introduction, Artificial Social Agents (ASAs) are autonomous, interactive entities designed to engage with humans without requiring direct human control. Unlike avatars or virtual humans—which either rely on user input or serve primarily as representational figures in virtual environments—ASAs operate independently using algorithms to mimic human behaviours and interactions (Kyrlitsias and Michael-Grigoriou, 2022;Blascovich and Bailenson, 2011;K. L. Nowak and Fox, 2018). They are deployed across diverse applications such as customer service, healthcare, education, and research simulations, with the required level of realism varying by context. For example, an ASA in customer service may need only basic conversational capabilities, whereas in therapeutic or educational settings, higher realism—particularly in movement and emotional expression—is crucial to foster user trust and promote effective outcomes. In healthcare, relational agents that exhibit naturalistic gestures and empathetic behaviours have been shown to improve patient adherence and perceived support in long-term interventions Bickmore and Picard, 2005a. In education, animated pedagogical agents whose movement realism and nonverbal cues align with instructional goals significantly enhance students' engagement and learning gains Rickel et al., 2000.

The distinction between ASAs, avatars, and virtual humans is critical. ASAs function autonomously and are engineered to exhibit social behaviours without human intervention, whereas avatars are user-controlled digital representations that act as proxies for individuals in virtual spaces. Virtual humans, which may operate autonomously or under human control, are typically designed to achieve a high degree of visual or contextual realism but do not necessarily engage in complex social interactions independently (Vinayagamoorthy et al., 2006). This differentiation clarifies that our focus is on the autonomous, behaviour-driven nature of ASAs.

Realism in ASAs encompasses several components, including visual appearance, movement, emotional expression, and behavioural responsiveness. The degree of realism is a key determinant of an agent's effectiveness: in customer service and retail, moderate realism may be sufficient to convey clear communication and maintain appropriate interpersonal distance Nass and Moon, 2000, while in healthcare and therapy, higher realism is essential—studies show that patients are more positively engaged and report greater trust when agents display human-like empathy and adaptive social behaviours, leading to improved therapeutic outcomes Bickmore et al., 2009. Similarly, in educational contexts, realistic movement and interactive behaviours in virtual tutors have been linked to deeper learning and higher retention rates Heerink et al., 2010. In research simulations, achieving high realism is critical to replicate human behaviour reliably.

Understanding the nuances between movement, locomotion, pathfinding, and navigation is essential for creating effective ASAs. Movement is the fundamental act of changing position or orientation, while locomotion describes the biomechanics of how that movement is achieved (e.g., walking, running) LaValle, 2006. Pathfinding involves determining the most efficient route to a destination by accounting for obstacles and terrain, and navigation integrates both pathfinding and movement with broader strategic decision-making Pelechano et al., 2008. Our research emphasizes the importance of incorporating subtle movement strategies—such as backstepping, strafing, and slight orientation adjustments—into these processes. By doing so, we enhance the overall realism of ASAs, making their interactions more lifelike and believable. This attention to detailed motor behaviours not only improves visual and behavioural fidelity but also deepens user engagement and trust, particularly in applications where high realism is critical Hancock et al., 2011.

1.4.1 Psychological Foundations of Human-ASA Interaction

The concept of interpersonal distance, which refers to the physical space individuals maintain between themselves and others, is deeply rooted in psychological and social dynamics. Research by Holt-Lunstad et al., 2010 and Holt-Lunstad et al., 2015 provides significant insights into the psychological underpinnings of interpersonal distance and its implications for human interactions.

Holt-Lunstad et al., 2010 investigated the role of social relationships in health outcomes, highlighting the importance of interpersonal distance as a component of social connectivity. Their study found that social isolation and lack of close relationships are linked to negative health outcomes, including increased mortality risk. This research underscores the psychological need for social proximity and meaningful interactions, suggesting that maintaining appropriate interpersonal distance is crucial for psychological well-being.

Building on this, Holt-Lunstad et al., 2015 conducted a meta-analysis to examine the impact of social relationships on mortality risk. Their findings reinforced the notion that social integration, which includes maintaining optimal interpersonal distances, is a critical determinant of health and longevity. The study revealed that individuals with strong social connections, who navigate interpersonal distances effectively, experience lower risks of mortality. This underscores the psychological importance of balancing personal space and social interaction to foster both mental and physical health.

These findings align with the broader body of psychological literature that explores the origins and functions of interpersonal distance. Hall, 1966 introduced the concept of proxemics, which examines how humans use space in communication and social interactions. According to Hall, interpersonal distance is categorized into four distinct zones: intimate, personal, social, and public distances. Each zone corresponds to different types of interactions and relationships, reflecting the psychological comfort and social norms governing personal space.

Further psychological insights are provided by Pincus et al., 2009, who explored the behavioural aspects of interpersonal interactions and their relation to personality traits. Their research suggested that interpersonal distance is influenced by several factors, including individual personality characteristics, situational context, and social dynamics. For instance, individuals with high levels of social anxiety may prefer greater interpersonal distances to reduce discomfort, while those with more extroverted personalities might seek closer interactions. These findings underscore the importance of considering these variables when analysing human behaviour in social contexts

These foundational insights suggest that while maintaining appropriate interpersonal distance is crucial for comfort and psychological well-being, it is not the sole determinant of realistic and effective human-ASA interactions. The research indicates that while interpersonal distance is essential for fostering a sense of presence and social appropriateness, achieving realism in ASAs requires integrating these proxemic principles with a broader set of human-like behaviours and social cues.

1.4.2 Psychological Theories of Interaction with ASAs

With a foundational understanding of ASAs and their varying levels of realism depending on the application, it becomes essential to explore the psychological mechanisms that govern human interactions with these agents. Understanding how ASAs can successfully navigate and maintain socially appropriate interactions requires delving into the psychological principles that underpin human social behaviour, particularly in relation to concepts like interpersonal distance and social presence. This psychological perspective provides the necessary framework for designing ASAs that can engage meaningfully with humans in diverse contexts.

Understanding the psychological theories that underpin human interactions with ASAs is crucial for designing agents that can engage effectively and naturally with users. Key contributions from Reeves and Nass, 1996 and Short et al., 1976 provide foundational frameworks that explain how humans relate to and perceive artificial agents. These theories offer insights into the cognitive and emotional processes that occur during human-ASA interactions and guide the design of more intuitive and engaging agents.

Reeves and Nass, 1996 introduced the "media equation" theory, which posits that people treat computers, television, and new media as real people and places. Their research demonstrated that users apply social rules and expectations from human interactions to their interactions with media, including ASAs. This theory suggests that humans are inherently predisposed to anthropomorphize and engage socially with artificial agents, responding to them as if they were human beings. For instance, users might show politeness, exhibit emotional responses, and follow social norms when interacting with ASAs.

The work of Short et al., 1976 on social presence theory also provides valuable insights into human-ASA interactions. Social presence is defined as the degree to which a person perceives another entity as being psychologically present in a communication interaction. Their research emphasized that the quality of interaction is influenced by the perceived presence of the interacting party. For ASAs, this means that the more they can project a sense of presence—through visual appearance, behaviour, and responsiveness—the more effective they will be in engaging users.

These theories indicate that for ASAs to be perceived as realistic, they must exhibit behaviours that align not only with proxemic norms but also with broader social and psychological expectations. The importance of behavioural realism—how well an ASA's actions and responses mimic those of a human—emerges as a critical factor in enhancing user engagement and interaction quality.

Building on these foundational theories, further research has explored various aspects of psychological interaction with ASAs. For example, Nass and Moon, 2000 extended the media equation theory by examining how people apply social categories to computers. Their findings indicated that users not only treat computers as social actors but also attribute social characteristics, such as gender and personality, to them. This research highlights the importance of carefully considering the design elements of ASAs, such as voice, appearance, and behaviour, to align with users' social expectations and enhance interaction quality.

In addition, the concept of "the uncanny valley" introduced by Mori, 1970 provides a psychological framework for understanding user discomfort with ASAs that are almost, but not quite, human-like. This theory suggests that there is a range of human likeness in ASAs where users experience unease and discomfort. As ASAs become more human-like, their slight imperfections become more noticeable and disturbing to users. This insight is crucial for designing ASAs that balance human likeness with user comfort, ensuring that they are engaging without falling into the uncanny valley.

The theory of mind (ToM), which refers to the ability to attribute mental states to oneself and others, is another important psychological framework relevant to human-ASA interactions. Research by Premack and Woodruff, 1978 introduced this concept, which has since been applied to ASAs. For instance, Breazeal, 2003 explored how ASAs can be designed to exhibit behaviours that suggest they have their own beliefs, desires, and intentions. By incorporating elements of ToM, ASAs can engage in more complex and meaningful interactions, as users are likely to respond more naturally to agents that appear to have their own mental states.

Furthermore, cognitive load theory, as described by Sweller, 1988, provides insights into how the design of ASAs can impact user interaction. This theory suggests that the cognitive load imposed on users should be minimized to facilitate learning and interaction. When applied to ASAs, this means designing agents that are intuitive and easy to interact with, reducing the cognitive effort required from users. This can be achieved through clear communication, consistent behaviour, and user-friendly interfaces.

The research by Reeves and Nass, 1996 and Short et al., 1976, along with subsequent studies, highlights the importance of understanding the psychological underpinnings of human-ASA interactions. These theories emphasize the role of social presence, anthropomorphism, and cognitive load in shaping user experiences with ASAs. By leveraging these insights, we can create more effective and engaging artificial agents that align with human social and psychological expectations.

As the aim to investigate interpersonal distance further stalled (as explained in Chapter 2), particularly in the context of human-ASA interactions, it became evident that the realism of ASAs was a prerequisite that could not be overlooked.

1.4.3 Proxemics and Social Interaction with ASAs

Having established the foundational concepts, we now turn our focus to proxemics and social interaction. The interaction between humans and artificial social agents (ASAs) has been a focal point of research, particularly in understanding how humans perceive and engage with these entities. The studies by Walters et al., 2005 and Strait et al., 2017 provide significant insights into this dynamic, offering a foundation for exploring the intricacies of human-ASA interactions.

Walters et al., 2005 investigated the nuances of human interactions with robots, specifically focusing on how the presence and actions of robots influence human behaviour. Their study emphasized the importance of physical embodiment in robots, noting that tangible, physical agents elicit more natural and socially appropriate responses from humans compared to artificial social agents. The research highlighted key factors such as proxemics, the physical distance maintained during interactions, which significantly impacts the comfort and engagement levels of human participants. Walters and colleagues found that humans tend to treat robots with physical presence similarly to how they treat other humans, maintaining similar social distances and exhibiting comparable social behaviours.

Building on this, Strait et al., 2017 explored the psychological and social dimensions of human interactions with artificial social agents, particularly focusing on the "uncanny valley" effect. Their study found that slight imperfections in an artificial social agent's human-like appearance can lead to discomfort and aversion among users. They highlighted that perceived realism and behavioural congruence of artificial social agents play crucial roles in determining the quality of interaction. When artificial social agents closely mimic human gestures and facial expressions, they are perceived as more lifelike and engaging, which enhances user experience and acceptance.

Moreover, Strait et al. underscored the importance of adaptive behaviour in artificial social agents (ASAs). They argued that agents capable of adjusting their responses based on human actions and emotions can create more meaningful and satisfying interactions. This adaptability includes recognizing and appropriately responding to human emotional cues, fostering a sense of empathy and connection between humans and artificial agents. The study also suggested that using advanced algorithms and machine learning techniques to enhance the adaptability and responsiveness of artificial social agents could significantly improve their effectiveness in various applications, from customer service to healthcare.

Gockley et al., 2005 conducted pioneering research on how robots influence interpersonal distance, focusing on proxemic behaviour in human-robot interactions. Their study revealed that humans tend to maintain a certain physical distance from robots, similar to how they would with other humans. This distance varies depending on the robot's behaviour, appearance, and perceived social presence. The researchers found that when robots exhibit human-like behaviours and social cues, people are more likely to interact with them within a closer personal space, suggesting a higher level of comfort and engagement.

The findings of Gockley et al., 2005 are supported by subsequent research that delves deeper into the factors affecting interpersonal distance in interactions with ASAs. Takayama and Pantofaru, 2009 explored the role of social cues in human-robot interaction, particularly how these cues impact proxemic behaviour. They found that robots capable of exhibiting social behaviours, such as maintaining eye contact, using gestures, and showing responsive behaviours, are perceived as more approachable. This perception results in reduced interpersonal distances, as people feel more comfortable and willing to engage in closer interactions with socially adept robots.

In addition to these primary studies, other relevant literature further elucidates the complexity of human-ASA interactions. For instance, Breazeal, 2003 discussed the social aspects of human-robot interaction, emphasizing the importance of robots that can understand and respond to social cues. This understanding enables more fluid and intuitive interactions, making robots more effective companions and assistants.

Similarly, Fong et al., 2003 explored the role of social intelligence in robots, arguing that robots equipped with such intelligence can better navigate human environments and perform tasks that require social cooperation. They highlighted various approaches to endowing robots with social skills, such as using sensors to detect human emotions and employing algorithms to generate appropriate social responses. These studies collectively underscore the need for ASAs to integrate both proxemic awareness and social cues to engage effectively with humans.

These studies collectively emphasize the need for ASAs to integrate both proxemic awareness and social cues to engage effectively with humans. However as previously mentioned, when we delved deeper into understanding proxemics, it became evident that while interpersonal distance is critical, it alone is insufficient to achieve the level of realism required for ASAs to be perceived as truly lifelike and engaging.

1.4.4 The Map of ASA Realism

Recent advancements in the simulation of personality through non-verbal behaviours in virtual agents, such as those presented in the "RealAct" model by Saberi et al., 2021, emphasize the critical role of non-verbal cues in enhancing perceived realism and social presence in ASAs. The "RealAct" model, as illustrated in figure 1.1, demonstrates how virtual agents can embody personality traits like extraversion and neuroticism through behaviours such as gaze direction, facial expressions, and gestures. Extraversion—characterized by sociability, assertiveness, and high energy levels—enables agents to appear outgoing and engaging, while neuroticism, associated with emotional instability and a tendency toward negative affect, introduces a nuanced depth to an agent's behaviour. These personality-driven non-verbal cues not only make the agents appear more lifelike but also foster more natural and engaging interactions with human users.

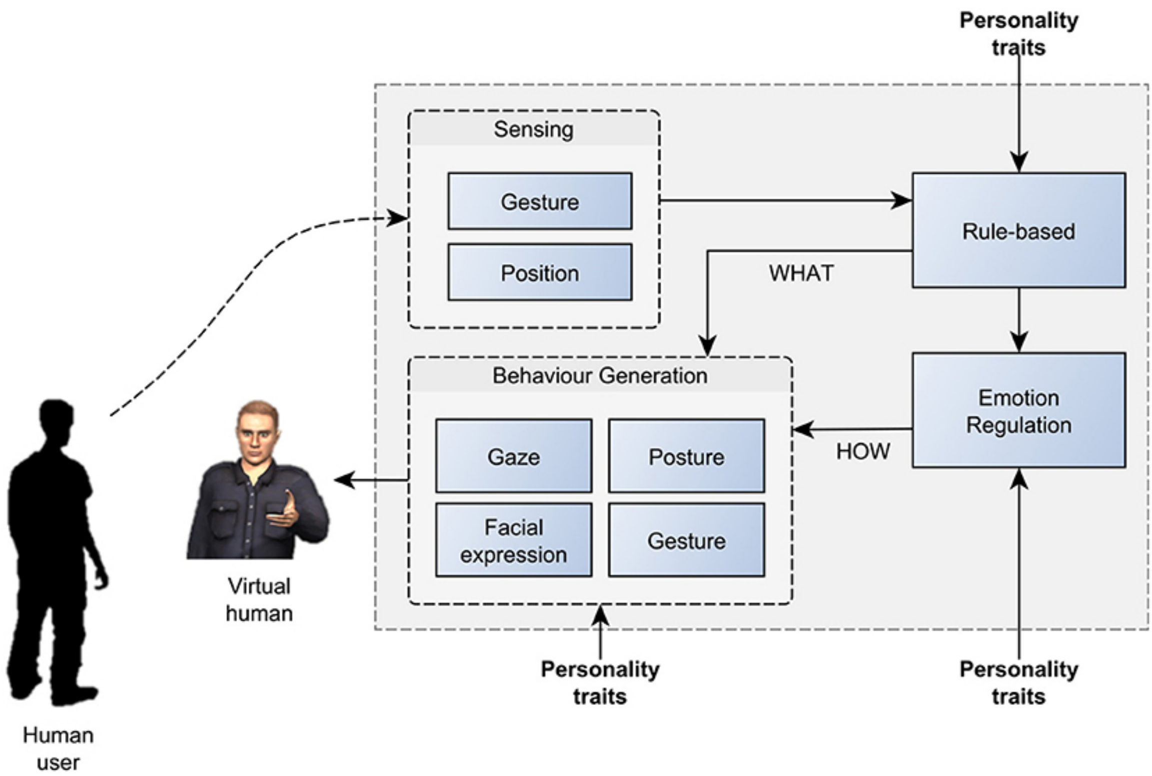


Figure 1.1: The "RealAct" model overview, demonstrating how personality traits like extraversion and neuroticism are mapped to specific non-verbal behaviours in virtual agents. This mapping enhances the perceived realism and social presence of the agents (Saberi et al., 2021).

This approach aligns with our realization that achieving a high level of realism, particularly in the subtleties of movement and expression, is crucial for effective human-ASA interaction. Without this realism, attempts to study and manage interpersonal dynamics, such as proxemics, would fall short due to the agents' inability to convincingly simulate human-like social presence. As shown in figure 1.2, the expression of non-verbal behaviours such as gaze and gestures varies significantly based on the agent's simulated personality traits, further contributing to a more lifelike interaction experience. The inclusion of such personality-driven non-verbal behaviours could significantly enhance the realism of ASAs, providing a more solid foundation for studying complex social interactions, such as interpersonal distance regulation.

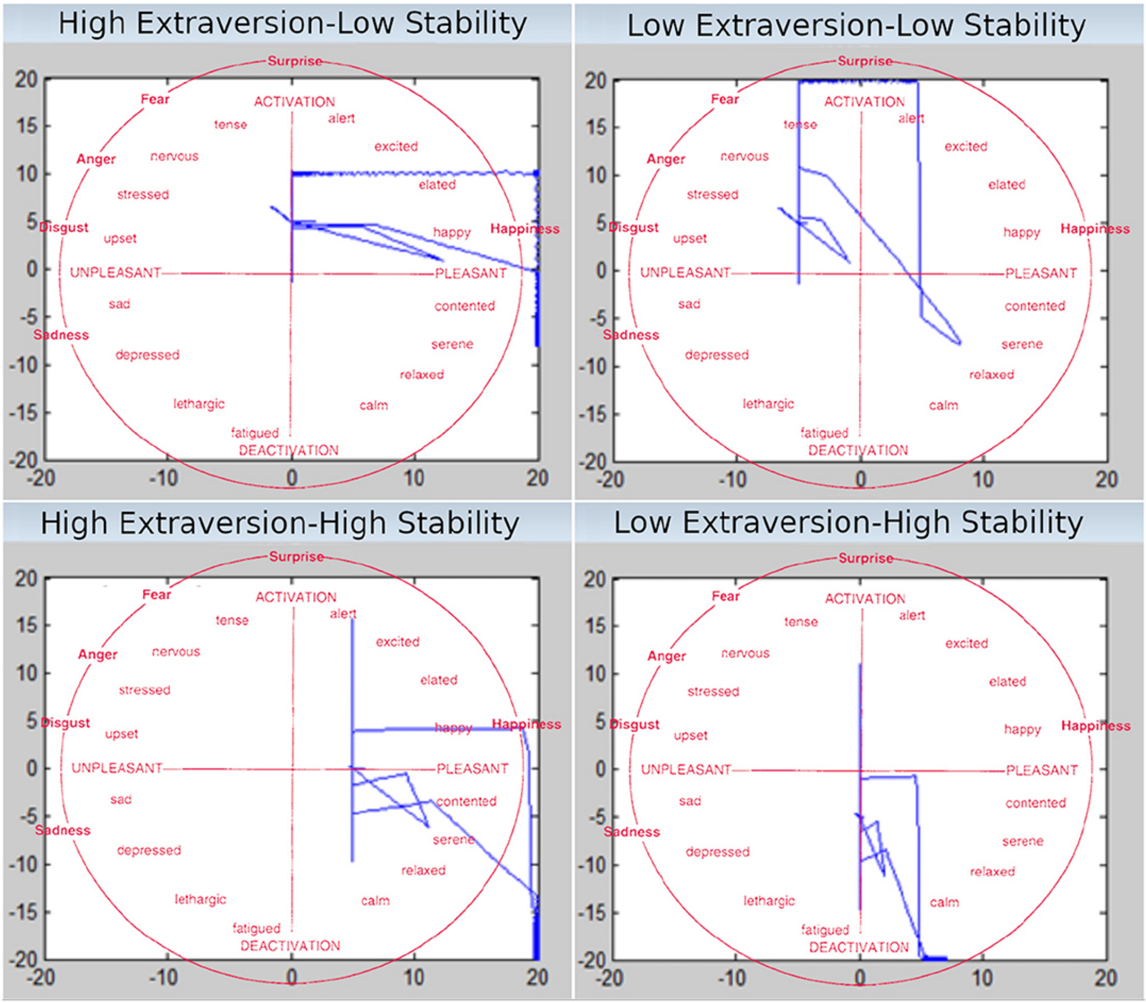


Figure 1.2: Examples of non-verbal behaviour expressions based on personality traits. This figure shows how different traits influence behaviours such as gaze direction and gestures, contributing to a more lifelike interaction experience with the agents (Saberi et al., 2021).

Incorporating these insights into our research framework supports the notion that before Artificial Social Agents (ASAs) can effectively manage social behaviours, they must first achieve a robust level of realism. This realism is not only about accurate movement patterns but also involves aspects like visual fidelity, movement realism, animation quality, facial expressions, and environmental interaction. These elements together form the foundation of the realism that supports effective human-ASA interaction.

In our conceptual framework—visualized as a concept map (see figure 1.3) —realism is depicted as a critical component that influences other factors like believability, which includes behavioural consistency, emotional expression, social cues, spatial awareness, interpersonal distance, and cultural implications. Movement strategies like linear walk, curved walk, backwards walk, and others play a crucial role in the pathfinding and movement processes, ultimately feeding into the realism that underpins ASA interaction capabilities.

Achieving a high level of realism in ASAs is essential before these agents can effectively manage interpersonal distance and other social behaviours, making realism the foundational layer in the development of socially adept ASAs.

Achieving and Evaluating Acceptable Levels of Realism

Achieving an acceptable level of realism in artificial social agents (ASAs) involves balancing technical feasibility with user expectations. Designers and developers can determine that an acceptable level of realism has been reached by employing both qualitative and quantitative measures. For instance, iterative user testing and validated presence questionnaires (such as the Artificial-Social-Agent (ASA) Questionnaire or Presence Questionnaire) can capture subjective user impressions of realism. Objective measures—such as performance metrics, error rates in task completion, or physiological responses—can complement these assessments. A key indicator is the extent to which users experience immersion, perceiving the agent as natural and engaging without distraction.

However, there is a critical threshold beyond which increased realism can be counterproductive. Excessive realism may invoke the "uncanny valley" phenomenon, where near-perfect imitation of human behaviour results in subtle imperfections that elicit discomfort or even repulsion. Additionally, striving for ultra-high realism can lead to escalating computational costs and diminished returns in user satisfaction if the extra detail does not contribute meaningfully to user experience. Therefore, developers must weigh the benefits of enhanced realism against potential drawbacks such as increased production complexity and the risk of alienating users with overly lifelike but imperfect agents.

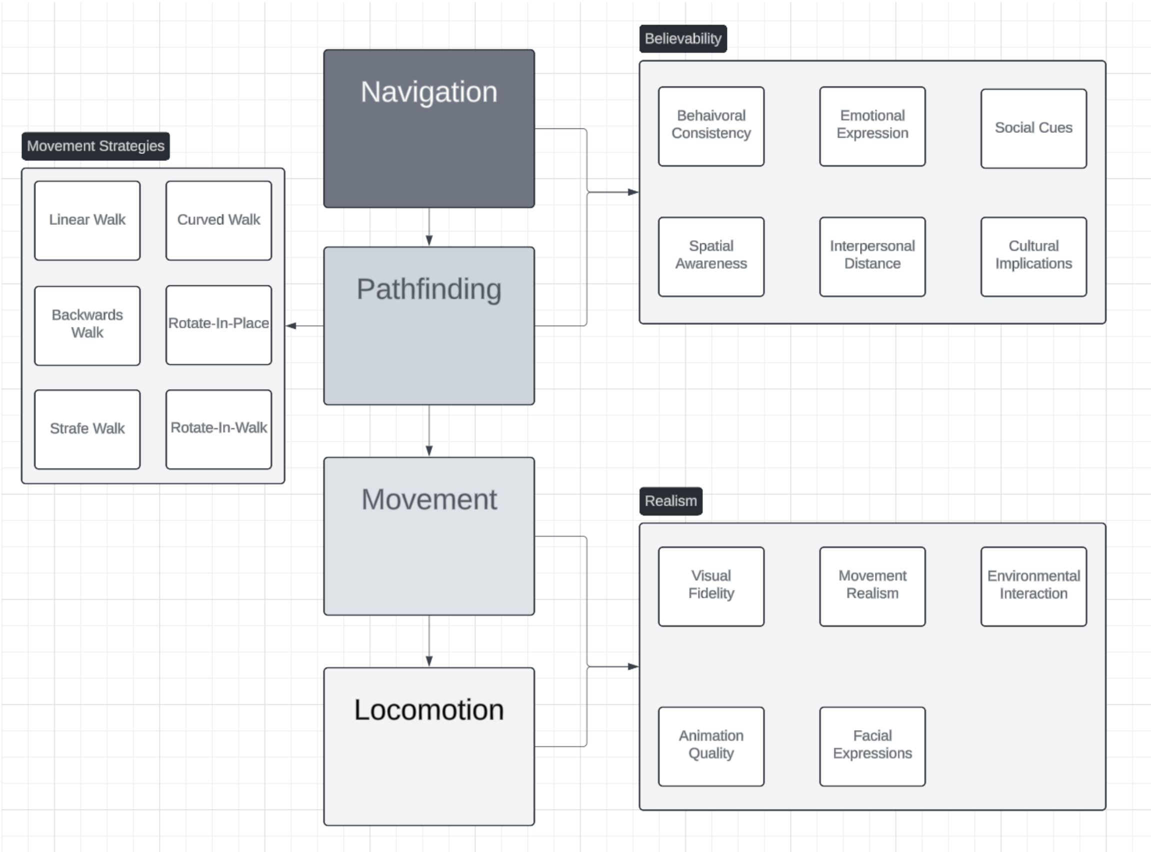


Figure 1.3: This concept-map illustrates the interconnected roles of navigation, pathfinding, movement, and locomotion in achieving both believability and realism in Artificial Social Agents (ASAs). Pathfinding impacts believability by guiding the agent to move in human-like, socially aware ways, enhancing its perceived intelligence. Movement influences realism by ensuring the agent's actions are smooth, natural, and physically accurate, contributing to a lifelike presence. The diagram also shows how various movement strategies feed into pathfinding, and how the realism of movement and locomotion, alongside pathfinding, collectively contribute to creating an ASA that not only appears real but also engages believably with users.

As mentioned, in this research, it initially was planned to explore how ASAs manage interpersonal distance in various scenarios. However, this investigation revealed significant shortcomings in the realism of these agents, particularly in their movement patterns. We concluded that for ASAs to effectively manage interpersonal distance and be perceived as lifelike, they must first achieve a foundational level of realism in their overall behaviour and interactions.

1.5 Applications and Implications of ASAs

Advancements in ASA realism and social interaction have significant applications and implications across various fields, including healthcare, robotics, virtual training and research.

1.5.1 Healthcare: Rehabilitation Protocols and Assistive Technologies

In the healthcare sector, realistic ASAs have the potential to revolutionize rehabilitation protocols and assistive technologies. Virtual rehabilitation systems that utilise ASAs with realistic movement patterns can provide patients with accurate demonstrations of exercises and therapies. These systems can adapt to the patient's progress and provide real-time feedback, enhancing the effectiveness of rehabilitation programs. Moreover, ASAs can be used in assistive technologies to support individuals with disabilities, providing personalized assistance and improving their quality of life.

Rizzo et al., 2011 discussed the use of virtual reality and ASAs in rehabilitation, emphasizing the benefits of immersive environments and realistic agent interactions. Their research highlighted how virtual agents can motivate patients and provide consistent, repeatable training that is tailored to individual rehabilitation needs. The incorporation of micro-movements in these agents can further enhance their effectiveness by making their demonstrations and interactions more lifelike.

1.5.2 Robotics: Navigation in Complex Environments

Robotics is another field that can greatly benefit from the integration of micro-movement strategies. Fong et al., 2003 discussed the challenges and advancements in robot navigation, particularly in complex environments. Realistic movement patterns can enhance a robot's ability to navigate and interact with its surroundings more effectively. This is especially important for robots designed for search and rescue missions, planetary exploration, and other tasks that require precise and adaptive movement in unpredictable environments. By incorporating these strategies, robots can achieve higher levels of functionality and reliability.

Research by Okada et al., 2005 explored the implementation of human-like movement patterns in humanoid robots. They demonstrated that incorporating micro-movement strategies improved the robots' ability to navigate cluttered environments and interact with humans more naturally. This has significant implications for the development of robots that can operate in diverse settings, from homes and workplaces to disaster response scenarios.

1.5.3 Virtual Training: Enhanced Realism for Skill Development

The integration of realistic ASAs into virtual training environments offers transformative potential for skill development across various disciplines. Virtual training systems that leverage ASAs with human-like micro-movements can provide users with a more immersive and authentic learning experience. This is particularly valuable in fields such as military training, medical education, and aviation, where trainees can practice complex scenarios in a controlled and safe environment.

For instance, Xie et al., 2021 reviewed various virtual reality (VR) skill training applications, highlighting how the realism of virtual agents plays a critical role in the effectiveness of these training experiences. By incorporating micro-movements, ASAs can simulate subtle human reactions, such as body language and slight adjustments in posture, which are essential for trainees to recognize and respond to in high-stakes environments, thus enhancing the overall training outcomes.

1.5.4 Research Simulations: Enhancing Experimental Validity and Data Accuracy

Realistic ASAs hold significant potential in the realm of research simulations, particularly within the social sciences and human-computer interaction (HCI). The ability to accurately simulate human behaviour in controlled environments is crucial for studying complex social interactions and understanding behavioural dynamics. ASAs that exhibit realistic micro-movements provide researchers with a powerful tool to conduct experiments that are both ethically sound and methodologically robust.

Blascovich et al., 2002 explored the use of immersive virtual environments as a research tool in social psychology, emphasizing that the realism of virtual agents directly impacts the validity of experimental findings. Incorporating micro-movements into ASAs can bridge the gap between real-world and simulated interactions, allowing for more nuanced studies of human behaviour. This level of detail ensures that the responses elicited from human participants are as close to real-life scenarios as possible, thereby enhancing the reliability of the data collected.

Realistic ASAs can be utilised in a variety of research contexts, such as simulating crowd behaviour, testing human responses in emergency situations, and exploring interpersonal dynamics in controlled settings. The ability to replicate subtle human actions, such as posture shifts and orientation changes, is particularly valuable in these simulations, as it allows for more accurate modelling of social interactions and their outcomes.

In sum, across these diverse domains—from search-and-rescue robots navigating debris-filled terrain, to flight and medical trainees practising complex scenarios in VR, to researchers probing social behaviour in virtual crowds—the incorporation of human-like micro-movements consistently enhances both functional performance and perceptual fidelity. By embedding subtle orientation shifts, posture adjustments, and fluid gait patterns, agents and robots become not only more effective at their core tasks but also more believable and engaging to human users, underscoring the broad applicability and importance of micro-movement strategies in advancing ASA realism and utility.

1.6 Realism and Presence in Virtual Environments

In creating immersive virtual environments, the application of user-centred design principles, coupled with careful attention to spatial navigation, interaction techniques, and sensory feedback, is critical. These elements are foundational to crafting experiences that not only engage users but also foster a strong sense of "presence" —a psychological state where the user feels as though they are truly "there" within the virtual space. One of the key contributors to "presence" is the perceived realism of an IVE or ASA.

As key factors of presence, the concepts of believability and realism in virtual environments are critical for understanding how users engage with and perceive these digital spaces. The work of Bulu, 2012 provides a comprehensive examination of these aspects, offering valuable insights into the factors that enhance the sense of presence and immersion in virtual environments.

Bulu (2012) explored the psychological and perceptual dimensions of believability and realism in virtual environments, emphasizing the importance of creating experiences that users perceive as lifelike and convincing. Their research identified several key elements that contribute to the sense of realism, including visual fidelity, interactivity, and the coherence of the virtual world. Visual fidelity refers to the quality and detail of the graphics, which should closely mimic real-world appearances to create a convincing environment. Interactivity involves the degree to which users can manipulate and engage with the virtual world, enhancing the sense of agency and presence. Coherence pertains to the consistency and logical structure of the environment, ensuring that all elements align with the user's expectations of a believable world. Recent opinion pieces further argue that perceived realism itself must be directly measured – beyond mere "being there" – to fully capture presence in VR (Weber et al., 2021).

The findings of Bulu (2012) are supported by subsequent research that delves into various dimensions of realism and their impact on user experience. For instance, Slater, 2009 emphasized the importance of "place illusion" and "plausibility illusion" as two components of presence in virtual environments. Slater's work highlights that achieving both illusions is essential for creating a compelling and immersive virtual experience.

Further research by Schubert et al., 2001 examined how different sensory modalities contribute to the sense of presence. They found that integrating multiple sensory inputs, such as visual, auditory, and haptic feedback, significantly enhances the realism of virtual environments. This multimodal approach ensures that users perceive the virtual world as more vivid and engaging, leading to higher levels of immersion. In particular, studies in VR have shown that congruent visual–haptic stimuli amplify both presence and perceived realism by leveraging multisensory integration (Jung and Lindeman, 2021).

Moreover, the study by Lombard and Ditton, 1997 on presence and telepresence explored how media experiences can create the illusion of "being there" in a virtual space. Their research identified several factors that influence this sense of presence, including the use of realistic and high-resolution displays, natural and intuitive interaction methods, and the integration of contextual cues that align with real-world experiences. This work underscores the importance of designing virtual environments that closely mimic real-world interactions and contexts to enhance believability and realism.

1.6.1 Factors influencing realism

The factors that influence realism in virtual environments are crucial for creating experiences that users perceive as genuine and engaging. The study by Chalmers et al., 2009 provides a detailed analysis of these factors, offering insights into how different elements contribute to the overall realism of virtual spaces.

Chalmers examined various technological, perceptual, and cognitive factors that affect the realism of virtual environments. Their research identified several key components, including graphical quality, physical simulation, behavioural realism, and user personalization. Graphical quality involves the level of detail and accuracy in the visual representation of the environment, which plays a critical role in user perception of realism. High-resolution textures, realistic lighting, and accurate shading are essential for creating visually convincing environments.

Physical simulation refers to the accurate modelling of physical properties and behaviours within the virtual world. This includes realistic physics, such as gravity, collision detection, and fluid dynamics, which ensure that virtual objects behave in ways that users expect based on their real-world experiences. behavioural realism involves the actions and interactions of virtual entities, such as characters or agents, which should exhibit lifelike behaviours and responses to enhance the sense of presence and engagement.

User personalization is another critical factor. This involves adapting the virtual environment to meet the specific preferences and needs of individual users, which can enhance the sense of ownership and connection to the virtual space. Personalization can include customizable avatars, adjustable environmental settings, and adaptive interfaces that respond to user behaviour and preferences.

Further supporting these findings, research by Steuer, 2006 on defining virtual reality emphasized the importance of interactivity and vividness in creating realistic virtual experiences. Steuer argued that the degree of interactivity, or the ability of users to influence the environment and receive immediate feedback, is a crucial determinant of presence. Vividness, or the representational richness of a mediated environment, also plays a significant role in how real and engaging a virtual space feels to users.

Additionally, the work of Biocca et al., 2003 explored the psychological aspects of presence and realism, highlighting the role of user expectations and cognitive processing. Their research suggested that users bring their real-world experiences and expectations into virtual environments, and the degree to which these expectations are met significantly influences their perception of realism. This insight emphasizes the need for designers to consider the cognitive and perceptual frameworks that users employ when interacting with virtual spaces.

1.6.2 Theories and models of Presence in Virtual Environments

Understanding presence in virtual environments involves exploring various theories and models that explain how and why users feel immersed and engaged in these digital spaces. The contributions from Witmer and Singer, 1998, Sheridan, 1992, and Zeltzer, 1990 provide essential frameworks for studying presence, each offering unique perspectives on the components and mechanisms that contribute to immersive virtual experiences.

Witmer and Singer (1998) developed one of the most widely cited models of presence, proposing that presence is a subjective experience influenced by multiple factors. Their model emphasizes two primary components: involvement and immersion. Involvement refers to the user's psychological engagement with the virtual environment, including their attention, interest, and emotional investment. Immersion, on the other hand, is the objective quality of the virtual environment that makes it capable of delivering an encompassing and vivid experience. This includes technological factors such as display quality, field of view, and interaction fidelity. Witmer and Singer argued that high levels of both involvement and immersion are necessary to achieve a strong sense of presence.

Their research also highlighted the importance of sensory fidelity and interactivity in enhancing presence. Sensory fidelity involves the accuracy and quality of sensory inputs, such as visuals, sound, and haptic feedback, while interactivity refers to the degree to which users can manipulate the environment and receive real-time feedback. These factors work together to create a seamless and convincing virtual experience that captures the user's attention and sustains their engagement.

Sheridan (1992) offered another influential perspective on presence, focusing on the concept of "telepresence." Sheridan's model is particularly relevant to remote and virtual operations, such as teleoperation and virtual reality. He identified three critical components of telepresence: extent of sensory information, control of relation of sensors to the environment, and ability to modify the environment. Extent of sensory information pertains to the richness and comprehensiveness of sensory data provided to the user. Control of relation of sensors to the environment involves the user's ability to change their viewpoint and interact with the virtual world dynamically. The ability to modify the environment refers to the user's capability to affect changes within the virtual space, enhancing their sense of agency and involvement.

Sheridan's model underscores the importance of user control and feedback in creating a compelling sense of presence. By allowing users to interact with and influence the virtual environment, designers can enhance the feeling of being "present" in the digital space. This model has been particularly influential in the development of virtual reality applications where user agency and interaction are crucial.

Zeltzer (1990) introduced a foundational model for virtual environments that focuses on the dimensions of presence: the "virtuality continuum." His work differentiates between different types of presence experiences, ranging from purely physical presence in the real world to fully immersive virtual presence. Zeltzer's model identifies three key dimensions: autonomy, interaction, and presence. Autonomy refers to the degree of independence of virtual entities and their ability to act without direct user input. Interaction involves the quality and extent of user interactions with the virtual environment, while presence pertains to the user's subjective feeling of being in the virtual space.

Zeltzer's framework highlights the importance of balancing these dimensions to achieve a high level of presence. For instance, virtual entities that exhibit high autonomy and realistic behaviours can enhance the believability of the virtual environment, making it more immersive. Similarly, high levels of interaction and user control contribute to a stronger sense of presence, as users feel more connected and engaged with the virtual world.

Further research has built on these foundational theories to explore additional factors influencing presence. For example, as mentioned in previous sections Slater and Wilbur, 1997 proposed the concept of "place illusion" and "plausibility illusion" as critical components of presence. Place illusion refers to the sensation of being in a specific location within the virtual environment, while plausibility illusion involves the degree to which events in the virtual world seem believable. These concepts align with and extend the ideas proposed by Witmer, Singer, Sheridan, and Zeltzer, emphasizing the multi-faceted nature of presence.

1.6.3 The Role of Immersive Virtual Environments in Enhancing ASA Realism

Immersive virtual environments (IVEs) have become a critical area of study within human-computer interaction (HCI), and are a key area in which this research could be leveraged. This area of study focuses on creating digital spaces that fully engage users' senses and promote a strong sense of presence. The foundational work of Watson and Graves, 1966 provides insights into the principles of creating immersive experiences, which continue to inform contemporary research and development in virtual reality (VR) and related technologies.

Watson and Graves investigated the psychological impact of simulated environments on user behaviour and perception. Their research emphasized the importance of sensory engagement and environmental consistency in creating immersive experiences. They found that environments that fully engage the visual, auditory, and tactile senses can significantly enhance the feeling of being "present" in the virtual space. This early work laid the groundwork for understanding how different sensory modalities contribute to the overall sense of immersion in virtual environments.

Building on the foundational principles established by Watson and Graves, subsequent research has explored various aspects of IVEs to enhance user experience and interaction quality. One key area of focus has been the development of high-fidelity visual displays. Modern VR systems utilise advanced graphics rendering techniques and high-resolution displays to create visually convincing environments. Research by Anthes et al., 2016 has highlighted the importance of these visual advancements in enhancing the realism and immersion of VR experiences. High-resolution displays reduce visual artifacts such as the screen-door effect, making the virtual environment appear more lifelike and engaging.

In addition to visual fidelity, the role of auditory and haptic feedback has been extensively studied. Research by Schubert et al., 2001 demonstrated that integrating high-quality auditory cues and realistic haptic feedback can significantly enhance the sense of presence in IVEs. Auditory cues, such as spatialized sound effects and ambient noise, help users orient themselves within the virtual space and contribute to the overall realism of the environment. Haptic feedback devices, which provide tactile sensations to users, allow for more interactive and engaging experiences by simulating the sense of touch.

Moreover, the development of motion tracking technologies has been crucial for improving the interactivity and immersion of IVEs. Advances in motion capture systems and sensor technologies enable precise tracking of user movements, allowing for natural and intuitive interactions within the virtual environment. Foundational research by Steuer, 2006 emphasized the importance of interactivity in creating immersive experiences, suggesting that the ability to influence and interact with the virtual world in real-time is a critical determinant of presence.

The concept of "presence" in IVEs has been further explored through models and theories that describe how users perceive and interact with virtual environments. Slater and Wilbur, 1997 introduced the concepts of "place illusion" and "plausibility illusion," which describe the psychological mechanisms underlying the sense of being in a virtual place and the believability of virtual events, respectively. These concepts align with the findings of Watson and Graves in 1966, underscoring the importance of sensory engagement and environmental consistency in fostering immersion.

In addition to sensory and interactive factors, cognitive and psychological aspects play a significant role in the effectiveness of IVEs. Research by Biocca and Delaney, 1995 explored the role of cognitive processing in virtual reality, suggesting that users' mental models and expectations influence their experience of presence. This highlights the need for virtual environments to be designed in a way that aligns with users' cognitive frameworks and real-world experiences.

Furthermore, the social dynamics within IVEs have been a topic of growing interest. Bailenson et al., 2008 examined how self-representations in immersive virtual environments influence social interactions and behaviours. he results showed that participants engaged in more intimacy-consistent behaviours, such as closer proximity and more direct eye contact, when interacting with representations of themselves compared to representations of others. This aligns with the early work of Watson and Graves, emphasizing the importance of integrating social dynamics into the design of immersive environments.

Recent advancements in IVEs have also focused on the integration of artificial intelligence (AI) to create more adaptive and responsive virtual environments. AI-driven virtual agents and characters can exhibit lifelike behaviours and interact with users in meaningful ways, enhancing the overall sense of immersion and engagement. Research by Traum and Rickel, 2002 explored the use of AI in virtual training environments, demonstrating how intelligent agents can provide realistic and contextually appropriate responses to user actions.

Additionally, the convergence of VR with other emerging technologies, such as augmented reality (AR) and mixed reality (MR), has expanded the possibilities for creating immersive experiences. Mixed reality environments, which blend digital and physical elements, offer new ways for users to interact with virtual content in real-world contexts. This integration allows for more flexible and context-aware applications, enhancing the practical utility and appeal of immersive environments.

The exploration of immersive virtual environments (IVEs) underscores the importance of sensory engagement, interactivity, and psychological presence in creating compelling user experiences. However, the effectiveness of IVEs is deeply intertwined with the technological advancements that drive their development. Understanding these technological developments is key to enhancing the realism, functionality, and accessibility of virtual environments. The following section discusses the latest innovations in virtual reality (VR) and related technologies, which are instrumental in pushing the boundaries of what can be achieved in immersive environments.

1.6.4 User Experience Design in Virtual Environments

Designing effective user experiences (UX) in virtual environments (VEs) is crucial for ensuring user engagement and satisfaction. The principles of UX design, established by pioneers like Norman, 2012 and Nielsen, 1994, provide foundational guidelines that can be adapted to the unique challenges and opportunities presented by VEs. This section explores the key concepts in UX design for VEs, the importance of cognitive load management, and highlights significant contributions from the literature.

The principles of user-centred design (UCD), as articulated by Norman, emphasize the importance of designing with the user's needs, behaviours, and limitations in mind. Norman's work, particularly his concept of affordances, provides valuable insights into how users perceive and interact with VEs. Affordances refer to the perceived and actual properties of an object that determine how it can be used. In the context of VEs, ensuring that virtual objects and environments have clear and intuitive affordances is essential for facilitating user interaction and immersion.

Nielsen had also previously contributed to UX design through his heuristics for usability. His ten heuristics, including visibility of system status, match between system and the real world, and user control and freedom, offer practical guidelines for creating intuitive and user-friendly interfaces. These heuristics are particularly relevant in VEs where users navigate and interact with complex, immersive environments.

While the foundational principles of user experience (UX) design provide valuable guidelines for creating intuitive and engaging interfaces, applying these principles to virtual environments requires special consideration of the unique challenges posed by immersive experiences. The following section delves into how these UX principles can be adapted to virtual environments, addressing key aspects such as spatial navigation, interaction techniques, and sensory feedback, all of which are critical for ensuring a seamless and satisfying user experience in digital spaces.

Adapting UX Principles to Virtual Environments

Adapting principles of spatial navigation and orientation to virtual environments (VEs) involves addressing unique challenges such as interaction techniques and sensory feedback. Research by Kotlarek et al., 2018 underscores the importance of spatial orientation in VEs, noting that poor design can lead to disorientation and reduced usability. Their study compared different approaches to improving spatial awareness in immersive environments and found that tools like 3D minimaps significantly enhance user navigation and overall experience. Ensuring that virtual environments provide consistent and clear spatial cues can greatly improve the user's ability to navigate effectively and maintain orientation within the virtual space.

LaViola, 2001 discusses interaction techniques in VEs, emphasizing the need for natural and intuitive controls. The study suggests that leveraging familiar real-world interactions, such as hand gestures and body movements, can significantly improve user engagement and reduce cognitive load.

Sensory feedback, including haptic, auditory, and visual cues, also plays a crucial role in enhancing the realism and immersion of VEs. Slater, 2009 explores the impact of multisensory feedback on presence in virtual environments, demonstrating that richer sensory experiences lead to higher levels of immersion and user satisfaction.

1.6.5 Technological Advances in Virtual Environments

The rapid advancement of technology has significantly enhanced the realism and interactivity of virtual environments, making them more immersive and engaging. The contributions of Anthes et al., 2016 and Lanier, 2017 are pivotal in understanding these technological developments, offering insights into the innovations that drive the evolution of virtual reality (VR) and its applications.

Anthes et al., 2016 provided a comprehensive review of the state of virtual reality (VR) technology, emphasizing several key innovations that have significantly improved user experience. One major advancement discussed is the development of high-resolution displays and advanced graphics rendering techniques. These technologies have dramatically increased the visual fidelity of VR environments, making them more lifelike and convincing. High-resolution displays reduce the screen-door effect, where the gaps between pixels become visible, thereby enhancing the sense of immersion by providing clearer and more detailed visuals.

Another critical technological development highlighted by Anthes et al. is the improvement in tracking systems. Accurate and low-latency tracking of head and body movements is essential for maintaining the illusion of presence in VR. Advances in motion capture and sensor technologies have enabled more precise tracking, allowing users to move naturally within the virtual environment without experiencing disorienting lag or inaccuracies. This development is crucial for applications that require fine motor skills and precise interactions, such as medical simulations and VR-based training programs.

The review also discussed the importance of haptic feedback and tactile interfaces in enhancing the realism of virtual environments. Haptic devices, which provide tactile sensations to the user, allow for a more immersive experience by simulating the sense of touch. These devices can replicate textures, vibrations, and forces, enabling users to feel virtual objects as if they were real. This technology is particularly valuable in fields such as surgery training, where realistic tactile feedback is essential for effective learning.

In addition to these technological improvements, the development of more sophisticated artificial intelligence (AI) and machine learning algorithms has significantly impacted VR environments. AI-driven virtual characters and agents can now exhibit more realistic and adaptive behaviours, responding to user actions in a believable manner. This enhances the sense of presence and engagement by making the virtual world feel more dynamic and interactive.

Lanier, 2017 explored the broader implications of these technological advancements in VR, emphasizing the transformative potential of VR technology across various domains. Lanier highlighted how VR can revolutionize education by providing immersive learning experiences that allow students to explore complex concepts in a hands-on manner. For instance, virtual field trips can take students to historical sites or distant planets, offering educational opportunities that would be impossible in the physical world.

Lanier also discussed the potential of VR in healthcare, particularly in therapeutic and rehabilitative contexts. VR can be used for pain management, where immersive environments distract patients from pain and discomfort. Additionally, VR-based rehabilitation programs can provide engaging and motivating exercises for patients recovering from physical injuries or neurological conditions. The ability to simulate real-world scenarios in a controlled and safe environment makes VR an invaluable tool for various therapeutic applications.

Furthermore, Lanier highlighted the social and collaborative aspects of VR technology. Advances in networked VR allow multiple users to interact in shared virtual spaces, enabling remote collaboration and socialization. This capability has profound implications for remote work, virtual meetings, and social interactions, offering new ways for people to connect and collaborate regardless of geographical barriers.

Supporting these perspectives, recent research has explored the integration of VR with other emerging technologies. For example, the combination of VR and augmented reality (AR) creates mixed reality environments that blend digital and physical worlds. This integration allows for more flexible and context-aware applications, such as AR-enhanced surgery where real-time data overlays assist surgeons during procedures.

Additionally, developments in cloud computing and 5G networks are enhancing the accessibility and scalability of VR applications. Cloud-based VR platforms enable high-quality VR experiences on a wider range of devices by offloading intensive processing tasks to remote servers. This reduces the hardware requirements for end-users and makes VR more accessible to a broader audience. Meanwhile, 5G networks provide the low-latency and high-bandwidth connectivity needed for seamless VR streaming and real-time interactions in virtual environments.

Technological advancements in virtual environments provide the foundation for creating more realistic and immersive experiences, but the success of these environments also hinges on how well they are designed from a user experience (UX) perspective. Recent VR hardware and AI-driven agent improvements give us the tools to render and control lifelike movements in real time. In this thesis, we harness these advances—high-fidelity tracking, continuous 0–100 rating scales, and ML-based motion prediction—to build and evaluate truly realistic ASAs. Effective UX design ensures that virtual environments are not only technically impressive but also intuitive and engaging for users. The next section explores the principles of user experience design in virtual environments, focusing on how these principles can be adapted to meet the unique challenges of creating immersive and user-friendly digital spaces.

1.7 Realism in Human-Agent Interactions

The quest for realism in human-agent interactions extends far beyond the mere appearance of virtual characters. It involves understanding the intricate dynamics of social interaction, cognitive processing, and emotional responses that occur when humans engage with artificial agents. As research in this field has advanced, it has uncovered the complex interplay between an agent's behavioural realism, social identity, and user perceptions, highlighting both challenges and developments in creating engaging and believable interactions.

One key aspect of this research involves the role of gender and behavioural realism in shaping user perceptions and responses. For example, Guadagno et al., 2007 investigated how the gender of virtual agents and their level of behavioural realism influenced their persuasiveness. Their findings revealed that agents with higher behavioural realism were more influential, particularly when they matched the user's gender, underscoring the significant role of social identity and behavioural cues in human-agent interactions.

Further exploring the impact of behavioural realism, a study by Herrera et al., 2020 examined how the realism of virtual characters affects social interactions in collaborative virtual environments. The study found that realistic behaviours in virtual characters can elicit social reactions similar to those experienced in human-to-human interactions, suggesting that behavioural fidelity is crucial for effective engagement. Their research highlights the importance of accurately modelling behavioural cues in virtual characters to enhance user experience and social presence in virtual environments.

Trust is a critical factor in human-artificial agent interactions, as explored by Kulms and Kopp, 2016. Their research examined how an agent's embodiment and competence influence trust and cooperation over time. Initially, trust was significantly influenced by the physical embodiment of the agent, meaning that agents with a more human-like appearance were trusted more in the early stages of interaction. However, as interactions continued, the agent's competence became more important in sustaining trust, illustrating the evolving nature of trust in prolonged interactions. This shift from reliance on physical embodiment to competence underscores the importance of designing agents that not only look trustworthy but also demonstrate reliable and effective performance over time.

The appearance of virtual assistants and how it affects user preferences has been investigated in various studies. For example, research by Amadou et al., 2023 examined how the realism of appearance and animation in virtual humans influences user perception. Their findings revealed that higher levels of realism in both appearance and animation significantly influenced users' perceptions of social presence and attractiveness. This study highlights the importance of tailoring virtual agent design to align with user expectations and preferences, emphasizing that realistic design elements are crucial for enhancing user engagement and satisfaction.

Adding to the discussion on realism, Bernardet et al., 2019 developed a control architecture for generating speech-breathing behaviours in virtual characters. Their empirical study demonstrated that incorporating naturalistic breathing movements, such as head tilts and chest expansions, significantly enhances the perceived realism of virtual characters during dialogue, contributing to a more immersive interaction experience.

Guadagno et al., 2011 explored the nuanced effects of nonverbal cues, such as digital smiles, on social evaluations following interactions with digital human representations. Their research showed that a digital smile could positively affect participants' social evaluations, especially when these were aligned with their beliefs about the interaction partner, highlighting the subtle yet powerful role of nonverbal communication in virtual interactions.

Rationality and belief dynamics in human-agent interactions were examined by Wenmackers et al., 2014. Their study provided a social-epistemology perspective, exploring how social-epistemic interactions between humans and agents can lead to changes in belief states, further illustrating the cognitive complexity involved in these interactions.

Lastly, Luckmann, 2008 delved into the social interaction and communicative construction of personal identity within virtual environments. This research contributed to a deeper understanding of how interactions with artificial agents influence the formation of both personal and social identities, reinforcing the broader implications of realistic human-agent interactions in virtual settings.

Together, these studies highlight the multi-dimensional nature of realism in human-agent interactions, encompassing not only visual and behavioural aspects but also the deeper cognitive and social dynamics that shape how humans perceive and engage with artificial agents.

1.7.1 Believability and realism in ASAs

Believability

Believability refers to the extent to which an ASA can be perceived as a certain type of entity, in this case, a real human being. In this context, believability is about creating an agent that users can accept as being "real" or human-like in its behaviours, emotions, and interactions. My definition of believability focuses on the idea that an ASA must convincingly portray human-like qualities to the point where users can suspend their disbelief and assume, even temporarily, that they are interacting with a real person. This concept is inherently subjective, as different users may have varying thresholds for what they find believable.

Believability involves various aspects, including:

- **behavioural Consistency:** The ASA should exhibit behaviours that are consistent with how a human would act in similar situations.
- **Emotional Expression:** The agent should be capable of displaying emotions in a way that aligns with human emotional responses.
- **Social Cues:** The ASA needs to effectively use social cues, such as eye contact, body language, and speech patterns, that humans naturally respond to.

In essence, believability in the context of ASAs is about achieving a level of human-likeness that makes the agent appear real, even if it is understood to be artificial.

Realism

Realism, on the other hand, refers to the degree to which the ASA's appearance, movements, and behaviours accurately mimic the physical and social reality of a human being. Realism is typically more objective and measurable than believability, as it can be evaluated based on how closely the ASA's features and actions align with those of a real human.

Key aspects of realism include:

- **Visual Fidelity:** The ASA's appearance, including facial features, skin texture, and clothing, should closely resemble that of a real person.

- **Movement Realism:** The ASA's movements, such as walking, gesturing, and facial expressions, should be smooth and natural, avoiding any robotic or unnatural motions.
- **Environmental Interaction:** The ASA should interact with the virtual environment in ways that are consistent with real-world physics and social dynamics.

Believability vs. Realism

While believability and realism are closely linked, they are not identical. Believability is about the perception of the ASA as a real entity, which may not necessarily require perfect realism. An ASA could have a stylized or less detailed appearance yet still be perceived as believable if its behaviours and interactions are convincingly human-like. Conversely, an agent might be highly realistic in its appearance but lack believability if its behaviour is inconsistent or does not align with human social norms. (see figure 1.4 for a visual summary of these distinctions.)

Measuring both realism and believability in ASAs typically involves user-reported assessments (e.g., adapted ASA questionnaires, presence scales), observational metrics (e.g., user engagement levels, error rates in collaborative tasks), and occasionally physiological indicators (e.g., eye tracking, heart rate) to capture deeper emotional responses. In this thesis, we specifically employ an adapted ASA questionnaire and motion capture data analysis to evaluate how micro-movement strategies affect perceived realism and social presence. Realism focuses on visual fidelity and lifelike motion, whereas believability hinges on behavioural consistency and social responsiveness. The intersection—where an agent is both physically plausible and socially coherent—often yields higher immersion and user trust.

Believable but Not Realistic

Example: Cartoon-style virtual assistants such as the characters in the game "Animal Crossing" (see figure 1.5). These characters are highly stylized, with exaggerated features and simplified animations. Despite not being realistic in their appearance or movements, they are still believable within the context of the game world because their behaviours are consistent, their interactions are well-designed, and they follow social norms that align with the expectations of the users in that particular environment.

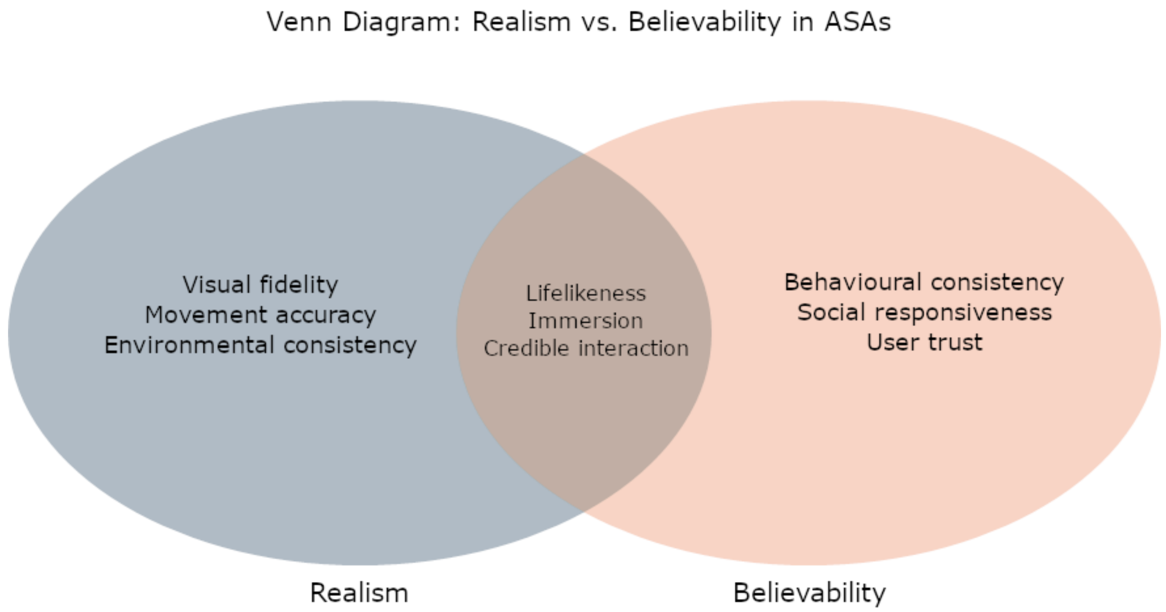


Figure 1.4: Venn diagram illustrating the intersection of realism and believability in ASAs. The realism circle highlights aspects such as visual fidelity, movement accuracy, and environmental consistency, while the believability circle encompasses behavioural consistency, social responsiveness, and user trust. Their intersection—marked by lifelikeness, immersion, and credible interaction—demonstrates how combining these attributes results in engaging and effective artificial social agents.

(a) Character from Animal Crossing

(b) Dr. Sbaitso

(c) Sophia the Robot

Figure 1.5: This figure illustrates the spectrum of realism and believability in Artificial Social Agents (ASAs). On the left, A Character from Animal Crossing demonstrates how stylized characters can still be believable through consistent behaviours and interactions. In the middle, Dr. Sbaitso represents early virtual assistants, which often lacked both realism and believability due to their simplistic, scripted responses. On the right, Sophia the Robot exemplifies the advanced blend of realism and believability, with lifelike facial expressions and sophisticated conversational abilities, bridging the gap between human and machine interaction. All images are Public Domain (Animal Crossing World (@ACWorldBlog), 2020, Microsoft Agent Plays Wiki community, n.d. Wikiquote contributors, n.d.)

Realistic but Not Believable

Example: Uncanny Valley robots or CGI characters—Consider a highly realistic CGI human character in a movie that looks almost identical to a real person. However, if this character exhibits stiff or unnatural movements, or if their facial expressions don't match the context of the scene, users may find the character unsettling or unconvincing, leading to a lack of believability despite the high realism.

Both Believable and Realistic

Example: Sophia the Robot (see figure 1.5) by Hanson Robotics—Sophia is designed with a realistic human appearance, including facial features and expressions. Moreover, her conversational abilities and social cues are well-developed, making her interactions with humans believable. Although far from perfect, she represents a strong blend of both realism and believability.

Neither Believable nor Realistic

Example: Early virtual assistants or chatbots—Imagine a virtual assistant from the early 1990s with a blocky, low-resolution avatar and limited, scripted responses that often don't align with the user's input such as Dr. Sbaitso (see figure 1.5). This agent neither looks realistic nor behaves in a way that users find believable, resulting in a lack of engagement and trust.

These examples show that believability and realism, while closely related, are distinct qualities that can vary independently. Achieving the right balance between the two depends on the specific goals of the ASA and the context in which it will be used.

1.8 Social behaviours and Cues in ASAs

To achieve a comprehensive understanding of ASAs, one must also consider the social behaviours and cues that these agents must exhibit to interact naturally with humans. Although the primary focus of this work is on enhancing the realism of movement, integrating social behaviours and cues is crucial for a holistic approach to ASA design. Social cues like emotional expressions, eye contact, and body language are vital for building trust, facilitating communication, and creating meaningful interactions. The following section examines how these social behaviours and cues can be incorporated into ASAs, ensuring that they not only move realistically but also engage with users in ways that feel authentic and intuitive.

1.8.1 The Language of Movement

Social behaviours and cues are fundamental components of human interaction, providing the basis for effective communication, understanding, and cooperation. When it comes to artificial social agents (ASAs), the incorporation of these social behaviours and cues is crucial for creating interactions that feel natural and intuitive to humans. The studies by Bartneck et al., 2007 and Nass and Moon, 2000 offer significant insights into how these elements can be integrated into ASAs to enhance their social presence and effectiveness.

Bartneck et al., 2007 explored the role of social cues in human-robot interaction, emphasizing the importance of emotional expression, eye contact, and gestural communication. Their research demonstrated that robots capable of displaying emotions through facial expressions and body language can elicit stronger emotional responses from humans. This emotional connection is critical for building trust and rapport, which are essential for effective collaboration and interaction. Bartneck and colleagues also highlighted the importance of eye contact, noting that robots that can make and maintain eye contact are perceived as more attentive and engaged, fostering a sense of presence and social connectedness.

The findings of Bartneck et al., 2007 are supported by Nass and Moon, 2000, who investigated how social cues influence user interactions with computers and other digital interfaces. Nass and colleagues introduced the concept of the "media equation," which posits that people tend to apply social rules and expectations to their interactions with computers and other media, treating them as social actors. Their research showed that when digital agents exhibit human-like social behaviours, such as politeness, empathy, and reciprocity, users respond more positively and engage more deeply with the technology. This principle underscores the importance of designing ASAs that can mimic human social behaviours to enhance user experience and acceptance and implies that humans might interpret the movements of an ASA in a social context, expecting it to follow social norms and conventions related to movement.

Further research has expanded on these foundational studies, exploring various aspects of social behaviours and cues in ASAs. For instance, Breazeal, 2003 discussed the importance of social robots in human environments, emphasizing that robots equipped with social intelligence can better understand and respond to human emotions and intentions. This capability allows robots to adapt their behaviour in real-time, providing more personalized and contextually appropriate interactions.

In addition, Fong et al., 2003 explored the integration of social intelligence in robots, focusing on the development of robots that can engage in meaningful social interactions. They highlighted various approaches to endow robots with social skills, such as using sensors to detect human emotions and employing algorithms to generate appropriate social responses. This research aligns with the findings of Bartneck et al., 2007 and Nass and Moon, 2000, reinforcing the importance of social behaviours and cues in enhancing the effectiveness of ASAs.

Moreover, research by Powers et al., 2007 examined the role of verbal and non-verbal communication in human-robot interaction, finding that robots that can use both types of communication are more effective in conveying information and building relationships with users. They emphasized that non-verbal cues, such as gestures, posture, and facial expressions, play a crucial role in complementing verbal communication, making interactions more natural and intuitive.

The significance of social behaviours and cues in ASAs is further highlighted by studies in virtual environments. Bickmore and Picard, 2005b explored the use of relational agents—virtual agents designed to build long-term social-emotional relationships with users. Their research demonstrated that relational agents capable of displaying social behaviours, such as empathy, humour, and politeness, can significantly enhance user engagement and satisfaction. This finding underscores the potential of virtual ASAs to create meaningful and impactful interactions through the effective use of social behaviours and cues.

1.8.2 Integrating Social and Emotional Aspects in ASA Navigation

While understanding and integrating social behaviours and cues are essential for fostering natural interactions between ASAs and humans, it is equally important to consider how these agents navigate their environments in ways that reflect these social dynamics. The next section delves into the integration of social and emotional aspects into the navigation systems of ASAs, ensuring that their movements and decisions align with the complex emotional and social contexts in which they operate.

Incorporating social and emotional aspects into agent navigation is crucial for creating agents that can realistically interact in virtual environments. This involves understanding and implementing complex emotional behaviours, social cues, and interaction strategies that mirror human social dynamics. Boucaud et al., 2019 explored the integration of social touch into interactions between humans and virtual agents in immersive environments. Their research demonstrated that adding modalities such as touch can enhance the emotional and social communication capabilities of virtual agents, making them more lifelike and engaging. By incorporating these elements, agents can navigate and interact in ways that are more attuned to human social behaviours, leading to more effective and satisfying user experiences. This approach highlights how emotional aspects can be effectively integrated into navigational systems to improve adaptive performance in various contexts. Cha et al., 2021 examined how voice-based conversational agents (VCAs) can assist adolescents with Autism Spectrum Disorder (ASD) in navigating daily life challenges. The study highlighted that VCAs can promote self-care skills, regulate negative emotions, and practice conversational skills, demonstrating the potential of integrating emotional and social support in agent navigation. Ramezani et al., 2011 introduced emotional-social agents to manage negotiation interactions in a multi-agent system. Their approach demonstrated that emotional-social negotiator agents could achieve fair agreements and more individual gain, indicating the importance of emotional factors in social decision making. Evers et al., 2014 developed an agent-based model, the EMO-model, to explore emotional bookkeeping in primate-like individuals. This model regulated social behaviours through emotional processes and partner-specific attitudes, providing insights into how emotional and social aspects could be integrated into agent behaviours. Abro et al., 2015 developed an agent-based social agent model that integrated emotion regulation, contagion, and decision making. Their simulations helped understand how decisions are affected by regulating emotions and how these emotions are influenced by emotion regulation and contagion.

1.9 Navigation of ASAs

While integrating social behaviours and cues into ASAs is essential for fostering natural and meaningful interactions, these agents must also navigate their environments in ways that reflect the social and emotional dynamics they are designed to mimic. The following section delves into the navigation strategies of ASAs, exploring how pathfinding and movement must evolve beyond efficiency to incorporate the nuanced, human-like behaviours that are crucial for realism in virtual environments.

1.9.1 Pathfinding Strategies in ASAs

Pathfinding, as a subset of navigation, has been a major focus of research due to its critical role in the control models of real-world robots. This research has yielded substantial advancements in enabling agents to determine the most efficient routes from point A to point B. However, this robotic focus has led to most systems exhibiting low measures of realism when applied to ASAs. The primary objective has been efficiency rather than the nuanced, human-like movement behaviours essential for realistic interactions in virtual environments.

When investigating multi-agent systems, Wang et al., 2013 focused on creating a dynamic system for controlling multiple agents in immersive environments, with a particular emphasis on path planning for avoidance. The goal of this research was to enhance the effectiveness of training simulations for scenarios like evacuation of multiple agents and other real-time crowd simulations. While this work is valuable, it overlooks the critical aspect of individual agent realism. The emphasis on macro-level path planning neglects the micro-level movement nuances that significantly contribute to the perception of realism.

Similarly, Zhukov and Iones, 2000's work on navigational control for intelligent agents focused on the creation of navigational maps aimed at decreasing computational load and increasing the complexity of navigation tasks. These maps were designed to translate an agent from point A to point B, but they did not incorporate higher-level movement functions, such as micro-movements. This gap is echoed in the work of Raees and Ullah, 2021, which also concentrates on pathfinding without addressing the intricate micro-movements that enhance realism.

Olcay et al., 2020 explored an intriguing approach by designing a simultaneous, collision-free motion planning system for fully autonomous robots. This system allows groups of autonomous robots to plan their movements even in environments with moving obstacles or poor sensor range. This kind of simultaneous localization and mapping (SLAM) control system is crucial for autonomous robots. However, for the purpose of creating lifelike ASAs, autonomy is not the primary requirement; instead, the focus should be on realistic movement patterns that mimic human behaviour.

Further reinforcing the importance of navigation in dynamic environments, Djerroud and Ali-Chérif, 2021 developed "VICA," a vicarious cognitive architecture for autonomous robots. This research is based on the "theory of mind," proposing that robots need a form of "vicariance" to interact with the world effectively. VICA employs a multi-agent system to enable robots to understand how their interactions affect their surroundings. Although this approach is innovative, it still does not address the specific micro-movements needed for enhancing ASA realism.

In another noteworthy study, Sutera et al., 2021 advanced the field by integrating ultra-wideband technology for precise tracking with a low-cost, point-to-point local planner learned through deep reinforcement learning. This approach allows robots to navigate robustly in noisy and complex environments, which is crucial for real-world robotics. However, such detailed environmental data is typically unnecessary for ASAs, as they operate within fully known virtual environments. The missing component in these approaches is the focus on micro-movements—subtle, naturalistic movements that are essential for creating believable ASAs.

In summary, while the field of pathfinding has seen significant advancements, there remains a crucial gap in incorporating micro-movements into ASA navigation systems. These movements are vital for achieving a higher level of behavioural realism, which enhances the overall immersion and effectiveness of virtual environments.

1.9.2 Challenges and Opportunities in ASA Navigation

While the previous sections have focused on the social and biomechanical aspects of human locomotion and their integration into ASAs, it's also essential to consider the broader challenges and opportunities that arise in virtual agent navigation. These aspects are pivotal for advancing the development of ASAs, as they must operate efficiently in dynamic and complex virtual environments. The following section delves into the specific challenges and innovative solutions that are shaping the landscape of virtual agent navigation, highlighting how these developments contribute to the overall effectiveness and adaptability of ASAs.

The domain of virtual agent navigation is rife with challenges and opportunities, each contributing to the evolving landscape of virtual environments and intelligent agent development. From large-scale mapping to the intricacies of social interaction, this field demands innovative solutions and offers exciting possibilities. Samperi, 2021 addressed the challenge of mapping large, dynamic virtual environments for mobile agents. The study explored how agents can generate, update, and use maps for navigation, highlighting the complexity of dealing with ever-changing virtual worlds and the necessity for agents to adapt accordingly. Lee et al., 2018 tackled the challenge of simulating believable virtual crowds in dynamically changing environments. Their approach using deep reinforcement learning demonstrated how agents could navigate complex scenarios with a simple reward function, pointing to significant advancements in agent navigation algorithms. van Luin et al., 2001 discussed the creation of natural language accessible navigation agents in virtual reality. These agents help visitors explore virtual environments and respond to inquiries, presenting an opportunity to make VR experiences more interactive and user-friendly. Bhanu et al., 2022 highlighted the challenges and opportunities in providing remote guidance in augmented reality (AR) and virtual reality (VR) settings. Their work showed how AR and VR technologies could enhance remote collaboration, especially in maintenance tasks, by providing users with interaction and awareness features to compensate for the lack of direct communication signals . Miyawaki and Sano, 2008 introduced a virtual agent in a cooking navigation system using ubiquitous sensors. This system recognized cooking progress and showed appropriate content, demonstrating how virtual agents can enhance practical applications like cooking by adapting to user behaviour. Finally Gayle and Manocha, 2008 addressed navigation of artificial virtual agents in online worlds with a centralized server network topology. They balanced the computation by performing local navigation on client machines and global navigation on the server, optimizing agent movement in a networked virtual environment.

1.10 Factors Influencing Human-ASA Interaction

It's also equally important to consider the broader factors that influence human-ASA interactions. Understanding these factors provides a comprehensive view of the elements that contribute to the effectiveness and acceptance of ASAs in various contexts. The following section delves into these influencing factors, examining how they shape the dynamics of human-ASA interaction and ultimately impact the success of these agents in real-world applications.

1.10.1 The Multifaceted Nature of Movement

The interaction between humans and artificial social agents (ASAs) is influenced by various factors that determine the quality, effectiveness, and acceptance of these interactions. Research by Baylor and Kim, 2004, Broadbent et al., 2009, and Borenstein and Arkin, 2015 sheds light on these critical factors, providing a comprehensive understanding of the elements that shape human-ASA interactions.

Baylor and Kim, 2004 explored the impact of agent characteristics on human learning and engagement. Their research focused on educational agents and how their design influences student motivation and learning outcomes. Baylor found that agents' visual appearance, voice, and personality traits significantly affect user engagement and perceived credibility. For instance, agents with more human-like appearances and expressive voices were found to be more engaging and trustworthy. Additionally, the alignment of an agent's personality with the task at hand enhances the effectiveness of interactions, suggesting that customizing agents to fit specific contexts and user needs can improve their impact.

Broadbent et al., 2009 examined the role of artificial social agents (ASAs) in healthcare, particularly how robots can assist in medical settings, highlighted several factors affecting human interactions with healthcare robots. These factors include the robot's task, appearance, and communication style. The study found that robots designed for specific healthcare tasks, such as patient monitoring or medication delivery, need to demonstrate a high degree of reliability and competence to gain patient trust. Additionally, the appearance of healthcare robots was shown to be crucial in avoiding anxiety or discomfort among patients. For instance, robots with a more human-like appearance were generally preferred for tasks involving direct patient interaction, while more machine-like appearances were acceptable for purely functional tasks Broadbent et al., 2009.

Borenstein and Arkin, 2015 focused on the ethical and practical implications of human-robot interaction, particularly in assistive and caregiving contexts. She identified several factors that influence the success of these interactions, including user autonomy, privacy, and emotional support. Borenstein argued that for ASAs to be effective in caregiving roles, they must respect user autonomy by allowing individuals to maintain control over their actions and decisions. Additionally, the design of these agents should ensure privacy and confidentiality, especially when dealing with sensitive health information. Emotional support is another critical factor, as robots that can provide empathy and understanding can significantly enhance user satisfaction and well-being.

In addition to these primary studies, other relevant research provides further insights into factors affecting human-ASA interactions. For example, Heerink et al., 2010 investigated the acceptance of assistive robots by older adults, finding that perceived ease of use, usefulness, and enjoyment are key determinants of acceptance. Their study suggested that robots should be designed with user-friendly interfaces and functionalities that address the specific needs of older adults to increase their acceptance and use.

Moreover, de Graaf et al., 2016 explored long-term acceptance of social robots in domestic environments. They identified factors such as the robot's ability to integrate into daily routines, its reliability, and the level of emotional attachment users develop over time. Their research emphasized that robots capable of adapting to changing user needs and preferences are more likely to be accepted in the long term.

Another important factor is the cultural context of human-robot interactions, which is explored in further detail later in the chapter. Research by Salem et al., 2014 demonstrated that cultural differences play a significant role in how people perceive and interact with robots. For example, in their study conducted in Qatar, they found that Arabicspeaking participants perceived the robot more positively and anthropomorphized it more than English-speaking participants. This finding underscores the need to consider cultural factors when designing and deploying robots in different regions, as cultural context significantly influences user acceptance and comfort levels.

Furthermore, the work of Dautenhahn, 2007 on social robotics emphasizes the importance of human-centred design in developing ASAs. Dautenhahn argued that understanding human social behaviour and incorporating these insights into robot design can lead to more intuitive and effective interactions. This approach involves iterative testing and refinement based on user feedback, ensuring that robots meet the social and practical needs of their users.

The factors influencing human interactions with ASAs are multifaceted, involving both the characteristics of the agents themselves and the environments in which these interactions occur. To further understand how ASAs can be effectively integrated into human experiences, it is crucial to explore the role of immersive virtual environments (IVEs). IVEs offer a unique context where the principles of human-ASA interaction can be tested and refined, providing insights into how digital spaces can be designed to support natural and intuitive engagements. The next section focuses on the development and impact of IVEs, highlighting their relevance to the ongoing evolution of ASAs.

1.11 Proxemics in Human-Computer Interaction

1.11.1 Approaches in the Social Robotics Domain

As we shift focus from the factors influencing human-ASA interaction back to the more social and interactive dimensions of ASA behaviour, we find valuable insights within the domain of social robotics. The field of robotics, particularly human-robot interaction (HRI), provides a wealth of valuable data on navigation due to its extensive research and practical applications. However, even within this large field, there is a noticeable absence of studies focusing on the micro-movements necessary for realistic artificial social agents (ASAs). Most related research primarily addresses interactive social robots, which, while important, often overlook the subtle movement behaviours that contribute significantly to perceived realism.

For example, Ghazali et al., 2019 investigated the effects of social cues in robots on users' psychological responses, including reactance and liking. While their study focused on head mimicry and social praise timing, it did not delve into navigational realism as a social cue. This illustrates a common trend in HRI research: an emphasis on specific social interactions without considering the comprehensive range of movements that make these interactions believable.

Similarly, Liu et al., 2018 explored human-robot behaviour in a shopkeeper scenario, incorporating locomotion into the robot's multi-modal behaviour. Their findings showed higher social appropriateness in the robot's behaviours, but the locomotion was limited to wheeled movement, which inherently lacks the complexity and subtlety of human-like walking and orientation changes.

Despite the extensive research in HRI, much of it is still directed towards navigation systems that create efficient routes for robotic agents rather than focusing on realistic human movement. Studies like those by Li et al., 2019; Olcay et al., 2020 demonstrate this focus on efficiency and collision avoidance, often at the expense of the nuanced behaviours that make ASAs appear lifelike.

The reason for this gap can be attributed to the current state of robotics technology. Many robots are not yet advanced enough to reliably mimic human movement, which requires a high level of precision and adaptability. This technological limitation means that the field of advanced realism in movement is often set aside in favor of more immediately achievable goals, such as basic pathfinding and obstacle avoidance.

However, as robotic technology progresses, the need for more advanced movement models will become increasingly apparent. Realistic human movement in ASAs will not only enhance their effectiveness in social and interactive applications but also contribute to more immersive and engaging virtual environments. The current state of the field presents an opportunity for future research to bridge this gap by developing and formalizing the micro-movements that are essential for creating truly realistic ASAs.

1.11.2 Ethical and Social Implications of ASAs and Virtual Environments

The integration of artificial social agents (ASAs) and virtual environments into various aspects of daily life brings with it significant ethical and social implications. The foundational works of Sharkey and Sharkey, 2010 and Sparrow, 2007 provide critical insights into these issues, addressing concerns about the ethical use of technology, the impact on human relationships, and the societal consequences of widespread adoption.

Sharkey and Sharkey (2010) explored the ethical dimensions of robotics and ASAs, particularly in caregiving roles. Their research highlighted several key ethical concerns, including the potential for reduced human contact, the quality of care provided by robots, and issues of autonomy and consent. They argued that while ASAs can offer significant benefits in terms of efficiency and support, there is a risk that over-reliance on these technologies could lead to diminished human interaction and companionship, particularly for vulnerable populations such as the elderly. This reduction in human contact could have profound psychological effects, as social interaction is crucial for mental health and well-being.

In addition, Sharkey and Sharkey (2010) raised concerns about the quality of care provided by ASAs. While robots can perform routine tasks reliably, they may lack the empathy and understanding necessary for nuanced caregiving. The authors emphasized the importance of maintaining a balance between technological assistance and human oversight to ensure that care recipients receive the emotional support and personal attention they need.

Autonomy and consent are also critical issues discussed by Sharkey and Sharkey. They highlighted the ethical dilemma of using ASAs with individuals who may not fully understand or consent to their use, such as those with cognitive impairments. Ensuring that the deployment of ASAs respects the autonomy and rights of all individuals is essential for ethical practice.

Sparrow (2007) delved into the broader societal implications of robotic and virtual technologies, focusing on the potential for dehumanization and ethical disengagement. He argued that the use of ASAs and virtual environments could lead to a form of ethical distancing, where individuals feel less responsible for their actions in a mediated environment. This detachment can result in behaviours that would be deemed unacceptable in face-to-face interactions, such as reduced empathy and increased aggression.

Sparrow also argues that ASAs and virtual environments could reinforce social inequalities, as advanced technological tools may be accessible only to certain socioeconomic groups, thereby exacerbating existing disparities. However, an opposite dynamic might also emerge. In some scenarios, the affluent may benefit from exclusive access to high-quality human caregivers—individuals capable of providing nuanced empathy and personalized interaction—while less affluent groups may increasingly rely on automated solutions. This dual possibility highlights the complex ethical challenges inherent in deploying these innovations, raising important questions about fairness, justice, and the future distribution of care.

The social implications of ASAs and virtual environments extend to changes in human relationships and social structures. Research by Turkle, 2011 examined how interactions with digital agents and virtual environments can alter human communication patterns and relationship dynamics. Turkle's research suggests that people may form attachments to ASAs, which can alter the way they interact with human counterparts, potentially diminishing the complexity and emotional richness typical of human-to-human relationships. This phenomenon is not merely theoretical; real-world examples underscore its immediacy. For instance, there have been reports of a Google engineer attributing sentience to an AI system (Lemoine, 2022), highlighting how individuals can project human-like qualities onto ASAs. Such instances suggest that as these agents become more sophisticated, they may increasingly influence interpersonal dynamics, raising important questions about the future quality of human relationships.

Moreover, the pervasive use of virtual environments for social interaction can impact societal norms and behaviours. Studies by Yee and Bailenson, 2007 showed that prolonged engagement in virtual environments could influence users' real-world behaviours and attitudes. For example, the anonymity and flexibility of virtual spaces might encourage behaviours that deviate from societal norms, potentially leading to changes in social conduct over time.

The ethical considerations surrounding ASAs and virtual environments also include issues of privacy and data security. ASAs often require access to personal information to function effectively, raising concerns about data protection and user privacy. Research by Zarsky, 2016 highlighted the risks associated with the collection and use of personal data by ASAs, emphasizing the need for robust privacy safeguards and transparent data practices. Additionally, the deployment of ASAs in sensitive areas such as healthcare, education, and law enforcement necessitates stringent ethical standards to prevent misuse and ensure accountability.

Finally, the ethical design of ASAs and virtual environments is crucial to mitigate potential negative impacts. Designers and developers must consider the ethical implications of their creations, incorporating principles of fairness, transparency, and accountability. Research by Friedman and Hendry, 2019 emphasized the role of value-sensitive design in ensuring that ethical considerations are embedded in the development process of technological systems. As the adoption of ASAs and virtual environments continues to grow, addressing these ethical and social challenges will be crucial to ensure that these technologies benefit society while minimizing potential harms.

The exploration of ethical and social implications underscores the complex impact that artificial social agents (ASAs) and virtual environments have on human interaction and societal norms. As we delve deeper into these effects, it is important to recognize that cultural differences also play a significant role in shaping interpersonal interactions. Cultural norms and expectations profoundly influence how personal space is perceived and maintained, adding another layer of complexity to the design and implementation of ASAs. The following section examines how these cultural variations in proxemics affect the use and acceptance of ASAs, providing a broader context for understanding their integration into diverse social environments.

Cultural differences

The previously explored ethical and social implications of integrating artificial social agents (ASAs) and virtual environments into daily life are profound, touching on issues of human interaction, privacy, and societal norms. As we explore these implications, it is important to consider how cultural differences shape the very foundations of interpersonal interactions, even if current research is mainly focused on proxemics, and not realism of movement. This concept is not only influenced by psychological and social factors but is deeply rooted in cultural norms and expectations.

Cross-cultural research has shown that cultural norms significantly influence how people perceive and maintain personal space during social interactions. For example, a study by Khan and Kamal, 2010 explored how university students from different cultural backgrounds reacted to invasions of personal space. Their findings highlighted that individuals from collectivist cultures, which emphasize close-knit relationships and community, tend to maintain closer interpersonal distances. In contrast, those from individualist cultures, which prioritize personal autonomy and privacy, prefer larger personal spaces. This research underscores the importance of considering cultural differences in social behaviour, particularly in settings involving interpersonal interactions.

These cultural differences in interpersonal distance are further supported by research from Sorokowska et al., 2017, who conducted a global study on personal space preferences (figure 1.6). Their findings indicated substantial variations in interpersonal distance prefer-

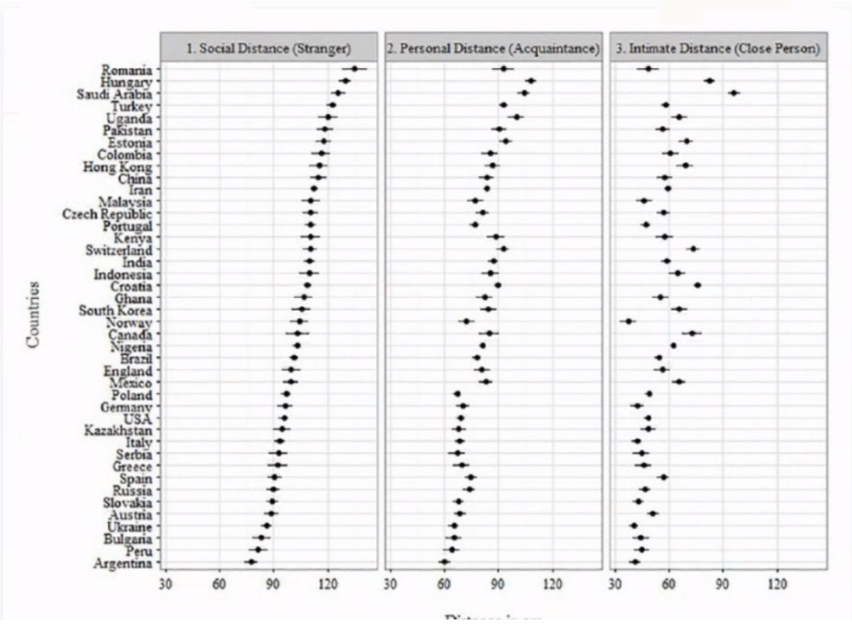


Figure 1.6: Sorokowska's investigation into cultural differences in proxemics showed a large range of preferred distances by country (Sorokowska et al., 2017).

ences across different countries. For example, participants from Latin American countries, known for their warm and expressive communication styles, reported smaller interpersonal distances compared to participants from Northern European countries, where social interactions are more reserved.

Moreover, the work of Hall, 1966 on proxemics provides a foundational understanding of how cultural norms shape interpersonal distance. Hall's research identified specific spatial zones that vary across cultures, reflecting the underlying social values and communication styles. For example, in Middle Eastern cultures, where social interactions are often close and personal, the intimate and personal distance zones are smaller compared to Western cultures.

Further research by Triandis, 2004 on cultural dimensions of individualism and collectivism offers additional insights into how cultural values influence interpersonal distance. Triandis suggested that collectivist cultures prioritize group cohesion and interdependence, leading to closer interpersonal distances and more frequent physical contact. In contrast, individualist cultures emphasize personal space and independence, resulting in larger interpersonal distances and less physical touch.

In summary, research from Khan (2010), Sorokowska (2017), Hall (1966), and Triandis

(2004) demonstrates that cultural norms play a fundamental role in shaping interpersonal space and social behaviour. These findings underscore the need for ASAs to be culturally adaptable by integrating localized proxemic behaviours and non-verbal cues that align with users' expectations. By tailoring ASAs to reflect the cultural nuances of different user groups (possibly through options within the settings of the ASA), developers can enhance the authenticity of human-agent interactions and help ensure that these technologies promote inclusivity and social equality in virtual environments.

1.11.3 Chapter Summary

This literature review has explored the multifaceted aspects of Artificial Social Agents (ASAs), focusing on the critical elements that contribute to their realism and effectiveness in human interactions. Beginning with an examination of the psychological foundations and proxemic principles underlying human-ASA interaction, the review highlighted the importance of behavioural realism, including movement dynamics and social cues, in creating believable and engaging agents.

We further delved into the technological advancements and user experience design principles that enhance immersive virtual environments, which are crucial for the effective deployment of ASAs. The discussion underscored the significance of incorporating subtle micro-movements and cultural considerations to ensure that ASAs are not only technically proficient but also socially intuitive and culturally sensitive.

Additionally, the ethical and social implications of integrating ASAs into daily life were examined, emphasizing the need for careful consideration of autonomy, privacy, and the potential impact on human relationships. The review also highlighted the importance of understanding cultural differences in proxemics, as these deeply influence how ASAs are perceived and accepted across various contexts.

In the upcoming chapter, we will focus on the more technical aspects of development and implementation of Artificial Social Agents (ASAs), emphasizing the importance of realistic movement and interaction in virtual environments. This includes the design of a Finite State Machine (FSM) to manage ASA locomotion and gaze control, exploring the role of machine learning in improving movement prediction, and examining key metrics for navigation.

Chapter 2

Challenges in Developing a Realistic Artificial Social Agent

2.1 Introduction

The objective of this research was to explore how humans manage physical space with ASAs during interactions. However, as we progressed in our implementation, it became evident that achieving a high level of realism in the agents' movements and behaviours was crucial to accurately simulate these interactions. Without realistic movement patterns, any study of social dynamics, such as interpersonal distance, would likely yield results that are not reflective of real-world human behaviour. This chapter discusses the critical metrics of distance and orientation that underpin ASA navigation, the design and function of the FSM, and how enhancing realism in agent movement is foundational to creating meaningful, human-like interactions in virtual settings. Through this exploration, we set the stage for more advanced studies on human-agent interactions, ensuring that our virtual agents not only move convincingly but also foster genuine engagement and trust with human participants.

This chapter is structured as follows: Section 2.1.1 delves into the Motivation behind the research, highlighting the importance of understanding how users manage physical space with ASAs and the need for realistic agent movement to accurately simulate these interactions. Section 2.2 provides an overview of the experimental methodology and structure, focusing on the design and procedural framework intended to explore the effects of different interpersonal distances on user interaction with Artificial Social Agents (ASAs) in a virtual environment. Section 2.3 discusses the Implementation of the Agent System, detailing the role of Finite State Machines (FSMs) in managing ASA locomotion and gaze control, as well as investigating some more technical aspects of literature in this area. Section 2.4 presents Insights from Initial Investigations, emphasizing the critical role of authentic movement in ASAs for replicating human-ASA interactions. Finally, Section 2.5 outlines Future Steps, proposing the formalization of micro-movements as a foundation for advancing ASA realism and engagement, setting the stage for more research in human-agent interaction.

2.1.1 Motivation

The original aim of this research was to explore how users regulate interpersonal distance with Artificial Social Agents (ASAs) within a virtual environment. Utilising Hall's theory of proxemics (Hall, 1966), which categorizes personal space into distinct "bubbles," the project was designed to investigate user preferences for these spatial boundaries when interacting with ASA assistants. Specifically, the motivation was to determine if there was a preferred interpersonal distance that users found more comfortable or effective, which could lead to increased usage and reliance on the virtual assistant. Understanding these preferences could pave the way for developing ASAs capable of autonomously adjusting their proximity based on social and behavioural cues from users, thereby enhancing the overall interaction experience in an almost automated manner.

To accomplish this, a system was developed where an ASA could follow the user at one of four predefined distances, with each distance corresponding to a different proxemic zone. The study also incorporated a task-oriented scenario where the ASA assisted users in locating hidden objects by providing "hot" or "cold" hints based on the user's proximity to the target. Metrics such as the frequency of assistance usage, the amount of time the user spent looking at the ASA, and the time taken to complete the task were carefully tracked for each distance variable. These metrics were crucial for evaluating how the interpersonal distance affected user interaction with the ASA, and whether certain distances fostered more effective and engaging assistance.

The entire system was integrated with the Cyberith Virtualizer, an omnidirectional treadmill, to allow for more natural and immersive movement within the virtual environment. This integration was essential for simulating a realistic and physically engaging interaction, enabling users to experience and respond to the ASA's proximity in a way that closely mimics real-world behaviour.

It became apparent that if the ASA's movement does not appear lifelike to participants, any findings related to interpersonal distance risk being fundamentally skewed. Users might respond to the agent's stiff or robotic locomotion rather than its intended proxemic behaviour, undermining the ecological validity of the study. In other words, a user's sense of immersion—and thus their willingness to treat the ASA as a genuine social entity—is diminished if the ASA's motion feels artificial. Consequently, we concluded that without first establishing a solid baseline of realistic movement, insights into user comfort or preferred distance would be unreliable, leading us to refocus on refining ASA realism before conducting an in-depth proxemics experiment.

2.2 Experimental Methodology and Procedure

Building on the foundational goals of the research, the experimental design and procedural framework were crafted to explore how different interpersonal distances could affect user interaction with Artificial Social Agents (ASAs) within a virtual environment. The study was intended to be conducted within a virtual office space, chosen for its neutral and familiar setting, which would not unduly influence user behaviour.

2.2.1 Experimental Setup

Participants would have been immersed in the virtual environment using the Cyberith Virtualizer, an omnidirectional treadmill that was expected to allow for natural and unrestricted movement within the virtual space. The ASA was programmed to maintain one of four predefined distances from the participant, corresponding to Hall's proxemic zones: intimate, personal, social, and public (Hall, 1966). The ASA's role in the experiment would have been to assist participants in a task that required finding hidden objects within the office. Assistance would have been provided through "hot" or "cold" hints, depending on the participant's proximity to the target object.

2.2.2 Procedural Details

During the task, several metrics were to be continuously tracked to analyze the interaction between the participant and the ASA:

- **Assistance Usage:** The frequency with which participants might have requested or relied on the ASA's guidance would have been recorded. This data was intended to provide insights into how interpersonal distance influenced the perceived utility of the ASA.

- **Gaze Tracking:** The system was designed to record the duration of time participants spent looking at the ASA, which would serve as a measure of engagement and trust.

- **Task Completion Time:** The time taken by participants to locate the objects would have been meticulously recorded for each distance variable, allowing for an assessment of how proximity might affect task efficiency.

- **True Distance from Agent:** The actual distance between the participant and the ASA throughout the task would have been continuously monitored, providing a more precise measure of how closely the ASA adhered to the intended distance variable and how participants naturally adjusted their spacing.

- **Active Distance Variable:** The specific proxemic distance variable (intimate, personal, social, or public) that was active during each session would have been logged, enabling a direct correlation between the distance setting and the other recorded metrics.

2.2.3 Data Collection and Analysis

Following each session, the collected data would have been analyzed to identify patterns that could indicate a preferred interpersonal distance. The analysis was to focus on whether certain distances led to increased usage of the ASA, more frequent gaze engagement, or faster task completion times. These findings would have informed the potential development of ASAs capable of autonomously adjusting their distance based on real-time user cues, thereby enhancing the overall interaction experience.

2.3 Implementation of the Agent System

2.3.1 Technical Background Literature

Distance and Orientation Metrics in ASA Navigation

In the quest to achieve realism in artificial social agents (ASAs), understanding the fundamental principles of distance and orientation becomes essential. The previous sections have emphasized the importance of proxemics, realism, social cues, and psychological theories in shaping human-ASA interactions. However, these interactions are underpinned by more concrete, measurable elements: the mathematical and geometrical foundations that govern how agents navigate and orient themselves in both physical and virtual environments.

These distance and orientation classifications are not merely abstract concepts but practical tools that allow ASAs to move and interact in ways that feel natural and intuitive to human users. By accurately calculating distances, angles, and orientations, ASAs can mimic human movement patterns, avoid obstacles, and engage in complex navigation tasks—all of which contribute to their perceived realism and effectiveness.

In this section, we explore various distance and orientation metrics, each of which can play a vital role in the design and functionality of virtual spaces and ASAs. Understanding these classifications will provide the groundwork for implementing the movement strategies and behavioural realism necessary to create truly lifelike agents.

- **Euclidean distance** is the most straightforward and commonly used measure of distance between two points in a Euclidean space. Defined as the straight-line distance between two points, it is calculated using the Pythagorean theorem. For two points (x_1, y_1) and (x_2, y_2) in a 2D space, the Euclidean distance d is given by:

  $$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

  In the context of human movement and virtual environments, Euclidean distance is frequently used to determine the direct distance between two positions. This measure is crucial for applications like navigation, where the shortest path between locations is often desired.

- **Manhattan distance**, also known as L1 distance or taxicab distance, measures the distance between two points in a grid-based system. It is calculated as the sum of the absolute differences of their coordinates. For two points (x_1, y_1) and (x_2, y_2), the Manhattan distance d is:

$$d = |x_2 - x_1| + |y_2 - y_1|$$

This distance metric is particularly useful in urban planning and robotics, where movement is restricted to grid-like patterns. In virtual environments, Manhattan distance can be applied to simulate realistic movement patterns in structured spaces, such as buildings or cities.

- **Minkowski distance** is a generalized form of both Euclidean and Manhattan distances and is defined as:

$$d = \left(\sum_{i=1}^{n} |x_i - y_i|^p \right)^{\frac{1}{p}}$$

where p is a parameter that determines the type of distance. When $p = 1$, it represents Manhattan distance, and when $p = 2$, it represents Euclidean distance. Minkowski distance is versatile and can be adjusted to fit different contexts by changing the value of p. This flexibility makes it valuable in machine learning and data analysis, where various distance metrics may be needed.

- **Geodesic distance** is the shortest path between two points on a curved surface, such as the surface of the Earth. This measure is essential for geographical and spatial analyses, where distances over the Earth's surface must be considered. The calculation of geodesic distance often involves complex mathematical models and algorithms. In virtual environments, geodesic distance is used to simulate realistic movement over terrain and landscapes.

- **Hamming distance** measures the number of positions at which the corresponding elements of two strings are different. It is widely used in computer science, particularly in coding theory and information retrieval. For two strings of equal length, the Hamming distance d is the count of differing characters:

$$d = \sum_{i=1}^{n} (x_i \neq y_i)$$

In the context of virtual environments, Hamming distance can be used to compare sequences of movements or actions.

- **Geographical distance** refers to the physical distance between two points on the Earth's surface, typically measured in kilometers or miles. This measure considers the Earth's curvature and is crucial for applications in GIS, navigation, and spatial analysis. Tools like the Haversine formula are often used to calculate geographical distances. In virtual environments, incorporating geographical distance can enhance the realism of simulations that involve real-world locations.

- **Azimuth angle** is the angle between the north direction and the projection of the vector pointing towards an object on the horizontal plane. It is measured clockwise from the north direction. Azimuth is commonly used in navigation, astronomy, and surveying. In virtual environments, azimuth angles are essential for orienting objects and avatars.

- **Bearing angle** is similar to azimuth but is specifically used in navigation to describe the direction one must travel to reach a destination. It is the horizontal angle between a reference direction (usually north) and the line connecting the observer and the point of interest. Bearing angles are critical for pathfinding and navigation in both real and virtual environments.

- **Aspect, dip, and dip direction** are geological terms used to describe the orientation of a planar surface, such as a rock face. Aspect is the compass direction that a slope faces, dip is the angle of the slope relative to the horizontal plane, and dip direction is the compass direction in which the slope descends. These measures are crucial for geological mapping and analysis. In virtual environments, aspect, dip, and dip direction can be used to create realistic terrain and landscape features.

The exploration of various distance and orientation classifications provides essential insights into the spatial dynamics that are fundamental for realistic movement in artificial social agents (ASAs). These classifications offer the mathematical and geometrical tools necessary for designing ASAs that can navigate virtual environments with precision and efficiency. However, while this thesis primarily focuses on the movement realism of ASAs, it's important to recognize that movement alone is not sufficient for creating agents that can engage with humans effectively.

2.3.2 Finite State Machine Controller for Artificial Social Agents

Introduction

In the development of Artificial Social Agents (ASAs), achieving realistic and responsive movement is crucial for creating believable interactions within virtual environments (see figure 1.3 for the components of an ASA). Movement realism not only enhances the immersive experience but also plays a vital role in how users perceive and engage with ASAs. One approach to managing complex and dynamic movement behaviours in ASAs is the use of Finite State Machines (FSMs). FSMs provide a structured framework for defining and controlling the various states of movement, such as idling, orienting, and walking, based on the agent's interaction with its environment.

In the context of this interpersonal distance experiment, the FSM (figure 2.3) was specifically designed to control the ASA's behaviour as it followed the user at varying interpersonal distances within a virtual office environment (figure 2.2). By managing the transitions between different movement states—such as approaching, stopping, or adjusting orientation based on user proximity—the FSM ensured that the ASA could maintain a realistic and responsive distance according to Hall's proxemic zones(Hall, 1966). This FSM-based control was integral to the experiment's goal of exploring how users regulate interpersonal distance with ASAs, allowing the agent to adapt its movements in real-time and provide a more immersive and lifelike interaction. Through the integration of FSMs with advanced pathfinding and locomotion controllers, we aimed to address the challenges of creating fluid and realistic movements, which are critical for maintaining the illusion of life in virtual environments.

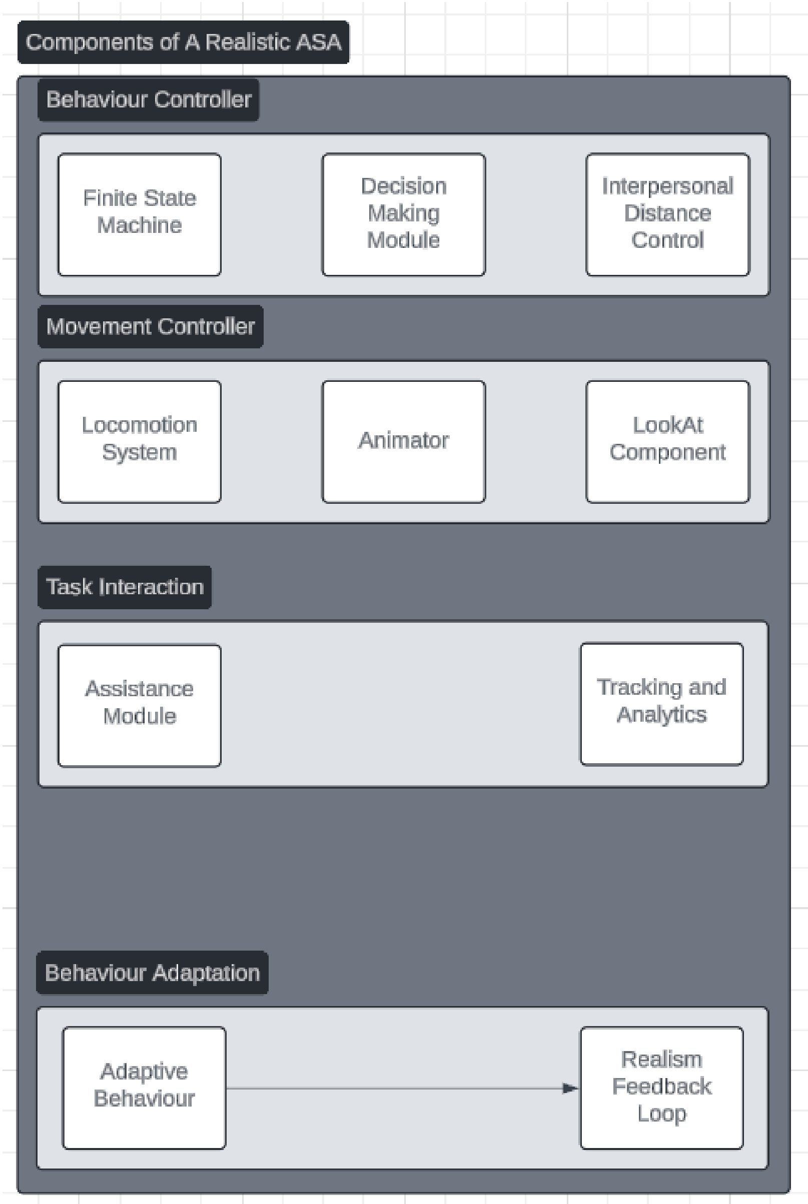


Figure 2.1: This diagram illustrates the key components required for a realistic ASA. The Behaviour Controller section manages the decision-making processes, interpersonal distance control, and the finite state machine that governs state transitions. The Movement Controller oversees the locomotion system, animation, and gaze direction via the LookAt component, ensuring natural and responsive movements. The Task Interaction section includes the assistance module and tracking/-analytics tools, enabling the ASA to engage meaningfully with users and gather interaction data. Lastly, the Behaviour Adaptation section represents a planned future development for the ASA, where the agent would be designed to adapt its behaviour through an adaptive behaviour module and a realism feedback loop. This system would be intended to continually refine the agent's actions, enhancing believability and realism in human-agent interactions over time.

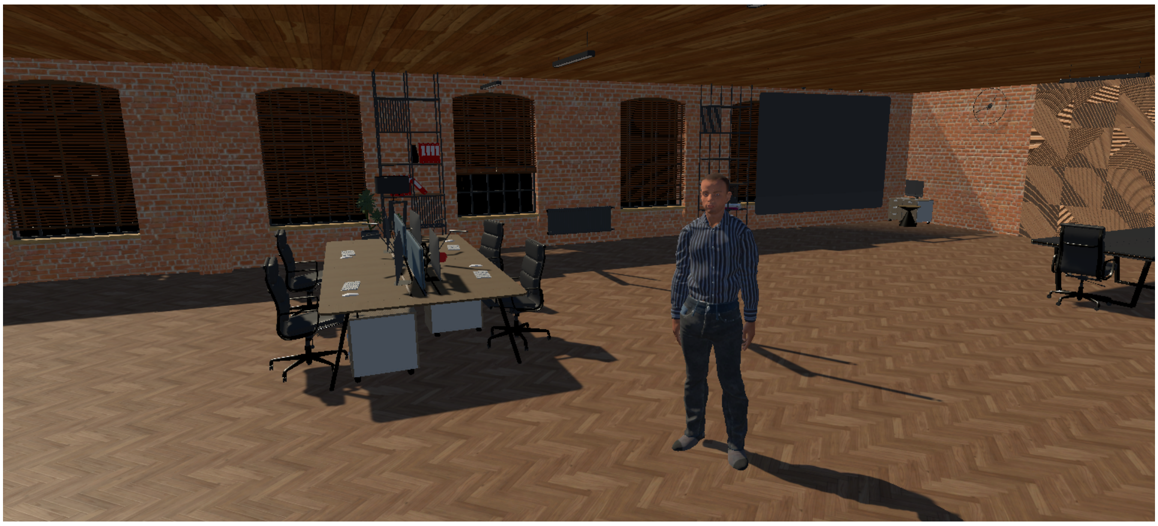


Figure 2.2: Example image showing the Office scene that was created, and the human artificial social agent designed to investigate distance regulation

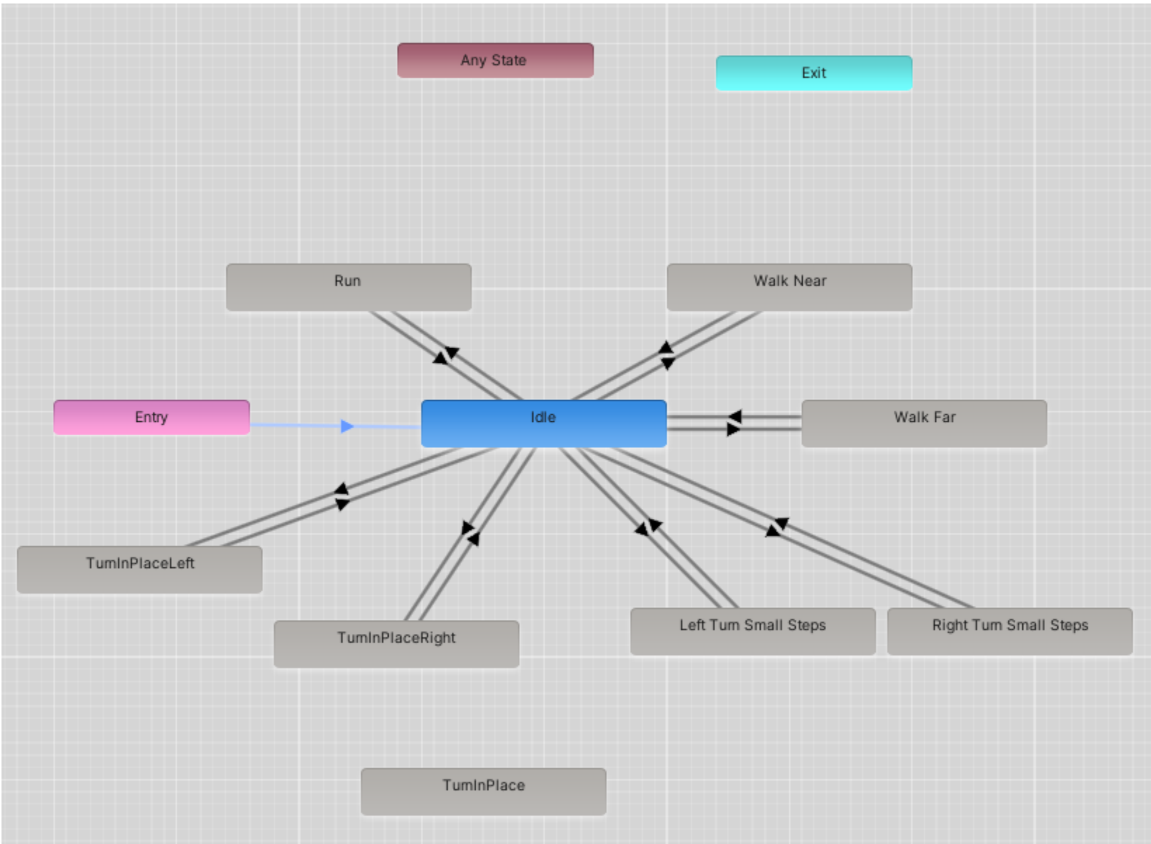


Figure 2.3: Example image showing the Finite State Machine overview for the ASA

As mentioned, while the system functioned as intended, significant limitations were identified regarding the movement realism of the ASAs. It became apparent that the agents lacked the subtle micro-movement strategies necessary to create a believable interaction, which would be crucial for a meaningful study on interpersonal distance. Consequently, the project shifted its focus towards improving the realism of ASA movements before further exploring interpersonal distance.

Locomotion Controller Design

The locomotion controller was initially developed to manage the agent's movement and orientation, leveraging Unity's `NavMeshAgent` for pathfinding, `Rigidbody` for physics-based movements, and `Animator` for handling animations. It uses a Finite State Machine (FSM) to govern transitions between states such as idle, orienting, walking far, and walking near, ensuring that the agent's behaviour appeared smooth and purposeful.

This initial Finite State Machine (FSM) was adopted to control the ASA's locomotion and gaze because it offered a straightforward way to implement basic, rule-based behaviours—like switching between "Idle" and "Walk." However, our early experiments quickly revealed that the FSM alone produced movements that felt stiff and robotic, lacking the nuanced micro-movements humans exhibit. This shortcoming highlighted the need for authentic human locomotion data to inform more realistic agent behaviours. We therefore treated the FSM as a preliminary investigation: it confirmed that simplistic, hard-coded transitions would not achieve human-like motion. Consequently, we decided to collect and analyse actual human movement data (Chapter 3) to guide the development of a more sophisticated control system capable of replicating subtle, lifelike locomotion.

Finite State Machine (FSM):

The FSM is a robust method for managing complex behaviours in interactive systems, allowing for clear and maintainable code (Besset, 2015). The states implemented in this controller are:

- **IDLE**: The agent is stationary.
- **ORIENTING**: The agent rotates to face the target.
- **WALK_FAR**: The agent moves towards a distant target. ($>$ 12ft distance)
- **WALK_NEAR**: The agent moves towards a nearby target. ($<$ 12ft distance)

The state transitions are governed by distance thresholds (`ModeThreshold`, `MoveThreshold`) and angular thresholds (`RotationThresholdFar`, `RotationThresholdNear`), the distances were informed by Halls proxemic zones (Hall, 1966).

The FSM framework was intended to handle complex behaviours systematically, but the lack of nuanced micro-movements in the agent's transitions (e.g., subtle turns in motion, backstepping) made the interactions feel stiff and artificial. This lack of fluidity in movement was particularly problematic for our intended study on interpersonal distance, where the perceived realism of the agent's approach and orientation towards the user is critical.

State Transitions and Algorithms:

The transition between states is dictated by the distance to the target and the angular difference between the agent's forward direction and the direction to the target. These transitions are encapsulated in the following pseudocode:

```
if (state == IDLE) {
    if (fDistance2Target > ModeThreshold && angleBetween2d >
        RotationThresholdFar) {
         state = ORIENTING;
    } else if (fDistance2Target < ModeThreshold && angleBetween2d
        > RotationThresholdNear) {
         state = ORIENTING;
    } else if (fDistance2Target > MoveThreshold &&
        fDistance2Target < ModeThreshold && angleBetween2d <
        RotationThresholdNear) {
         state = WALK_NEAR;
         fEnterTimeWalkNear = Time.time;
    } else if (fDistance2Target > ModeThreshold && angleBetween2d
        < RotationThresholdFar) {
         state = WALK_FAR;
    }
}
```

In mathematical terms, the conditions for state transitions can be expressed as:

$$\text{Transition to ORIENTING:} \quad (D_t > T_m \wedge |\theta_t| > \Theta_f) \vee (D_t < T_m \wedge |\theta_t| > \Theta_n)$$

$$\text{Transition to WALK\_NEAR:} \quad T_m > D_t > T_v \wedge |\theta_t| < \Theta_n$$

$$\text{Transition to WALK\_FAR:} \quad D_t > T_m \wedge |\theta_t| < \Theta_f$$

where:

- D_t is the distance to the target.
- T_m is the mode threshold.
- T_v is the movement threshold.
- θ_t is the angle between the agent's forward direction and the target.
- Θ_f and Θ_n are the far and near rotation thresholds, respectively.

Movement Algorithms:

The movement towards the target is managed by different methods depending on the state. For instance, in the `WALK_NEAR` state, the agent can use Rigidbody forces or Animator root motion. The force-based movement can be described by:

$$\mathbf{F} = \mathbf{d}_{\text{target}} - \mathbf{d}_{\text{current}}$$

where $\mathbf{d}_{\text{target}}$ and $\mathbf{d}_{\text{current}}$ are the target and current positions, respectively.

The velocity adjustment for the Animator root motion is given by:

$$\mathbf{v}_{\text{adjusted}} = k \cdot \frac{\mathbf{d}_{\text{target}} - \mathbf{d}_{\text{current}}}{\Delta t}$$

where k is a gain factor and Δt is the time delta.

Implementation Details

The `LocomotionController` script integrates several components to achieve responsive and realistic movement. Key components include:

- **NavMeshAgent**: Handles pathfinding and navigation.
- **Rigidbody**: Facilitates physics-based movement.
- **Animator**: Manages animation states and root motion.

These components work in tandem to ensure the agent responds appropriately to the target's position and orientation changes. The script also includes mechanisms to visualize the target position and debug information through UI elements.

Rotation Towards Target:

To ensure the agent is oriented correctly towards the target, the `RotateTowardsTarget` method calculates the planar difference and applies the corresponding rotation:

```
public void RotateTowardsTarget() {
    Vector3 planarDifference = (LocomotionTarget.transform.
        position - transform.position);
    planarDifference.y = 0;
    Quaternion targetRotation = Quaternion.LookRotation(
        planarDifference.normalized);
    transform.rotation = targetRotation;
}
```

LookAt Implementation

In addition to the locomotion controller, the `LookAt` script provides an essential functionality for enhancing the realism of artificial social agents by managing their gaze direction. This script ensures that the agent can focus its gaze on a specified target, adding a layer of social realism crucial for natural interactions.

The gaze control mechanism improves social realism by ensuring that the agent can visually focus on a target in the environment, which is critical for natural interactions in virtual environments. The `LookAt` script uses the Animator component to smoothly transition the agent's gaze towards the target, accounting for both the angular difference and the necessary blending time for the transition.

The weight adjustment for the gaze direction can be described by the following equation:

$$w_{\text{lookAt}} = \text{lerp}(w_{\text{current}}, w_{\text{target}}, \frac{\Delta t}{\text{blendTime}})$$

where:

- w_{lookAt} is the current weight of the look-at blend.
- lerp represents the linear interpolation function.
- w_{current} is the current weight.
- w_{target} is the target weight.
- Δt is the time delta.
- blendTime is the blending duration.

2.4 Insights from Initial Investigations on the Importance of Authentic Movement

The initial intention of this research was to explore how humans regulate interpersonal distance with ASAs. However, the early findings from our locomotion experiments revealed that without a high degree of realism in these fundamental behaviours, it is impossible to accurately simulate the nuanced social interactions required for such a study. Realism in movement is not just a nice-to-have feature; it is the foundation upon which studies of social dynamics in virtual environments must be built.

Achieving realism is crucial because it directly impacts the validity of the research findings. If the ASAs do not move or behave in ways that are perceived as realistic by human participants, the data on interpersonal distance and other social interactions will be skewed, leading to incorrect conclusions. Therefore, before we could proceed with any meaningful investigation into interpersonal distance, we needed to address these deficiencies in ASA realism. This realization led to a significant shift in our research focus toward the development of more lifelike and responsive virtual agents. Only by ensuring that these agents move, orient, and interact in a manner that closely mimics human behaviour can we create the conditions necessary to explore more complex social phenomena.

2.5 Future Steps

Moving forward, our research will continue to define and investigate these movement strategies that we posit are missing and conducting further experiments to ensure that ASAs can realistically interact with human participants. By achieving this level of realism, the tools will exist to allow researchers to be better equipped to study how humans perceive and maintain interpersonal distance in virtual environments, ultimately contributing to the broader field of human-agent interaction.

In the next chapter we will discuss formalization. By formalizing these micro-movements, we provide a foundation for future research and development in the field of ASA navigation. This formalization is just the first step. Future work must involve collecting data on these micro-movements from real-life human participants and creating autonomous systems that can replicate and simulate these behaviours in ASAs. Whether through reinforcement learning systems, finite control models, or other approaches, this research will advance the realism of ASAs and enhance user immersion in virtual environments. The framework we propose aims to standardize these concepts, facilitating better understanding and implementation in various applications.

Chapter 3

Formalisation of Micro-movement Strategies

Navigation is critical to an intelligent social agent's ability to interact with the world and any other agent, virtual or otherwise. In order to create a truly realistic artificial social agent, unconscious human micro-movements need to be simulated. We see this as an important goal for the research area. Examples of these micro-movements include orienting while walking and back-stepping, strafing with attention focused elsewhere, and micro-orientations during locomotion. We postulate that there is a gap in research around these micro-movements within the field of navigation that we hope to contribute to filling. Most research in this field is focused on the understandably important pathfinding aspect of navigation; moving between two spatial locations. There is little to no research being done on micro-movements and making a truly realistic navigation system for artificial social agents. Moreover, there exists no canonical way of describing these movements and "micro-movements" that are so characteristic for human spatial behaviour. Here we propose a set of standardised descriptors of movement configurations, that will be able to be used as building blocks for spatial behaviour experimentation, and as the basis for behaviour generation models. We see this as an important tool in the creation of navigation systems that are able to more readily include these kinds of behaviours, with hope that the aforementioned configurations will improve the development of realistic movement systems.

3.1 Chapter Publications

.

].

3.2 Introduction: Hierarchy of Navigational Realism

The navigational behaviour of artificial social agents (ASAs) is pivotal in shaping the perception of realism in human interactions with these agents. Current research predominantly emphasizes realistic pathfinding and enhancing the visual fidelity of ASAs, yet there remains a significant gap in exploring the micro-movements and orientations that enhance the realism and immersion users experience—the subjective sensation of being in an alternate world Bartle, 2004.

Immersion is a crucial element of virtual experiences, significantly impacting the effectiveness of virtual worlds used for training, education, and therapy (Lele, 2013; Merchant et al., 2014). Immersive training simulations, for instance, provide controlled environments for learning complex tasks, making the realism of virtual agents essential. Latoschik, Roth, et al., 2017 found that avatar realism positively affects various measures, increasing humaneness and attractiveness, though it may also increase eeriness. Similarly, Pütten et al., 2009 demonstrated that greater behavioural realism in virtual avatars enhances social presence.

Movement is a critical aspect of realism in ASAs, arguably one of the most vital. Pedica and Vilhjálmsson, 2008 discovered that social perception and reactive maneuvering in the form of grouping around o-spaces (the circular, interaction-focused area formed at the centre of a conversational group) Burgoon and Kendon, 1992 heighten the realism of avatars in online chat rooms. This underscores the importance of orientation and positioning in realistic interactions. Motion capture technology, despite its high cost and time investment, uses recorded human movements to create realistic animations for virtual characters. Simulating these micro-movements without the high costs associated with motion capture could significantly enhance the realism and believability of ASAs, thereby improving the overall immersion of the experience (Pedica and Vilhjálmsson, 2008).

The primary focus of existing research has been on pathfinding—determining the path an agent takes from point A to point B. This focus is understandable, as micro-movements and navigation occur within a movement scenario. Pathfinding provides the basic movement from location to location, which is essential for any higher-level behavioural realism to be built upon. The requirements of a realistic human artificial social agent can be organized as a three-layer pyramid (Figure 3.1). At the base is *pathfinding*, the routing method that computes the sequence of waypoints an agent must follow to reach its destination. The middle layer is *locomotion*, the actual execution of that route—translating the planned path into continuous walking, turning, or other modes of movement. Topping the pyramid are *micro-movements*: the small, often unconscious adjustments humans make while navigating—rotating slightly as they step, weight-shifts, subtle strafing or back-stepping—that imbue motion with natural fluidity and social nuance. When micro-movements are omitted, agents move in a stiff, mechanical fashion, significantly lowering perceived realism. This concept is inspired in part by A. Maslow's hierarchy of human needs Maslow, 1943, where basic needs must be met before higher-level needs can be addressed.

Despite the importance of pathfinding, the omission of micro-movements—such as orienting while walking, back-stepping, strafing, and micro-orientations during locomotion—presents a significant gap in the realism of ASAs. These micro-movements are subtle yet crucial, as they reflect the unconscious adjustments humans make while navigating their environment. The lack of these movements results in ASAs that move in a mechanical fashion, breaking the immersive experience and reducing the perceived authenticity of the interaction.

Moreover, the significance of these micro-movements extends beyond just enhancing immersion. They are vital for the believability and social presence of ASAs, which are critical for applications ranging from virtual therapy and education to customer service. Social presence, defined as the feeling of being in the presence of another social entity, is enhanced when virtual agents exhibit natural movement patterns (K. Nowak and Biocca, 2003). For instance, Gong, 2008 found that virtual agents displaying human-like anthropomorphism, including realistic micro-movements, were perceived as more credible and engaging, receiving more social responses from users.

This chapter is structured as follows: Section 3.2 begins with an introduction that outlines the importance of micro-movements in enhancing the realism and immersion of Artificial Social Agents (ASAs), positioning this research within the broader context of navigational realism. Section 3.3 reviews existing literature, identifying a significant gap in research focused on micro-movements within human navigation and proposing a framework for formalizing these movements to improve ASA behaviour. Section 3.4 provides an analysis of human movement data, demonstrating the complexity of human locomotion and underscoring the necessity for detailed tracking and modelling to capture the nuances of these movements. Section 3.5 formalizes micro-movement strategies, categorizing them into six fundamental types and introducing standardized descriptors essential for the development of realistic navigation models in ASAs. Finally, Section 3.6 summarizes the key contributions of the chapter, and 3.7 discusses future research directions, and highlights the importance of further studies to refine and implement these micro-movement strategies in artificial social agents.

This chapter aims to address the gap in the literature by proposing a framework for formalizing these micro-movements. By developing standardized descriptors for these behaviours and integrating them into the design of ASAs, we can create more lifelike and immersive virtual agents. The following sections will delve deeper into the current research on the critical role of micro-movements, providing a comprehensive overview of the field and highlighting the areas where this research can make significant contributions.

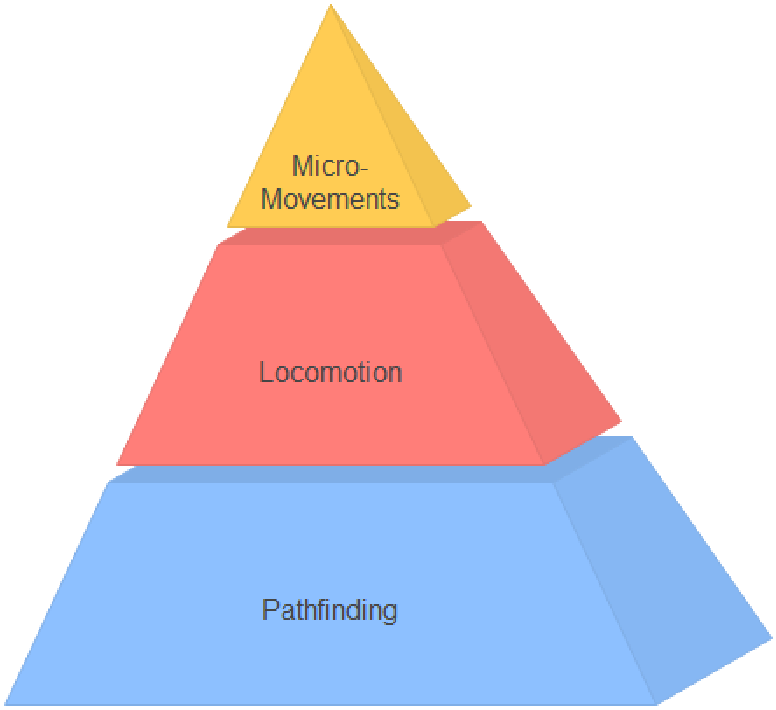


Figure 3.1: The requirements of a realistic human artificial social agent as a hierarchical pyramid; Pathfinding describing the routing method that generates the path for an artificial social agent to take. Locomotion is the actual movement the agent employs to displace itself to the intended direction. Micro-Movements are the small movements and orientations humans use during navigation such as rotating while stepping, that when lacking cause a lowering of realism of the agent.

3.3 Micro-Movements in Human Navigation

The intricate dynamics of human-agent interactions, particularly the realism of such interactions, hinge not only on the behavioural and cognitive responses of artificial social agents (ASAs) but also on the subtle nuances of movement that define human locomotion. As we delve deeper into these interactions, it becomes evident that enhancing the believability and immersion of ASAs requires a focus on the often-overlooked micro-movements that characterize natural human navigation. We posit that these small yet significant movements, including both involuntary actions like twitches and small adjustments, as well as purposeful micro-movement strategies, are pivotal in creating a more authentic and engaging virtual experience. This marks a critical area of study in the broader field of navigation, essential for developing ASAs that can navigate and interact within their environments as naturally as humans do.

3.3.1 Human Locomotion and Micro-Movement Dynamics

The incorporation of micro-movements into artificial social agents (ASAs) is crucial for enhancing realism and social presence in virtual environments. By focusing on subtle, often unconscious movements, we can significantly improve the realism of ASAs, making their interactions with human users more natural and immersive. However, to fully replicate human-like behaviour, it is essential to expand our understanding beyond these micro-movements and consider the broader context of human locomotion.

Human movement is not merely a series of isolated actions but a complex interplay of physiological, biomechanical, and cognitive processes. These processes govern how we walk, adjust our stride, and interact with our surroundings—factors that must be understood and accurately modelled to achieve high-fidelity simulations in ASAs. This leads us to a more comprehensive exploration of human locomotion and the strategies that underpin natural movement.

Gait Patterns, Stride Length, and Speed

Human locomotion, particularly the study of gait patterns, stride length, and speed, is essential for understanding the dynamics of movement. Gait patterns refer to the rhythmic and cyclic motion of limbs during walking or running, which are influenced by various factors including biomechanical efficiency, energy expenditure, and environmental context. Moussaïd et al., 2011 conducted a comprehensive study on human gait patterns, highlighting how individuals adapt their stride and speed in response to environmental constraints and social interactions. Their research underscores the importance of these parameters in navigating complex environments.

Stride length and speed are closely linked to the efficiency of movement. Longer strides can reduce the frequency of steps, thereby conserving energy, but may also increase the risk of instability. Conversely, shorter strides can enhance stability but may lead to higher energy expenditure. Understanding these trade-offs is critical for replicating realistic human movement in artificial social agents (ASAs). Studies have shown that stride length and speed are modulated based on task requirements and environmental conditions (McNeill Alexander, 2002), which should be mirrored in ASAs to ensure they move in a natural and believable manner.

Social Implications of Gait Characteristics

The social implications of gait characteristics extend beyond mere physical movement; they encompass the communication of social signals and the coordination of group dynamics. A study by England and Petro, 1998 explored how variations in perceived group characteristics, such as those observed in gait, can influence social perceptions and interactions. For instance, a confident and steady gait might be perceived as a sign of leadership, while a hesitant or irregular gait could indicate uncertainty or nervousness. These subtle cues play a significant role in social contexts and must be considered when designing artificial social agents (ASAs) to interact seamlessly with human users. Understanding these nuances can help ensure that ASAs are perceived positively in social settings, enhancing their effectiveness and acceptance.

Miles et al., 2011 delved into the synchronization of walking patterns among individuals. Their research demonstrated that people tend to subconsciously synchronize their gait when walking together, which fosters social bonding and cooperation. This phenomenon, known as interpersonal entrainment, highlights the importance of incorporating synchronized movement patterns in ASAs to enhance their social presence and interaction capabilities.

Wiltermuth and Heath, 2009 further investigated the effects of synchronized movements on group cohesion and collective action. Their findings revealed that synchronized gait and coordinated movements can lead to increased cooperation and collective efficacy among group members. This insight is particularly valuable for the development of ASAs intended for collaborative tasks or social simulations, as it emphasizes the need for these agents to not only move realistically but also to align their movements with those of human counterparts to foster a sense of unity and cooperation.

The social implications of gait characteristics highlight how our movements communicate subtle cues that influence social interactions and group dynamics. These non-verbal signals, such as the confidence conveyed by a steady gait or the synchronization of walking patterns among group members, are not just surface-level phenomena. Instead, they are the visible manifestations of complex physiological, biomechanical, and cognitive processes that operate beneath the surface.

3.3.2 Human Locomotion: Physiological, Biomechanical, and Cognitive Processes

Understanding these processes will be a crucial step for replicating human-like movement in artificial social agents (ASAs). To create ASAs that move and interact as naturally as humans, it will be essential to delve deeper into the physiological mechanisms that power movement, the biomechanical principles that optimize it, and the cognitive processes that guide it. By exploring these foundational aspects of human locomotion, it can be better understood how to replicate not just the appearance of human movement, but the underlying dynamics that make it so fluid, adaptive, and socially meaningful.

Physiological Processes

Physiologically, human locomotion involves the coordination of multiple systems, including the musculoskeletal, cardiovascular, and nervous systems. The musculoskeletal system provides the structural framework and force generation needed for movement, while the cardiovascular system ensures the delivery of oxygen and nutrients to the muscles Winter, 2009. The nervous system, particularly the central nervous system, plays a crucial role in initiating and regulating movement.

Biomechanical Processes

Biomechanically, human movement is characterized by a series of mechanical events and forces. Lu and Chang, 2012 provided an in-depth analysis of these processes, highlighting how joint angles, muscle activations, and ground reaction forces contribute to overall locomotion. Their research underscores the importance of understanding the motion dynamics, energy expenditure, and efficiency of human movement. This field of study is essential for replicating human-like movement in autonomous systems and assistive technologies, ensuring that their motions appear natural and fluid.

Cognitive Processes

Cognitively, locomotion involves complex decision-making processes that are influenced by sensory input and prior experience. Cognitive processes are responsible for planning and adjusting movements in response to changing environmental conditions Rosenbaum, 2010. The integration of visual, auditory, and proprioceptive information allows humans to navigate their surroundings effectively, avoid obstacles, and maintain balance.

Lu and Chang, 2012 emphasized the importance of integrating these physiological, biomechanical, and cognitive aspects to develop a comprehensive model of human locomotion. Their research suggests that understanding the interplay between these components is crucial for designing ASAs that can perform human-like movements with high fidelity.

3.3.3 Neural Mechanisms: Brain Regions and Networks

The neural mechanisms underlying human locomotion are equally complex and involve a network of brain regions and pathways. Castermans and Duvinage, 2013 explored these neural substrates, providing insights into how the brain controls and coordinates movement.

Brain Regions Involved in Locomotion

Several brain regions are involved in the control of locomotion, including the motor cortex, basal ganglia, cerebellum, and brainstem. The motor cortex is responsible for planning and initiating voluntary movements, while the basal ganglia modulate movement patterns and ensure smooth execution Nudo, 2013. The cerebellum plays a crucial role in maintaining balance and coordinating fine motor skills, and the brainstem integrates sensory inputs and regulates automatic movements.

Neural Pathways and Networks

Neural pathways, such as the corticospinal tract, are crucial for transmitting movement commands from the brain to the spinal cord and peripheral muscles. Research by Castermans and Duvinage, 2013 highlighted the role of these pathways in executing precise and coordinated movements, particularly during locomotion. Their study demonstrated that the motor cortex is actively involved in controlling muscle activity during walking, emphasizing the importance of corticospinal connectivity for real-time adjustments and maintaining rhythmic movement patterns. Additionally, they discussed how neural networks involving feedback loops between the brain and sensory organs allow for continuous adjustments, ensuring smooth and coordinated locomotion.

Plasticity and Adaptation

Neural plasticity, the ability of the brain to adapt and reorganize itself, is a critical factor in learning and refining movement strategies. Studies have shown that repeated practice and experience can lead to changes in neural pathways, enhancing movement efficiency and coordination Adkins et al., 2006; Hebb, 1949.

While the physiological and neural mechanisms underlying human locomotion are foundational, this thesis primarily focuses on the biomechanical and cognitive aspects of movement. By understanding and replicating the detailed mechanical events and decision-making processes involved in human locomotion, we aim to develop artificial social agents (ASAs) that exhibit highly realistic and adaptive movements. These agents will be capable of performing micro-movements and situating themselves in ways that closely mirror human behaviour. This approach will enhance the overall realism and situational appropriateness of ASAs, thereby improving user interaction and immersion in virtual environments.

Integration into ASAs

Incorporating realistic gait patterns, stride length, and speed into ASAs requires a detailed understanding of the biomechanical and social aspects of human locomotion. By integrating findings from studies like those mentioned above conducted by Moussaïd et al., 2011, England and Petro, 1998, Miles et al., 2011, and Wiltermuth and Heath, 2009, developers can create ASAs that move in a way that is not only physically accurate but also socially meaningful. This dual focus on biomechanics and social signaling is crucial for enhancing the realism and effectiveness of ASAs in various applications, from virtual training environments to interactive social simulations.

Purposeful Micro-Movement Strategies

Purposeful micro-movement strategies are small, deliberate adjustments that humans make to their posture and movement direction in response to environmental changes. These micro-movements play a crucial role in maintaining smooth and effective locomotion, especially in dynamic and unpredictable environments. Research by Patla and Vickers, 2003 has shown that such minor adjustments, particularly those guided by visual cues, are integral to navigating through complex spaces. These strategies enable individuals to avoid obstacles, maintain balance, and adapt to sudden changes in terrain or movement demands, optimizing the efficiency of movement and enhancing overall coordination. By continuously fine-tuning their movements, individuals can achieve their navigation goals with greater precision, demonstrating the sophisticated interplay between sensory input, motor control, and cognitive processes.

Similarly, Pham et al., 2015 emphasized the importance of nuanced movements in realistic human navigation, particularly focusing on the recognition of human gait patterns. Their research highlighted that smooth transitions in movement direction, gradual orientation changes, and precise foot placement are essential for maintaining natural gait patterns. These findings underscore the need for autonomous systems and assistive robots to replicate these subtle yet critical aspects of human movement to enhance their realism and effectiveness. By accurately recognizing and mimicking these micro-movements, robots can achieve more natural and fluid interactions in dynamic environments, thereby improving their functionality and user acceptance.

3.3.4 Integration Micro-Movement Strategies into ASAs

Integrating these purposeful micro-movement strategies into ASAs involves understanding the biomechanics and cognitive processes underlying human locomotion. For instance, understanding how humans coordinate their limbs and adjust their centre of mass during movement can inform the development of algorithms that enable ASAs to mimic these behaviours.

Research by Hicheur et al. Hicheur et al., 2005 on human locomotion patterns provides valuable insights into how trajectory planning and execution are influenced by both biomechanical constraints and cognitive planning. By incorporating these insights, ASAs can be designed to perform smooth, natural movements that enhance their realism and user engagement.

Realistic Interaction and Navigation

To achieve realistic interaction and navigation, ASAs must be capable of performing a wide range of micro-movements that are contextually appropriate and responsive to environmental cues. Studies by Warren et al. Warren et al., 2001 have shown that human navigation involves continuous adjustments based on sensory feedback, such as visual and proprioceptive information. ASAs equipped with similar feedback mechanisms can dynamically adjust their movements, making them more adaptive and lifelike.

Moreover, research by Winter, 1995 highlights the importance of anticipatory adjustments in human locomotion. These adjustments, which occur before actual movement changes, are crucial for maintaining balance and ensuring smooth transitions during movement. By implementing such anticipatory control mechanisms in artificial social agents (ASAs), these systems can significantly improve their ability to navigate and interact in ways that feel natural and intuitive to human users, thereby enhancing the overall user experience.

3.3.5 Micro-Movements - The Small Movements We Make

Research into the small, often unconscious movements that humans make during locomotion is an emerging but crucial subset of the broader navigation field. These subtle behaviours, when accurately simulated or replicated, can significantly enhance the realism and immersion of artificial social agents (ASAs). Despite their importance, most research to date has predominantly focused on facial or arm movements due to their critical role in human perception and communication. Facial realism and animation have advanced considerably, bolstered by the development and widespread use of motion capture technology. For instance, Davison et al., 2018 have established a formalized dataset of micro-facial movements, setting a new standard in the field. However, a similar comprehensive dataset for human navigational movements does not yet exist, highlighting a significant gap in the literature.

This gap is particularly evident in the context of high-budget projects like the video game "Star Citizen." Despite substantial investments, non-player characters in these games often display substandard performance, characterized by simplistic movement patterns such as moving to a location, stopping abruptly, rotating, and then continuing along a path. This lack of nuanced movement detracts from the overall realism and immersion of the game, underscoring the need for further research and development in this area Ahrens et al., 2019.

Several researchers have recognized the importance of capturing realistic human movements. For example, Onishi et al., 2003 developed a new laboratory application to record human-robot movements and test new humanoid robots. Their work emphasizes the necessity of capturing accurate human locomotion data to create robots that move realistically like humans. This recognition of the need for realistic movements has spurred efforts to improve data capture systems used in spatial control systems, confirming the necessity for further research into agent navigation to enhance the "sense of realism."

Similarly, Kuffner et al., 2003 have contributed significantly to the field by working on digital humans, incorporating sophisticated models of human physiology and biomechanics. However, their focus has been primarily on arm motion and upper body movements, rather than the full range of locomotion behaviours that are critical for realistic navigation. This highlights a gap in the existing research that our work aims to address.

Kagami et al., 2003 explored the use of motion capture systems, force plates, and distributed force sensors to record data from both human participants and humanoid robots. They encountered difficulties comparing human data with robot movements due to differences in mechanical nature, such as link parameters, walking speed, step length, step cycle, and mechanisms. These challenges emphasize the need for formalizing naturalistic, realism-focused micro-movements, especially in virtual environments where such mechanical constraints do not exist.

Moreover, even comprehensive studies on virtual human realism, such as those by Gratch et al., 2002, often overlook the specifics of navigation and micro-movements. While these studies acknowledge the broad range of requirements for virtual humans, they do not delve into the detailed micro-movements necessary for achieving true realism in ASAs.

To bridge this gap, our research focuses on formalizing the micro-movements involved in human locomotion. By doing so, we aim to enhance the realism and immersion of ASAs in virtual environments. This formalization involves not only capturing and analyzing human movement data but also developing standardized descriptors for these movements. Such descriptors will enable more detailed and accurate simulations of human-like behaviours in ASAs, thereby improving their social presence and overall effectiveness in various applications, including training, education, and therapy.

The need for formalizing these micro-movements is underscored by the challenges faced in accurately capturing and replicating human locomotion data. For instance, simple location tracking can show where a person moved but does not provide information about the order of movements or the direction faced during movement. More comprehensive tracking, such as shoulder positions, provides better insights into orientation and movement, conveying behaviours like turning while moving and strafing. This richer dataset highlights the complexity of human locomotion and the necessity for detailed descriptions to implement micro-behaviours in ASAs.

Illustrative human acceleration data further underscores the complexity of locomotion. Human movement is not merely linear; it involves various movements and angular velocities, demonstrating that humans naturally employ micro-movements. Simulating these in ASAs can significantly enhance their realism. Annotated navigational data shows that specific parts of the movement can be attributed to defined micro-movements, which are further detailed in the subsequent section.

3.3.6 Modelling Micro-Navigational Strategies in Virtual Environments

Building on the understanding of micro-movements, the modelling of micro-navigational strategies within virtual environments becomes crucial. These strategies encompass the subtle yet significant aspects of movement, such as slight orientation adjustments and intricate path planning, which enhance the authenticity of agent navigation. Lin et al., 2022 developed a personalized and emotion-based virtual simulation model to study pedestrian-vehicle collision avoidance strategies. This model incorporates personality traits and emotional factors to generate realistic pedestrian-vehicle interactions in various traffic scenarios. The simulation adjusts parameters to reflect different behaviours, such as careful or aggressive driving, and pedestrian reactions based on their emotional state. The study effectively replicates macro-level pedestrian behaviour, demonstrating the importance of micro-level simulations in understanding and predicting navigation strategies and collision avoidance in virtual environments. Lavigne et al., 2015 analyzed navigation logs in a virtual learning environment, highlighting how students apply different learning strategies and follow individualized navigation paths. This study emphasized the diversity of navigational approaches users can take in a virtual environment and the importance of understanding these patterns for optimizing virtual experiences. Brilli et al., 2021 proposed a reactive collision avoidance strategy for a micro aerial vehicle (MAV) using only onboard RGB camera data. The strategy utilised virtual force fields and demonstrated successful obstacle avoidance, emphasizing the potential of such micro-navigational techniques for enhancing autonomous navigation in complex environments.

3.4 Human Movement Data

As can be seen from the previous sections; human navigational behaviour is inherently complex, characterized by a multitude of nuances that arise from the intricate nature of human movement. Analyzing tracked data of human movement in an environment, as depicted in figure 3.2, reveals that simple location tracking provides a basic representation of the path taken by an individual. However, it fails to convey critical details such as the sequence of movements or the direction the individual was facing during locomotion. This limitation becomes apparent when developing a control system for human-like artificial social agents (ASAs) with an emphasis on realism. While such data may be useful for basic pathfinding, it lacks the depth required for creating a control model that includes detailed micro-movements.

When shoulder positions are tracked, as shown in figure 3.3, the data offers a richer perspective. It provides insights into the direction the individual was facing, capturing nuances of turning while moving and strafing. This added layer of detail highlights the complexity of human locomotion, illustrating that humans do not merely move in straight lines but constantly adjust their orientation and positioning. This understanding is essential for the development of ASAs that can move in a manner that feels natural and realistic.

The complexity of human movement is further underscored by examining illustrative human acceleration data, such as that shown in figure 3.4. Human locomotion is not characterized by simple linear movement but involves a dynamic array of movements and angular velocities. This data demonstrates that human acceleration and orientation change frequently, reflecting a complex pattern of movement that simple (a) to (b) models fail to capture. The ability to simulate these micro-movements in ASAs is crucial for enhancing their realism.

Annotated human navigational data, as presented in figure 3.3, allows for specific parts of the movement to be attributed to defined micro-movements. This detailed annotation process enables a clearer understanding of the various components of human locomotion, facilitating the implementation of these behaviours in ASAs. By formalizing these micro-movements, researchers and developers can create more realistic and immersive virtual environments, where ASAs move in ways that closely mimic real human behaviour.

This highlights the necessity for advanced data collection and analysis methods that can capture the full range of human navigational behaviours. By integrating these detailed datasets into the design and development of ASAs, it becomes possible to move beyond simplistic models of movement and towards a more nuanced, accurate representation of human locomotion. This, in turn, can significantly enhance the realism and immersion of virtual environments, making them more effective for applications such as training, education, and therapy.

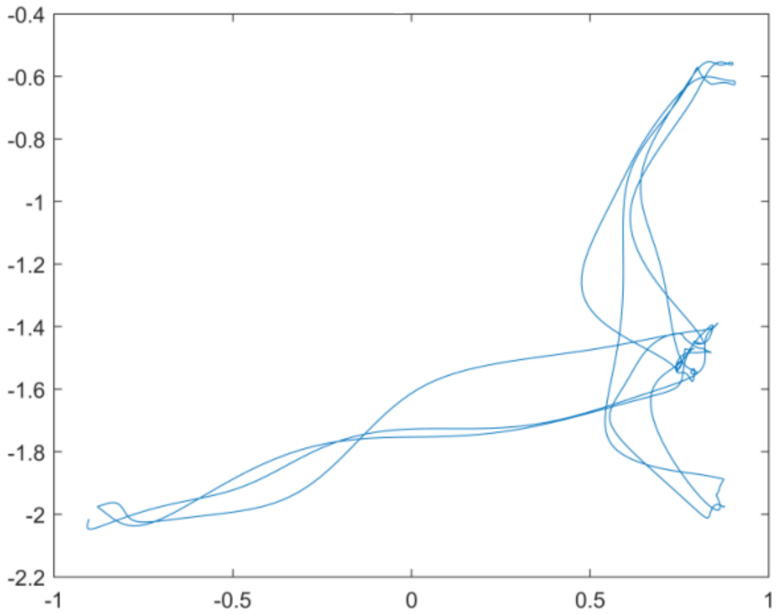


Figure 3.2: Centre of mass of a person moving through space between 4 different spatial locations

When examining the illustrative human acceleration data in figure 3.4, it becomes evident that human locomotion involves much more than simply moving to a location, stopping, turning, and then continuing along a predetermined path. The acceleration data showcases a complex array of movements and angular velocities, underscoring the multifaceted nature of human movement. Rather than exhibiting a straightforward linear acceleration and deceleration pattern, human locomotion is characterized by continuous adjustments and subtle changes in speed and direction. This intricacy highlights the need to capture and simulate these variations to enhance the realism of artificial social agents (ASAs).

The diverse range of movements illustrated by the acceleration data includes not only linear movements but also rotational and angular changes. These variations reflect the micro-movements that humans naturally employ—small adjustments in orientation, balance, and positioning that are critical for naturalistic movement. These micro-movements, often overlooked in conventional navigation research, play a significant role in creating a believable and immersive experience when interacting with ASAs. The absence of these movements can result in robotic, unnatural behaviour that disrupts user immersion and reduces the perceived realism of the agent.

By annotating human navigational data, as depicted in figure 3.3, it is possible to break down the complex sequence of movements into specific micro-movements. Each segment of the movement data can be associated with distinct behaviours, such as rotating in place or rotating while walking. This detailed annotation provides a framework for understanding and categorizing the various components of human locomotion, facilitating the development of more sophisticated models for ASA navigation.

The importance of formalizing these micro-movements lies in their potential to significantly enhance the realism of ASAs. By incorporating these detailed behaviours into the movement algorithms of ASAs, developers can create agents that move in a manner that is indistinguishable from real humans. This advancement is crucial for applications that rely on high levels of immersion and interaction fidelity, such as virtual reality training, educational simulations, and therapeutic environments.

Moreover, the ability to accurately simulate human micro-movements has broader implications for the field of artificial intelligence and robotics. It can lead to the development of more advanced, context-aware systems capable of adapting to their environment in a human-like manner. These systems could improve the efficacy of ASAs in various domains, from customer service bots to social companions for the elderly.

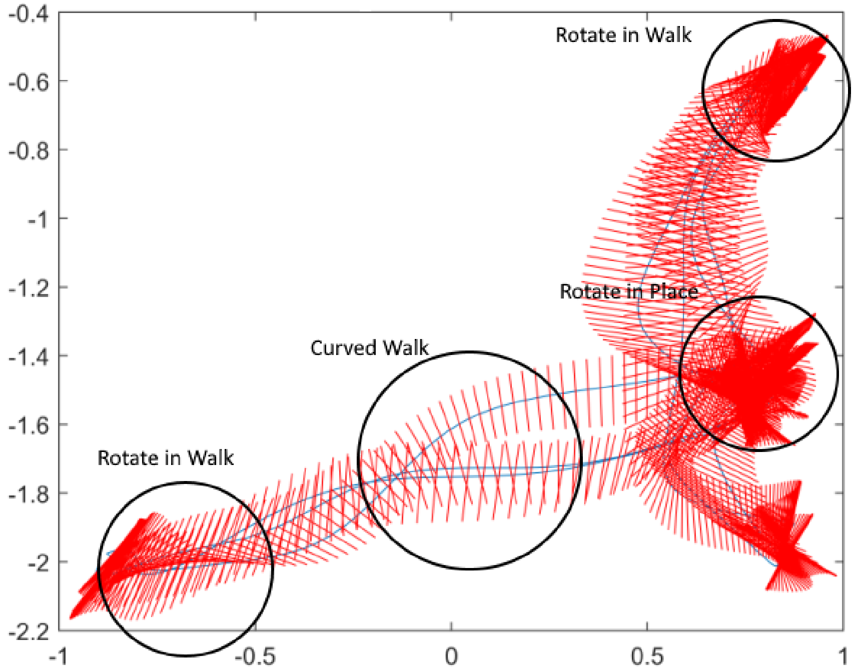
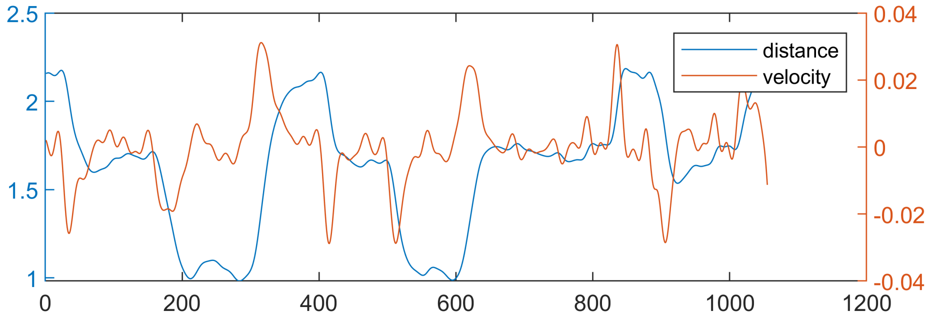


Figure 3.3: Orientation during locomotion between 4 different spatial locations, with specific micro-movement strategies from the proposed formalisation annotated

The challenge of accurately translating human movement into virtual environments has been a longstanding issue in the fields of artificial intelligence and robotics. While significant progress has been made, there remains no definitive solution to perfectly replicate the subtleties and complexities of human locomotion. This gap underscores the necessity for continued research and innovation. To address this challenge, we propose a comprehensive framework aimed at describing and formalizing human movement behaviours. This framework seeks to bridge the current gap by providing standardized methods for capturing, analyzing, and implementing micro-movements in artificial social agents (ASAs).



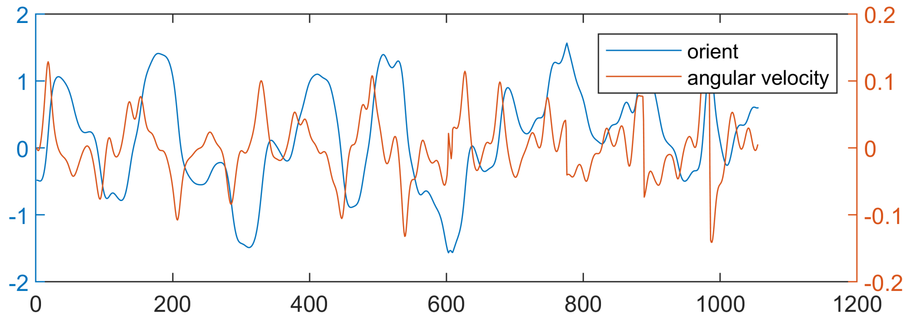


Figure 3.4: These Plots of Orientation, distance, and velocity show that the orientation of a human is constantly changing and complex in its nature, there is a lot of changes in acceleration, velocity, and orientation rather than a simple (a) to (b) with constant velocity

3.5 Formalising Micro-Movement Behaviour

To achieve realistic agent behaviour in artificial social agents (ASAs), it is essential to develop spatial models that accurately represent micro-movements. This paper proposes the formalization of a comprehensive testing framework, associating specific descriptors with these micro-movements. The diagrams representing the six fundamental behaviours are illustrated in figure 3.5. Assuming that there are a finite set of movement strategies employed by humans, we categorize human locomotion into six key behaviours, designed through observing human movement and using domain insight.

The six key behaviours are defined as follows:

1. **Linear Walk:** This behaviour involves an agent walking in a direct line congruent with their orientation direction. It represents the simplest form of movement where the agent's trajectory aligns with its facing direction.

2. **Backwards Walk:** In this behaviour, an agent steps backward without altering its

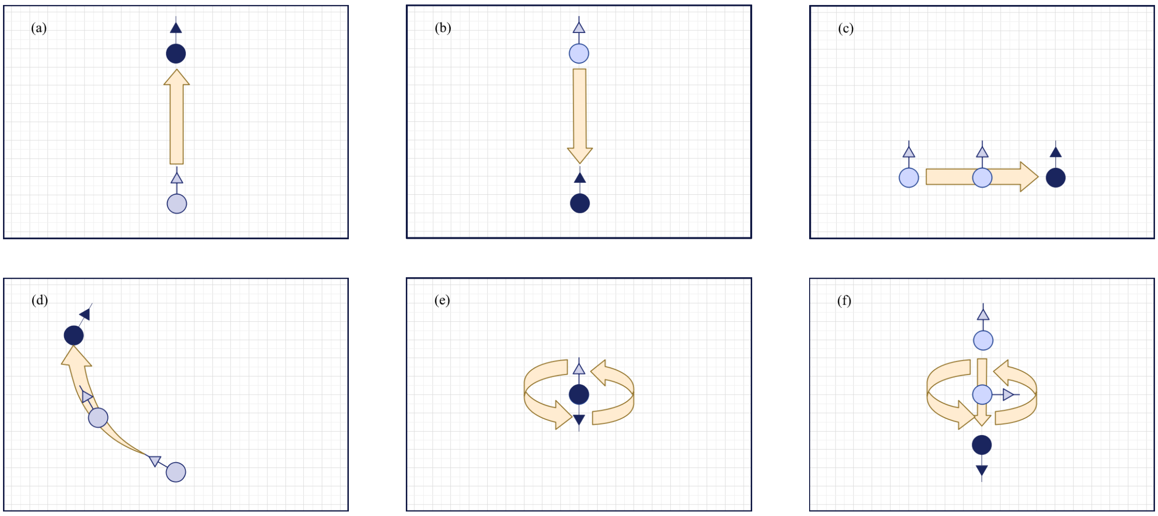


Figure 3.5: Proposed list of atomic micro-movements, complete in that we posit there is no further way to break these motions down in a meaningful way. The start location of the agent is the lighter blue circle, the darker blue circle denotes the end location of movement. The arrows on the circle show body orientation, the yellow arrows denote the displacement path irrespective of body orientation. (A) Linear walk in a direct line congruent with body orientation. (B) Linear back-step in a direct line. (C) Strafe (side-step) to the side while facing forward. (D) Curved walk with gradual body orientation along the curve. (E) Rotating in place with no translation of the centre of mass of the body, the original and final orientation differ by 180°. (F) Rotation during displacement along a path, the original and final orientation also differ by 180°.

orientation. This movement is essential for scenarios where agents need to retreat while maintaining their focus on a particular direction.

3. **Strafe Walk:** This involves an agent stepping to the side while still facing forward. Strafe walking is common in human locomotion when individuals need to shift laterally without turning their entire body.

4. **Curved Walk:** Here, an agent gradually orients itself while walking along a curved path. This behaviour reflects the natural tendency of humans to adjust their direction smoothly rather than making abrupt turns.

5. **Rotate in Place:** This behaviour involves an agent turning on the spot without any translational movement. It is crucial for scenarios where an agent needs to reorient itself without changing its location.

6. **Rotate in Walk:** This complex behaviour involves an agent rotating its orientation while moving along a specific path. An example is turning while back-stepping into a forward walk, reflecting the fluid nature of human movement.

By categorizing human locomotion into these six fundamental behaviours, we provide a structured approach to understanding and describing the nuances of human movement. Each movement from point (a) to point (b) can be viewed as a combination of these actions, enabling researchers to describe and explain recorded movement behaviours more accurately.

The formalization of these micro-movements is not merely an academic exercise; it has significant practical implications for the field of agent navigation. Recognizing and incorporating these micro-movements into ASA control systems are paramount for developing more realistic and immersive virtual agents. These detailed movements are essential for enhancing the realism and social presence of ASAs, thereby fostering a deeper sense of immersion in users.

To facilitate the development and testing of these behaviours, we propose the following descriptors for each micro-movement, which are essential for creating a standardized framework:

- **Movement Type:** Specifies the category of movement (e.g., linear walk, strafe walk).
- **Turning Onset:** Describes any changes in the agent's facing direction during the movement.
- **Trajectory:** Defines the path taken by the agent, including any curvature or deviations.
- **Movement Onset/Stop:** Measures when the acceleration or deceleration has reached a threshold.

These descriptors provide a common language and framework for researchers to study, simulate, and implement human-like micro-movements in ASAs. By formalizing these behaviours, we aim to bridge the gap between human and artificial movement, paving the way for more advanced and realistic virtual agents.

In conclusion, the formalization of micro-movement behaviour is a critical step toward achieving realistic and immersive agent behaviour. By recognizing and standardizing these fundamental behaviours, we can enhance the realism and functionality of ASAs, ultimately improving user experiences in virtual environments. The next chapters will delve deeper into the methodologies for capturing and analyzing these movements, providing a comprehensive overview of the current state of the field and highlighting the gaps that this research aims to address.

3.5.1 Clarifying the Origin of Atomic Movement Sets

The six atomic micro-movement sets proposed in this chapter (linear walk, back-step, strafe walk, curved walk, rotate in place, and rotate while walking) were not derived from a specific dataset or formal motion-capture study. Instead, they were developed through a conceptual analysis of human locomotion patterns, drawing on existing literature Onishi et al., 2003; Pedica and Vilhjálmsson, 2008 and our own informal observations of everyday movement. Consequently, there were no participants recruited or specialized equipment employed at this stage, and no ethical approval was necessary for this conceptual work. Rather than stemming from new empirical data, these movement categories serve as a theoretical framework—a concise classification of common locomotion strategies that humans appear to use in navigating their environment.

The diagrams illustrating these movements were created by staging or sketching prototypical examples of each category, rather than capturing live participants in a laboratory setting. As such, there are no data collection procedures or replication details specific to these figures. Instead, these foundational definitions will inform future data collection and analysis (see Chapter 4), where we record and quantify real human locomotion. By establishing these categories first, we aimed to provide a structured baseline that researchers can adapt or refine once motion-capture data becomes available. This two-stage approach ensures that our conceptual definitions of micro-movements can be systematically tested and iterated upon with empirical evidence, ultimately guiding the development of more lifelike ASAs.

3.6 Key Contributions

- **Standardized Descriptors for Movement Configurations:**
  - Proposed a set of standardized descriptors for movement configurations, enabling a common language and framework for describing, studying, and simulating human-like micro-movements in artificial social agents.

- **Identification of Key micro-movement strategies:**
  - Identified and categorized six fundamental micro-movement strategies crucial for realistic navigation: "Linear walk," "Backwards walk," "Strafe walk," "Curved walk," "Rotate in Place," and "Rotate in Walk."
- **Framework for Enhanced Immersion in Virtual Environments:**
  - Established the importance of micro-movements in enhancing the realism and immersion of artificial social agents, contributing to more engaging and effective virtual environments for applications such as training, education, and therapy.
- **Identification of Research Gaps and Future Directions:**
  - Highlighted the lack of research and formalization in the field of micro-movements for artificial social agents, providing a clear direction for future research to fill these gaps and advance the realism of virtual human interactions.

3.7 Future Directions

From the research discussed above, it is clear that there exists a gap within the field of navigational research centred around the simulation of micro-movements that humans unconsciously employ during path-planning and movement execution. These behaviours are crucial for fostering a higher sense of immersion within virtual worlds, a key element in creating impactful and efficient virtual simulations. This is especially significant in virtual reality training, where the resemblance to the real world enhances its effectiveness as a training tool. Formalizing these micro-movements enables researchers to analyze complex human locomotion data and categorize different micro-movement techniques. This, in turn, equips researchers with the tools to address the challenge of creating realistic human movement in virtual spaces, thus enhancing the realism of ASAs that inhabit these environments. While formalization is the initial step, future work must involve collecting data on these micro-movements from real-life human participants and developing autonomous systems that can realistically replicate and simulate these behaviours in artificial social agents. These systems might utilise reinforcement learning, finite control models, or other approaches. This focus is specifically for AI-controlled agents in virtual spaces, as user-controlled agents do not face this issue since the user naturally controls the navigation. The list of micro-movements presented here serves as a starting point for standardizing these concepts, facilitating ease of understanding and further research.

3.7.1 Chapter Summary

In this chapter, we focused on the conceptual framework and formalization of micro-movements, treating locomotion broadly—whether walking, jogging, or even skipping—as variations of forward movement. While we have identified six core movement types (linear walk, backstep, strafe, curved walk, rotate in place, and rotate while walking), we recognize that humans may also incorporate other forms of movement (e.g., hopping, jumping) that still align with these fundamental directions and orientations.

Moving Forward to Chapter 4: Having grounded our model in conceptual and biomechanical terms, the next chapter details the systematic analysis of our recorded human locomotion data. We illustrate how the dataset collected in chapter 4 is parsed and examined to confirm the presence (or absence) of these six movement categories in real participants' navigation. By bridging the conceptual framework here with empirical data in Chapter 4, we demonstrate how micro-movement strategies can be rigorously identified, quantified, and ultimately integrated into Artificial Social Agents to enhance their realism, thereby closing the loop between human movement analysis and the design of truly lifelike agent locomotion.

Chapter 4

How Do Humans Really Move? A Study on Human Movement Strategies

This study investigates the micro-navigational strategies that enhance the realism of artificial social agents, such as virtual characters in training simulations and non-player characters (NPCs) in video games. By focusing on subtle human movement adjustments, such as orientation changes and strategic planning, we aim to elevate these agents beyond simple A-to-B trajectories. To explore these micro-navigational strategies, we conducted an experiment in a controlled setting without obstacles to capture pure movement data. We collected video footage, orientation, speed, and angular velocity from 9 participants navigating through specific waypoints, with each participant completing the trial 6 times—3 times following the order of waypoints 1 to 11, and 3 times in reverse order from 11 to 1.

Our analysis involved calculating onset, turn, and stop indices for each participant, followed by correlation and classification analyses. Distance angle and threshold plots were used to visualize the relationships between distance and angle over time, aiding in the calculation of these indices. Correlation analysis revealed strong and moderate relationships between key indices, while mixed linear regression analysis identified significant trial and segment effects on the onset and stop indices. Principal Component Analysis (PCA) and hierarchical clustering identified distinct behavioural patterns among participants.

Our findings affirm the hypothesis that micro-navigational strategies exist and can be utilised to develop advanced locomotion models for artificial agents. These insights lay the groundwork for enhancing interaction quality in digital spaces. Future efforts will focus on investigating the realism of specific movement strategies.

4.1 Motivation

The authenticity of artificial social agents' navigation, such as virtual characters in training simulations or NPCs in video games, significantly influences the realism of human-agent interactions. While much research has focused on enabling these agents to navigate paths realistically or enhancing their visual fidelity, there is a noticeable gap in addressing the nuances of micro-navigational strategies. These are not merely small, unconscious movements but distinct strategies employed during navigation, such as strafing, turning while walking, or curved walking patterns. These strategies add depth to an agent's navigation, distinguishing it from simplistic point-to-point trajectories characterized by straight lines and turns in between.

The application of virtual environments for critical tasks such as training (Lele, 2013; Merchant et al., 2014) underscores the necessity of creating worlds that are not only captivating but also provide substantial, realistic experiences. Despite the potential impact, empirical movement data capturing these micro-navigational strategies is scarce, necessitating a study to evaluate these hypothesized behaviours in a controlled setting.

Human movement is inherently complex and influenced by numerous factors, including physiological, psychological, and environmental variables. Previous studies have extensively analysed macroscopic movement patterns, such as walking speeds, trajectories, and overall path planning Helbing and Molnár, 1995. However, the finer granularity of micro-navigational strategies—specific, deliberate adjustments made during movement—has not been as thoroughly explored. Understanding these nuanced behaviours is crucial for creating more realistic artificial agents that can navigate environments in a human-like manner.

The concept of micro-navigational strategies involves not just the physical act of moving from one point to another, but the myriad of small, adaptive behaviours that make human movement appear fluid and natural. These include minor shifts in body orientation, variations in stride length, and adjustments in speed and direction in response to perceived obstacles or social cues (Karamouzas et al., 2017; Newn et al., 2019). Such behaviours are often automatic for humans but require sophisticated programming and data to replicate in artificial agents.

To investigate these micro-navigational strategies, it is essential to collect detailed movement data in controlled environments. This involves using advanced motion capture technologies and other tracking systems to record the nuances of human movement. Systems like Vicon motion capture (Vicon, 2020) and inertial measurement units (IMUs) are commonly used to ensure high precision in capturing these subtleties. By analysing this data, researchers can identify patterns and develop models that mimic these subtle strategies in artificial agents. This approach not only enhances the realism of virtual characters but also improves the functionality of robots and other autonomous systems operating in dynamic, human-populated environments.

Moreover, the ability to classify and replicate these micro-movements has significant implications beyond entertainment and training simulations. In fields such as healthcare, more realistic movement models can enhance the effectiveness of rehabilitation protocols and assistive technologies. For example, research by Holden, 2005 demonstrated that incorporating realistic motion capture data into virtual rehabilitation environments significantly improves patient outcomes by providing more accurate and adaptive feedback during physical therapy sessions. This approach underscores the potential of realistic movement models in developing more effective therapeutic interventions and assistive devices. In robotics, understanding these strategies can lead to the creation of agents that can navigate complex, real-world environments more effectively and safely (Fong et al., 2003).

This chapter is structured as follows: Section 4.2 outlines the experimental design, which was specifically created to capture pure movement data by eliminating obstacles and focusing solely on navigational strategies. Participants navigated through specific waypoints, completing multiple trials in both forward and reverse orders. This approach enabled the collection of comprehensive data on their movements, including video footage, orientation, speed, and angular velocity.

In Section 4.3, the background to the analytical techniques employed are described, including the calculation of correlations between key indices like onset, turn, and stop points, and the use of mixed linear regression to understand the effects of different trials and segments. Principal Component Analysis (PCA) and hierarchical clustering were used to identify distinct behavioural patterns among participants, allowing for a detailed examination of the variability in micro-navigational strategies across different individuals and conditions.

Section 4.4 provides a comprehensive analysis of the experimental data, focusing on the interpretation of key findings related to participant behaviour. This section investigates the correlations between indices such as the Onset Index, Stop Index From End, and Angle Start Index, revealing significant relationships that enhance our understanding of micro-navigational strategies. Through detailed statistical techniques, including mixed linear regression, Principal Component Analysis (PCA), and hierarchical clustering, the analysis uncovers distinct behavioural patterns and clusters among participants. These findings offer critical insights into the complexity of human movement, emphasizing the implications for improving the realism and effectiveness of artificial agents by incorporating these nuanced strategies into their design, this section is followed by Section 4.5 which summarises the findings from the data analysis.

Section 4.6 discusses key contributions from the chapter and finally, Section 4.7 concludes by discussing the broader implications of the findings. The results support the hypothesis that micro-navigational strategies exist and can be leveraged to develop more advanced and realistic locomotion models for artificial agents. These insights lay the groundwork for enhancing the quality of interactions in digital spaces and underscore the importance of incorporating these micro-movements into the design of artificial agents to ensure a higher degree of realism and immersion in virtual environments.

Future work in this thesis, as originally mentioned in Chapter 1, will focus on realism perception scores for individual movement strategies. This will involve further refining and validating these models through more complex experimental setups and broader participant samples. These insights will be crucial in understanding and implementing these micro-navigational strategies, thereby enhancing the perceived realism of artificial agents.

4.2 Methodology

This research aims to enhance the perceived realism of artificial social agents—virtual humanoid characters encountered in digital training environments or as non-player characters (NPCs) in video games. While substantial efforts have been devoted to improving the aesthetic realism of these agents, the dimension of navigational realism remains underexplored. Our objective is to examine human movement patterns to validate the existence of proposed micro-navigational strategies, which we hypothesize contribute to the navigational realism inherent to human navigation. By replicating these strategies in artificial agents, we aim to elevate their realism and, consequently, the immersion of the environments they inhabit. The methodology of this study is structured as follows:

This study was approved by the Aston University Research Ethics Committee, and all participants provided written informed consent prior to participation. Nine healthy adults (6 male, 3 female; aged between 20 and 30) were recruited from the university community. Participants were instructed to navigate between five distinct locations within a room (see figure 4.1 and 4.2). These locations, marked by numbered signs, have been strategically selected to elicit specific movement behaviours hypothesized to be fundamental to human navigation. The choice of an open movement environment, free of obstacles, allows for the capture of pure navigational strategies without interference from external factors. This design decision is supported by studies suggesting that unobstructed environments facilitate the observation of natural movement patterns, which are essential for understanding the intrinsic behaviours of human navigation. For instance, O'Callaghan et al., 2011 demonstrated that unobstructed spaces allow for the capture of human motion patterns in a more natural and unimpeded manner. Their research focused on how robots could learn navigational maps by observing human movement in these environments. The clarity of movement observed in such settings helps isolate specific navigation strategies, providing deeper insights into the mechanisms underlying human locomotion and offering valuable data for developing more effective autonomous systems.

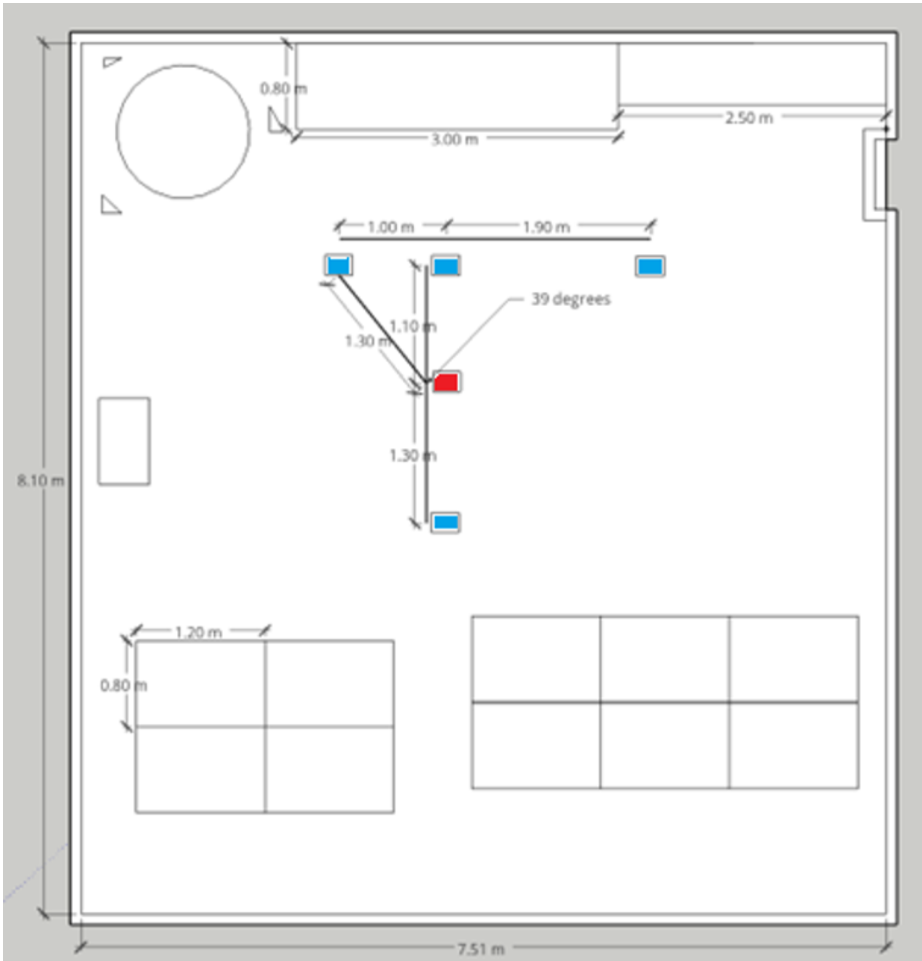


Figure 4.1: This map illustrates the layout of waypoints used in the study, where participants were instructed to navigate between specific locations. The blue squares represent the waypoints, the red square was used for placement of the waypoints and is not a waypoint itself.

Participants were equipped with a sequential stack of 11 cards, numbered 1 through 11, dictating the order of waypoints to be visited. This method ensures a controlled and repeatable task, enabling the collection of consistent and comparable data across multiple trials and participants. The sequential card system is an effective way to guide participants through a predefined path, thereby standardizing the movement patterns for analysis. This approach is aligned with the experimental designs used in studies of human spatial navigation, where participants follow specific instructions to ensure uniformity in data collection. This method helps in reducing variability caused by different navigation choices, allowing for a focus on the micro-navigational strategies being employed.

At each waypoint, participants deposited the corresponding card, proceeding to the next target as indicated by the subsequent card in the stack. Waypoints are indicated by tripods, providing a non-hazardous surface for card placement. The use of tripods ensures that waypoints are easily identifiable and accessible, minimizing the risk of accidents and ensuring the safety of participants. This setup also allows for clear demarcation of navigation targets, which is crucial for accurate tracking and data collection. Ensuring the safety and clarity of waypoints is vital for maintaining the naturalness of participants' movements.

Each participant will complete a total of six trials, with three trials progressing through waypoints 1 to 11 and another three trials moving in reverse order from waypoint 11 back to 1. This bidirectional navigation ensures that any order effects or biases are accounted for, providing a more robust dataset. Repeating the trials in reverse order helps in identifying consistent patterns and variations in movement strategies, offering insights into the adaptability and flexibility of human navigation behaviours. This methodological approach helps in understanding how directionality influences navigational strategies.

Figure 4.2: This still from the experiment captures a participant in the process of moving between designated waypoints. The participant's movements were recorded to analyse the micro-movement strategies employed during navigation, such as orientation adjustments and path selection.

Throughout this navigation task, participants' movements will be captured via overhead video recording and a proprietary system developed by Daniel Rodriguez-Criado and Luis J. Manso at the university, which records skeletal data without the need for wearable sensors. The choice of overhead video recording combined with a non-intrusive skeletal tracking system is crucial for maintaining natural movement patterns. Wearable sensors, while accurate, can sometimes restrict movement or cause participants to alter their behaviours. The proprietary system used here provides high precision in capturing the x/y coordinate positions of various body points, allowing for detailed analysis of movement strategies (Rodriguez-Criado et al., 2024). This technology ensures high-quality data collection without interfering with the participants' natural navigation behaviours.

This dual data collection approach yields two primary data forms: video footage and skeletal movement data. Video footage provides a comprehensive visual record of each participant's navigation path, which can be analysed to identify overall movement patterns, behaviours, and any deviations from expected routes. Skeletal movement data, consisting of x/y coordinate positions of various body points, allows for a more granular analysis of specific micro-navigational strategies, such as minor shifts in body orientation, variations in stride length, and adjustments in speed and direction. The combination of these data forms allows for a multifaceted analysis, integrating visual and quantitative insights.

The use of video footage complements the skeletal data by providing context to the captured movements, enabling a more holistic understanding of navigation behaviours. This approach is consistent with methodologies in biomechanics and movement science, where multi-modal data collection is employed to gain a comprehensive view of human motion Winter, 2009. By combining qualitative and quantitative data, researchers can develop more accurate and detailed models of human navigation strategies.

Additionally, the proprietary skeletal tracking system developed by Rodriguez-Criado and Manso, 2020 offers several advantages over traditional methods. By eliminating the need for wearable sensors, this system minimizes any potential discomfort or restriction of movement for participants, thereby preserving the naturalness of their navigational behaviours. The system's ability to accurately track and record skeletal data in real-time provides high-resolution insights into the micro-navigational strategies employed by participants.

The rationale behind selecting a controlled environment, using a card system for waypoint navigation, and employing advanced tracking technologies is to ensure that the collected data is both accurate and representative of natural human navigation. By using an open, obstacle-free space we remove environmental confounds—participants aren't forced into unnatural detours or hesitant pauses caused by furniture, doors, or walls. The sequential card system imposes a simple, transparent goal ("go here next") that mirrors real-world wayfinding tasks (e.g. following signs) without introducing extra cognitive overhead or trial-and-error exploration. Finally, the non-wearable, skeletal tracking captures each participant's natural posture shifts and gait dynamics without the encumbrance of sensors or markers that might subtly alter how they move. Together, these design choices isolate pure navigational intent and motor behaviour, yielding data that reflects how people "just walk and turn" in everyday settings. This methodological rigor is necessary to validate the proposed micro-navigational strategies and to develop realistic models for artificial agents. By maintaining a controlled yet naturalistic experimental setup, the study aims to produce findings that are both scientifically valid and applicable to real-world scenarios.

4.3 Data Collection and Analysis of Human Movement Background

Having explored the intricate aspects of human locomotion, including physiological, biomechanical, and cognitive processes, as well as the ethical, social, and cultural considerations surrounding artificial social agents (ASAs), it is clear that replicating human-like movement in ASAs requires not only theoretical understanding but also precise and robust data. The previous sections have underscored the importance of micro-movements in achieving realistic and adaptive ASA behaviour, which are influenced by a complex interplay of social cues and cultural norms. To bridge the gap between theoretical insights and practical implementation, this section will delve into the methodologies for collecting detailed and accurate data on human micro-movement strategies. Collecting accurate and detailed data on human micro-movement strategies is a complex task that requires advanced technologies. Several methods are commonly used to capture these subtle movements, each with its advantages and limitations.

Motion Capture Motion capture (mocap) technology is one of the most precise methods for recording human movement. It involves placing markers on a person's body and tracking their positions in three-dimensional space using multiple cameras. This technology captures detailed information about joint angles, limb positions, and body orientation. Lamb et al. (2015) utilised motion capture to study the intricacies of human locomotion, providing high-resolution data that can be used to model micro-movements accurately.

Tracking Systems Various tracking systems are employed to capture movement data, including video footage, skeletal movement data, and inertial measurement units (IMUs). Each system offers unique benefits:

- **Video Footage:** High-definition cameras record the subject's movement, which can be analysed using computer vision algorithms to extract movement patterns.

- **Skeletal Movement Data:** Systems like Microsoft's Kinect provide real-time tracking of skeletal positions in three-dimensional space, enabling the analysis of posture and limb movement.
- **Motion Capture Technologies:** As mentioned earlier, mocap systems provide precise and comprehensive data on body movements.
- **Inertial Measurement Units (IMUs):** These sensors measure acceleration and angular velocity, offering valuable data on dynamic movements and orientation changes.

4.3.1 Specific Tracking Systems

Various proprietary and commercially available tracking systems have been developed to capture human movement data:

Proprietary Skeletal Tracking System by Rodriguez-Criado and Manso Rodriguez-Criado and Manso developed a proprietary multi-person 3D pose estimation system that captures intricate skeletal movement data by leveraging cutting-edge self-supervised learning techniques. Unlike traditional approaches that require expensive, annotated datasets and specialized hardware, this system combines the precision of motion capture with the convenience of standard RGB cameras, making it a versatile solution for both laboratory and field applications. The system's core innovation lies in its ability to estimate 3D poses without the need for ground truth data, a significant advancement that reduces costs and enhances scalability.

The system operates through a three-staged pipeline. The first stage involves 2D skeleton detection, which can be integrated with any third-party detector. The second stage employs a Graph Neural Network (GNN) to establish cross-view correspondences of detected persons, effectively handling scenarios with multiple individuals. The final stage utilises a Multi-Layer Perceptron (MLP) to transform 2D information into 3D pose estimations. This approach not only ensures high accuracy but also allows the system to function robustly in various environments, including those with occlusions or partial views.

This system has been rigorously evaluated, demonstrating faster performance compared to other state-of-the-art algorithms while maintaining comparable accuracy. Its ability to provide complete 3D pose estimations, even in challenging conditions, makes it a powerful tool for applications ranging from video surveillance and assisted living to autonomous vehicles, human-robot interaction and human-ASA interaction (Rodriguez-Criado et al., 2024).

Vicon Motion Capture The Vicon motion capture system is renowned for its precision and is widely used in research and industry. It employs multiple high-speed cameras to track reflective markers placed on the body, providing comprehensive data on joint angles, limb trajectories, and body orientation.

Overhead Video Recording Systems Overhead video recording systems use strategically placed cameras to capture movement from above. This method is particularly useful for analysing spatial navigation and crowd behaviour, as it provides a top-down view of the subject's movement patterns.

4.3.2 Data Analysis Methods

Once data is collected, various analytical techniques are employed to interpret and utilise the information effectively:

- **Differential Analysis:** This method compares the differences in movement patterns under various conditions to identify significant changes or trends.
- **Onset and Turn Indices Calculation:** These indices measure the timing and degree of directional changes, providing insights into movement strategies and coordination.
- **Correlation Analysis:** By examining the relationships between different movement variables, researchers can identify key factors influencing locomotion.
- **Mixed Linear Regression Analysis:** This statistical method models the relationship between multiple independent variables and a dependent variable, allowing for the prediction of movement outcomes.
- **Principal Component Analysis (PCA):** PCA reduces the dimensionality of movement data, highlighting the most significant patterns and variations.
- **Hierarchical Clustering:** This technique groups similar movement patterns, helping to identify common strategies and behaviours.

4.3.3 Comparative Analysis of Tracking Technologies

Comparative studies have evaluated the effectiveness of different tracking technologies in virtual reality (VR) environments. For instance, Llorens et al., 2015 conducted a comparative analysis of various motion tracking systems, including optical, electromagnetic, and skeleton tracking, specifically for VR-based rehabilitation. Their study highlighted the strengths and weaknesses of these systems, such as accuracy and jitter, in capturing detailed movement data. The optical tracking system demonstrated the best accuracy, while the electromagnetic system provided the most consistent jitter performance. However, preferences varied among different user groups, with healthy participants and professionals favoring skeleton tracking for its ease of use, while stroke survivors preferred the optical system for its precision. This study underscores the importance of considering both objective performance metrics and subjective user experiences when selecting tracking technologies for VR applications. Suo et al., 2024 provided a comprehensive review of the latest advancements in tracking technology for sports sciences, discussing their implications for research.

4.4 Data Analysis

4.4.1 Objectives

The analysis presented in this thesis aims to comprehensively understand participant behaviour by examining various indices and their interrelationships. Specifically, this study investigates the correlations between the Onset Index, Stop Index From End, and Angle Start Index (described in next section). By averaging these indices across all trials and segments for each participant, we aim to capture the general tendency of their actions, providing a more stable and representative measure of their behaviour.

The primary goals of this analysis are to: Identify significant correlations to determine the relationships between the key indices to understand how changes in one metric influence the others. Perform mixed linear regression to elucidate the factors influencing the onset and stop indices across different trials, segments, and participants. Conduct PCA and hierarchical clustering to analyse participant behaviours by considering multiple variables simultaneously and identify distinct clusters based on their behavioural patterns.

4.4.2 Differential Analysis Summary

This comprehensive analysis highlights the complex interplay between various behavioural indices in participants. By employing statistical techniques, we were able to uncover significant relationships and patterns within the data. The correlation analysis revealed strong and moderate relationships between the key indices.

Onset, Stop and Turn Indices: Calculation and Observation

Figures 4.3, 4.4 and 4.5 illustrate how we extract three key indices—Onset, Stop, and Angle-Start (Turn)—from each participant's distance and heading-angle traces. By overlaying our detection thresholds on these time series, we can clearly see where each phase of movement begins and ends. All thresholds were chosen by visually inspecting multiple raw traces until we found values that consistently matched our intuitive identification of "start walking," "stop accelerating," and "begin turning" events.

Onset Index We define the Onset Index as the moment when a participant first begins to move away from the start position. To detect this, we slide a fixed-length window (about 1.5 seconds of data at our 20Hz sampling rate) over the distance-from-start signal. The first time the increase in distance within that window exceeds 0.30m, we record the frame number as the Onset Index.

Stop Index After movement has begun, we similarly slide the same window along the trace to find when forward acceleration effectively ends. Specifically, we look for the first window in which the increase in distance falls to 0.15m or less. We then convert that frame into the number of frames remaining until the end of the segment, yielding our Stop Index.

Angle-Start Index (Turn) To capture when turning begins, we compute the instantaneous angular velocity from the heading-angle trace and identify the first frame at which this exceeds 4°/s. That frame marks the Angle-Start Index, indicating the onset of a deliberate turn.

By plotting these indices against the raw distance and angle traces (see Figures 4.3, 4.4, and 4.5), we ensure our algorithmic detections align with what an observer would intuitively recognize as the start of walking, the end of forward acceleration, and the start of turning.

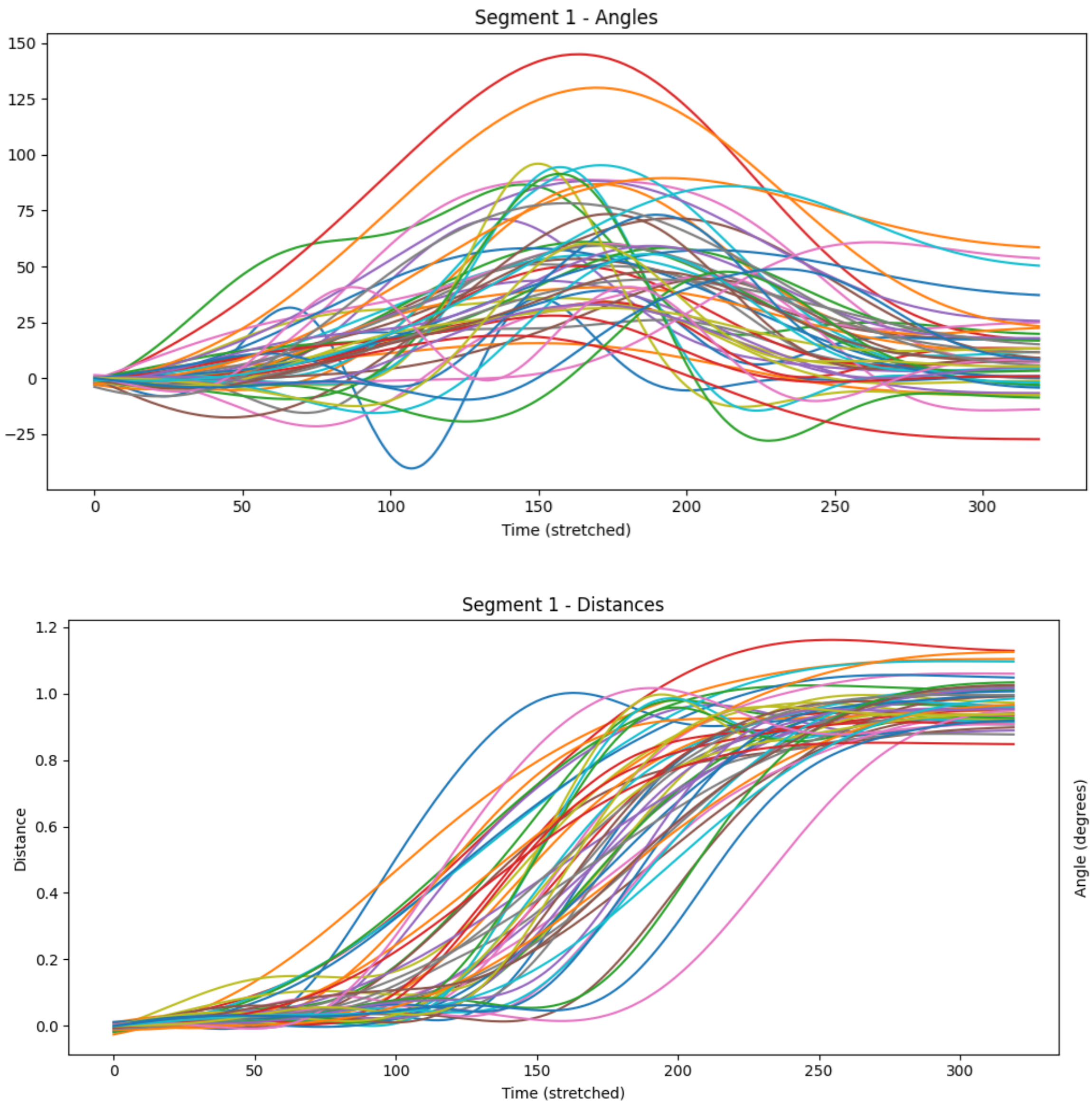


Figure 4.3: Absolute heading angle (top) and distance (bottom) over time for Segment 1.

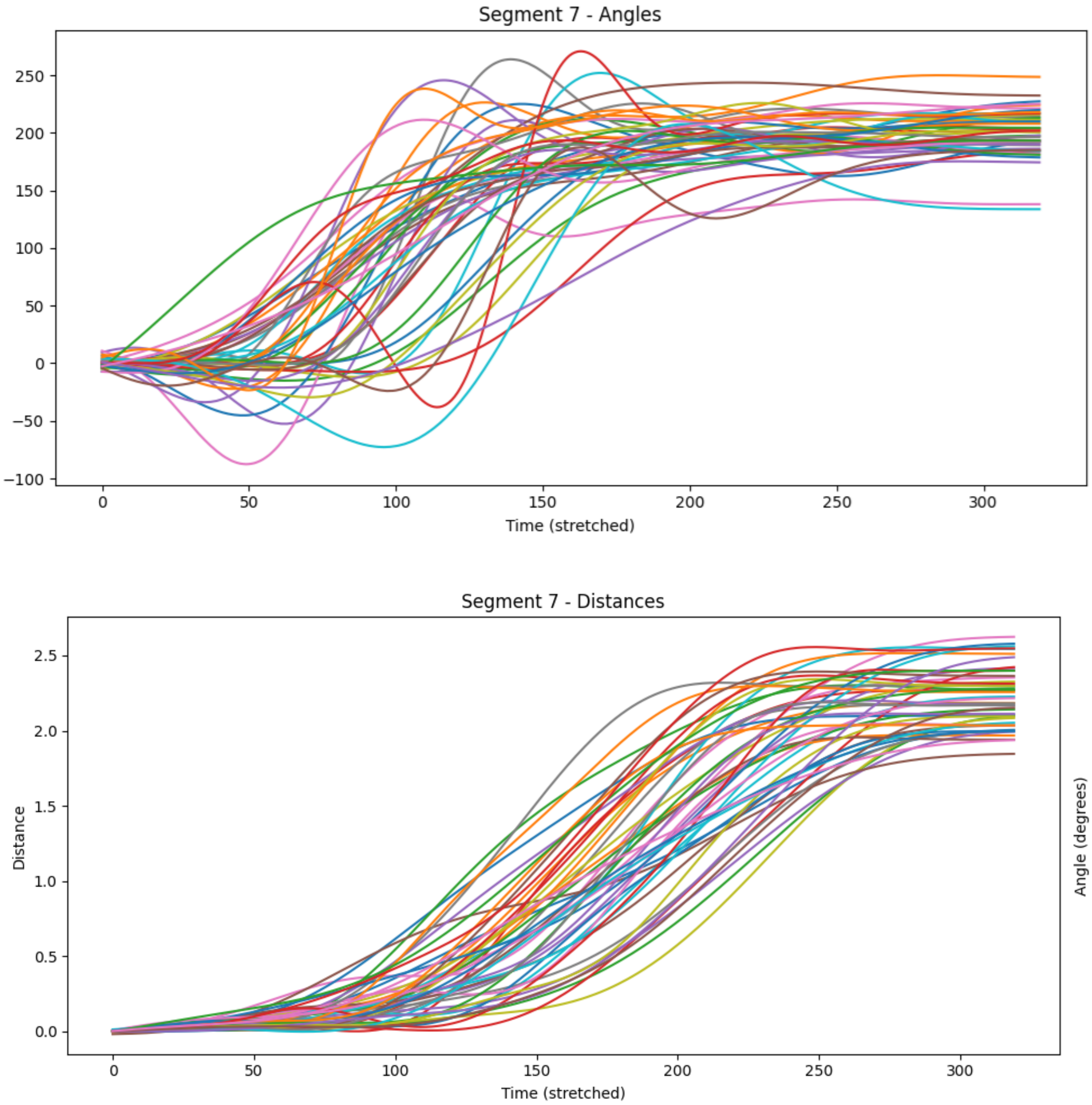
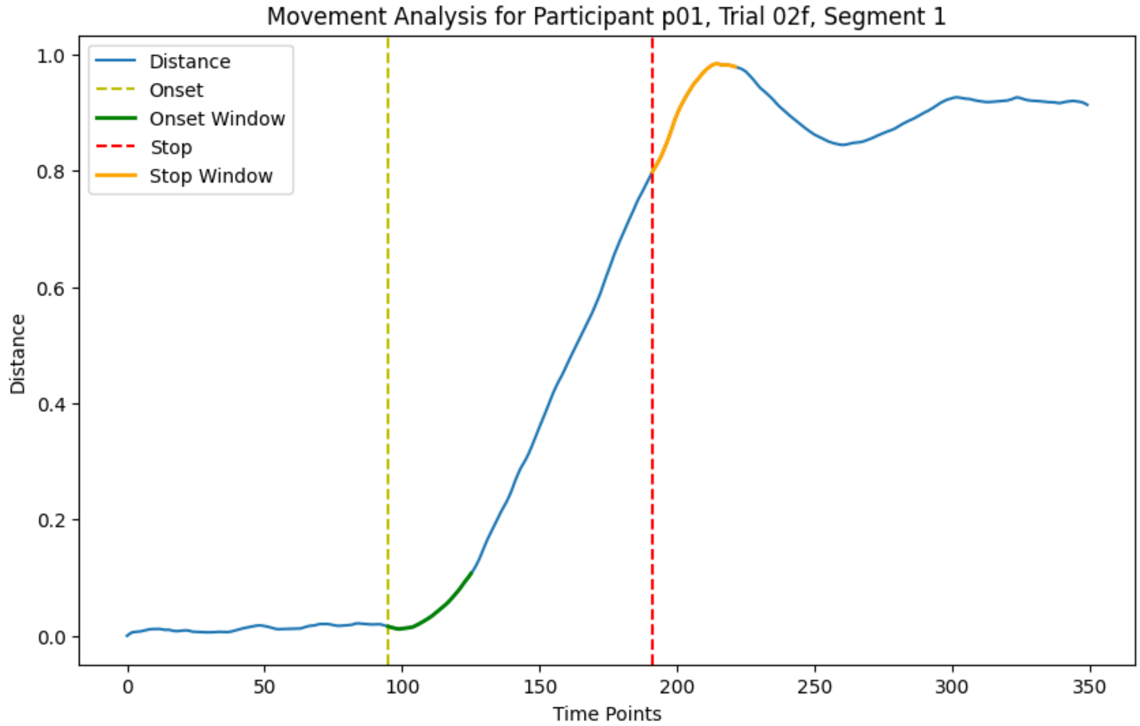


Figure 4.4: Absolute heading angle (top) and distance (bottom) over time for Segment 7.



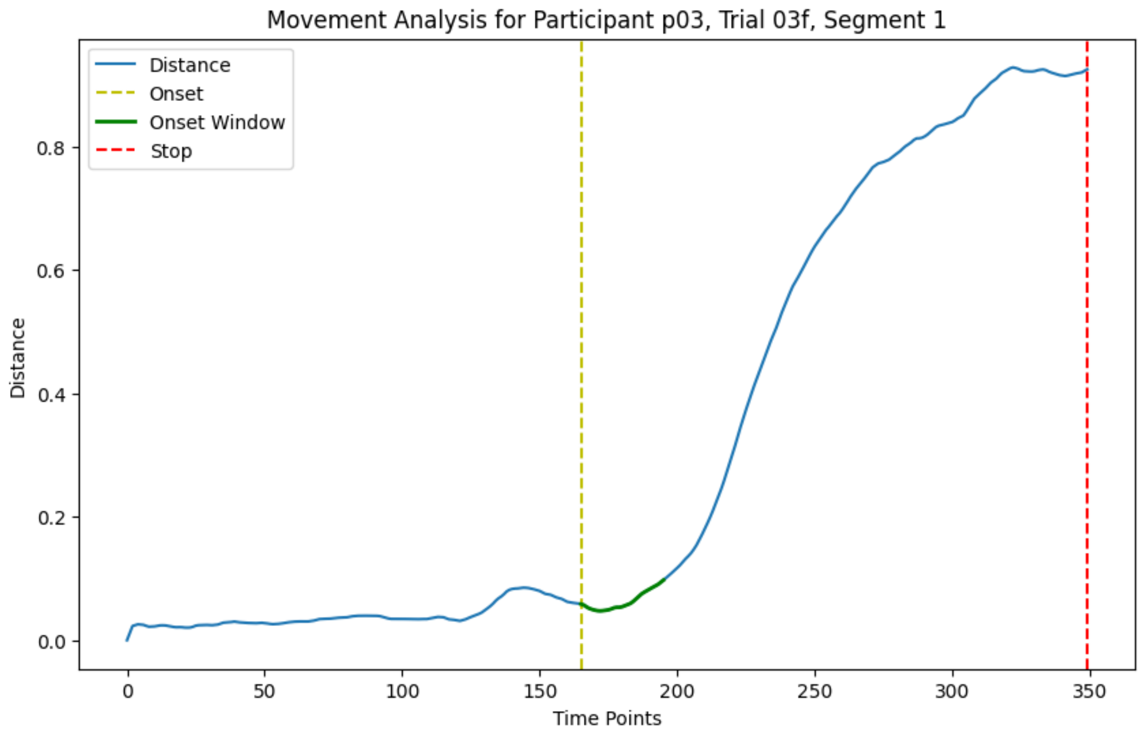


Figure 4.5: Views of distance-vs. time for two participants, showing the 0.30m onset threshold (green window) and the 0.15m stop threshold (orange window) over 30-frame intervals.

Correlation Analysis

The correlations were calculated using the Pearson Product Moment Correlation Coefficient and the mean values of the onset and stop indices for each participant, rather than individual data points. This approach smooths out the variations within individual trials, providing a more stable and representative measure of each participant's typical behaviour. By averaging the onset and stop indices across all trials and segments for each participant, we capture the general tendency of their actions, leading to more reliable and interpretable correlations (figures 4.6, 4.7, and 4.8).

A strong positive correlation ($r = 0.729$, $p = 0.026$) was found between the Onset Index and Stop Index From End, suggesting that as the Onset Index increases, the Stop Index From End also increases. Additionally, a strong positive correlation ($r = 0.758$, $p = 0.018$) was observed between the Onset Index and Angle Start Index, indicating that an increase in the Onset Index is associated with an increase in the Angle Start Index. Similarly, the Stop Index From End and Angle Start Index were strongly correlated ($r = 0.763$, $p = 0.017$), suggesting that as the Stop Index From End increases, the Angle Start Index also increases.

Specific correlations of interest include a significant correlation between 'Early Starters' and 'Early Turners' ($r = 0.756$, $p = 0.018$), indicating that participants who generally start their actions earlier also tend to complete their actions earlier, relative to the end of the segment. A moderate correlation was observed between 'Late Starters' and 'Late Turners' ($r = 0.598$, $p = 0.089$), suggesting a similar but less pronounced relationship for those who start actions later.

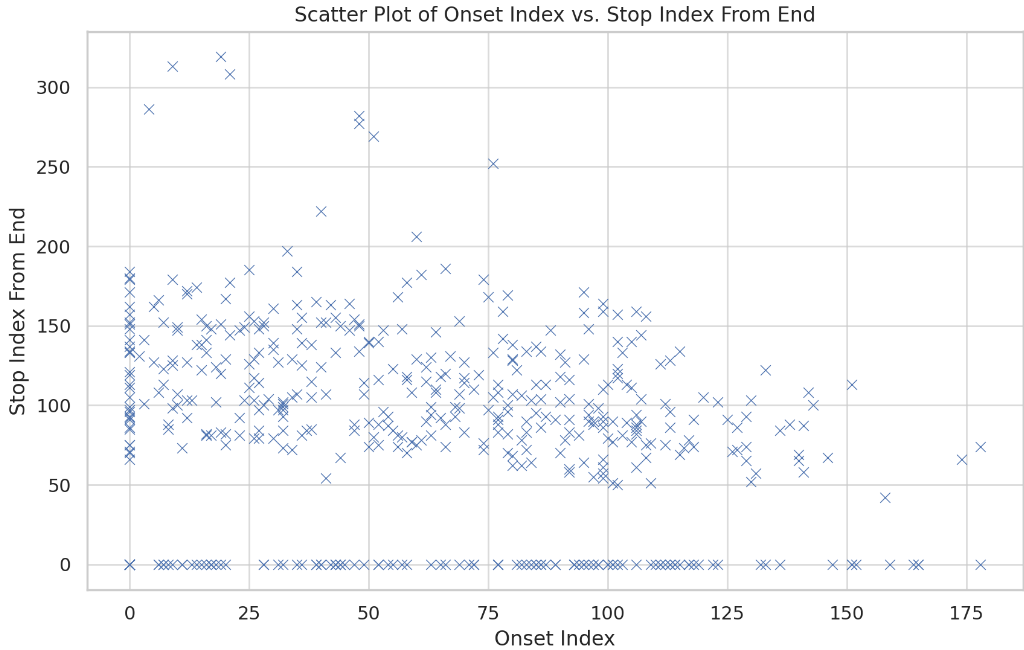


Figure 4.6: Onset Index vs. Angle Start Index: Strong positive correlation ($r = 0.758$, $p = 0.018$).

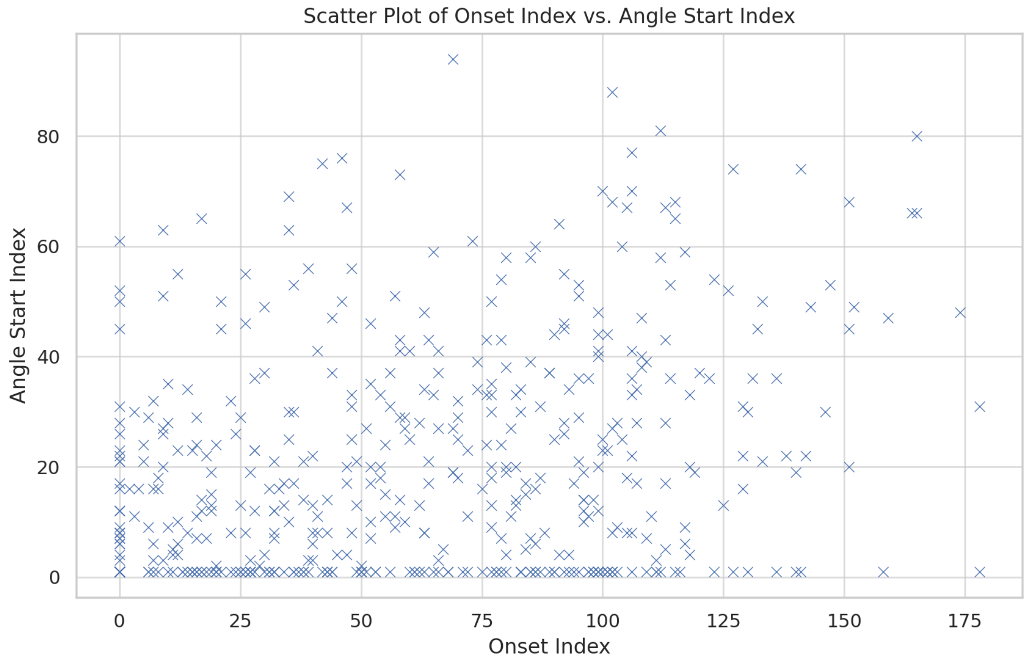


Figure 4.7: Onset Index vs. Stop Index From End: Strong positive correlation ($r = 0.729$, $p = 0.026$).

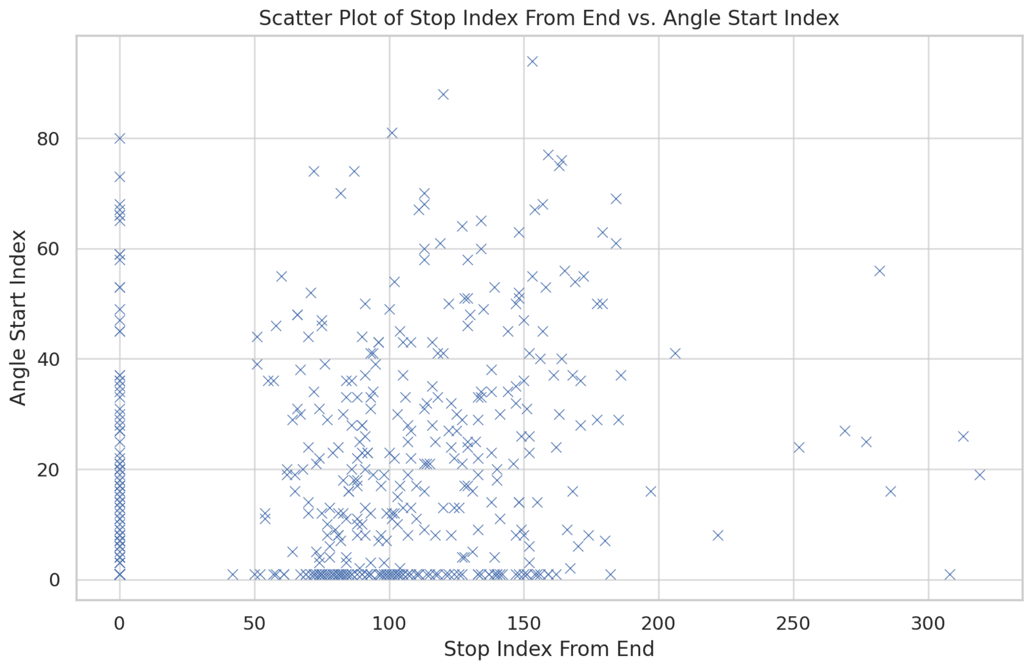


Figure 4.8: Stop Index From End vs. Angle Start Index: Strong positive correlation ($r = 0.763$, $p = 0.017$).

Classification by Segment and Participant

These tables (Tables 4.1 and 4.2) summarize the distribution of classifications across different segments and participants, including both the counts and their corresponding percentages. These classifications were derived using threshold algorithms applied to the start and turn indices. "Turn Then Move" is the predominant classification across all segments and participants. Notably, segments 3 and 8 show higher instances of "Turn during Move," while segments 8 and 10 have higher counts of "Strafe then Move." Among participants, Participant 8 has the highest count of "Strafe then Move," and Participant 9 has the most "Turn during Move" classifications.

Segment	Strafe then Move	Turn Then Move	Turn during Move
1	4 (7.8%)	41 (80.4%)	6 (11.8%)
2	4 (8.0%)	42 (84.0%)	4 (8.0%)
3	2 (3.8%)	37 (71.2%)	13 (25.0%)
4	4 (7.7%)	42 (80.8%)	6 (11.5%)
5	6 (12.0%)	37 (74.0%)	7 (14.0%)
6	7 (13.7%)	39 (76.5%)	5 (9.8%)
7	3 (6.4%)	34 (72.3%)	10 (21.3%)
8	8 (16.0%)	29 (58.0%)	13 (26.0%)
9	4 (7.8%)	39 (76.5%)	8 (15.7%)
10	7 (13.7%)	33 (64.7%)	11 (21.6%)

Table 4.1: Classification counts and percentages by segment.

Participant	Strafe then Move	Turn Then Move	Turn during Move
1	1 (1.7%)	53 (91.4%)	4 (6.9%)
2	3 (6.2%)	38 (79.2%)	7 (14.6%)
3	7 (11.7%)	53 (88.3%)	0 (0.0%)
4	8 (14.5%)	38 (69.1%)	9 (16.4%)
5	6 (10.9%)	43 (78.2%)	6 (10.9%)
6	4 (7.1%)	43 (76.8%)	9 (16.1%)
7	8 (14.0%)	34 (59.6%)	15 (26.3%)
8	11 (19.0%)	32 (55.2%)	15 (25.9%)
9	1 (1.7%)	39 (67.2%)	18 (31.0%)

Table 4.2: Classification counts and percentages by participant.

The high frequency of the "Turn Then Walk" classification observed in the dataset may be attributable to the structured nature of the experimental task. This structured environment contrasts with natural, spontaneous movement patterns observed in everyday life, where individuals might exhibit more varied and fluid movement strategies. Furthermore, the artificial context of a walking task, designed to elicit specific behaviours, could have constrained participants' movement strategies, leading to a higher incidence of "Turn Then Walk" actions.

4.4.3 Inferential Analysis

Mixed Linear Regression Analysis

A mixed linear regression analysis was conducted to elucidate the factors influencing the onset and stop indices across different trials, segments, and participants. The model had residual degrees of freedom of 123, indicating that the analysis is based on a substantial number of observations. The model for the onset index revealed a significant intercept coefficient of 84.003 ($p < 0.001$). Specific trials, such as T.04b (sd = -20.582, $p < 0.001$), T.05b (sd = -27.670, $p < 0.001$), and T.06b (sd = -27.660, $p < 0.001$), significantly lowered the onset index. Segment effects were also notable, with significant negative impacts observed in segments 2 (sd = -14.790, $p = 0.039$), 3 (sd = -23.131, $p = 0.001$), 6 (sd = -18.888, $p = 0.009$), 8 (sd = -35.938, $p < 0.001$), and 10 (sd = -32.537, $p < 0.001$). Furthermore, the angle start index positively correlated with the onset index (sd = 0.340, $p < 0.001$), indicating that an increase in the angle start index results in a higher onset index (Table 4.3).

Predictor	Coefficient	Std. Error	t-value	P-value	95% Confidence Interval
Intercept	84.003	5.123	16.40	<0.001	[73.234, 94.772]
T.04b	-20.582	3.876	-5.31	<0.001	[-29.942, -11.222]
T.05b	-27.670	3.454	-8.01	<0.001	[-34.779, -20.561]
T.06b	-27.660	3.875	-7.14	<0.001	[-36.019, -19.301]
Segment 2	-14.790	6.123	-2.42	0.039	[-27.823, -1.757]
Segment 3	-23.131	5.232	-4.42	0.001	[-33.667, -12.595]
Segment 6	-18.888	5.879	-3.21	0.009	[-31.723, -6.053]
Segment 8	-35.938	7.823	-4.59	<0.001	[-52.872, -19.004]
Segment 10	-32.537	8.879	-3.67	<0.001	[-50.723, -14.351]
Angle Start Index	0.340	0.072	4.72	<0.001	[0.196, 0.484]

Table 4.3: Regression Table for Onset index

For the stop index, the regression model identified a significant intercept coefficient of 74.950 ($p < 0.001$). Trials T.04b (sd = 17.676, p = 0.036), T.05b (sd = 31.829, $p < 0.001$), and T.06b (sd = 31.559, $p < 0.001$) exhibited positive effects on the stop index. Segment effects varied, with segment 4 (sd = 27.823, p = 0.011) showing a significant positive impact, while segments 7 (sd = -20.842, p = 0.065) and 9 (sd = -30.101, p = 0.007) had significant negative impacts. The angle start index did not significantly affect the stop index (sd = 0.198, p = 0.155) (Table 4.4).

Predictor	Coefficient	Std. Error	t-value	P-value	95% Confidence Interval
Intercept	74.950	4.123	18.18	<0.001	[64.832, 85.068]
T.04b	17.676	5.567	3.17	0.036	[3.567, 31.785]
T.05b	31.829	4.876	6.53	<0.001	[20.234, 43.424]
T.06b	31.559	5.467	5.78	<0.001	[18.765, 44.353]
Segment 4	27.823	6.678	4.17	0.011	[12.765, 42.881]
Segment 7	-20.842	7.234	-2.88	0.065	[-37.123, -4.561]
Segment 9	-30.101	7.876	-3.82	0.007	[-46.234, -13.968]
Angle Start Index	0.198	0.134	1.48	0.155	[-0.084, 0.480]

Table 4.4: Regression Table for Stop index

In summary, strong correlations were found between Onset Index, Stop Index From End, and Angle Start Index. A significant correlation between ‘Early Starters’ and ‘Early Turners’ indicates that participants who generally start their actions earlier also tend to complete their actions earlier. A moderate correlation for ‘Late Starters’ and ‘Late Turners’ suggests a similar but less pronounced relationship for those who start actions later. The regression analysis revealed significant trial and segment effects on both the onset and stop indices, highlighting specific trials and segments that significantly influence these indices. The positive correlation between Angle Start Index and Onset Index suggests that an increase in the angle start index results in a higher onset index.

Principal Component Analysis (PCA) and Hierarchical Clustering

PCA and hierarchical clustering were performed to further analyse the participants' behaviours by considering multiple variables simultaneously. Three distinct clusters were identified (figures 4.9 and 4.10:

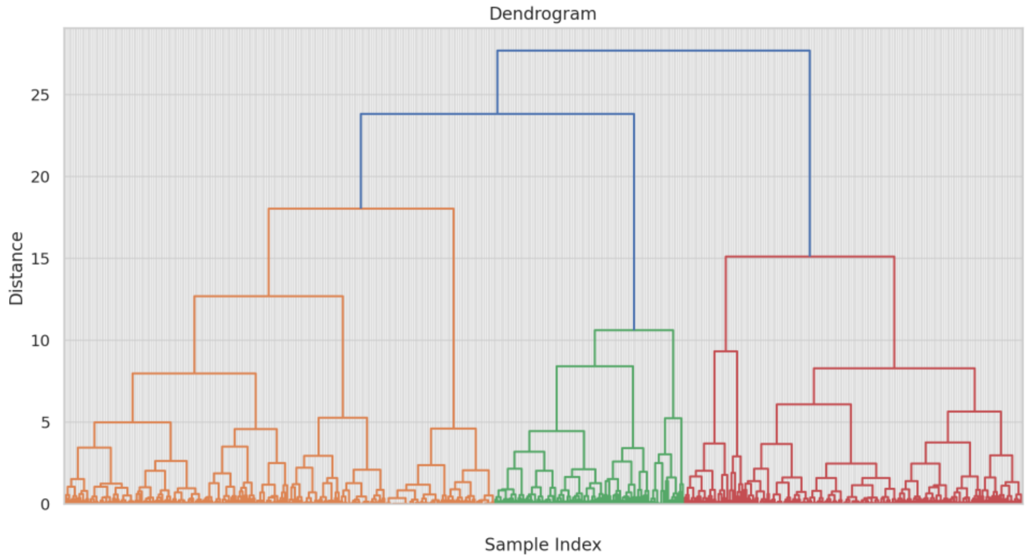


Figure 4.9: This dendrogram visualizes the hierarchical clustering process, the three main clusters identified are marked, corresponding to the distinct behavioural patterns observed in the PCA scatter plot.

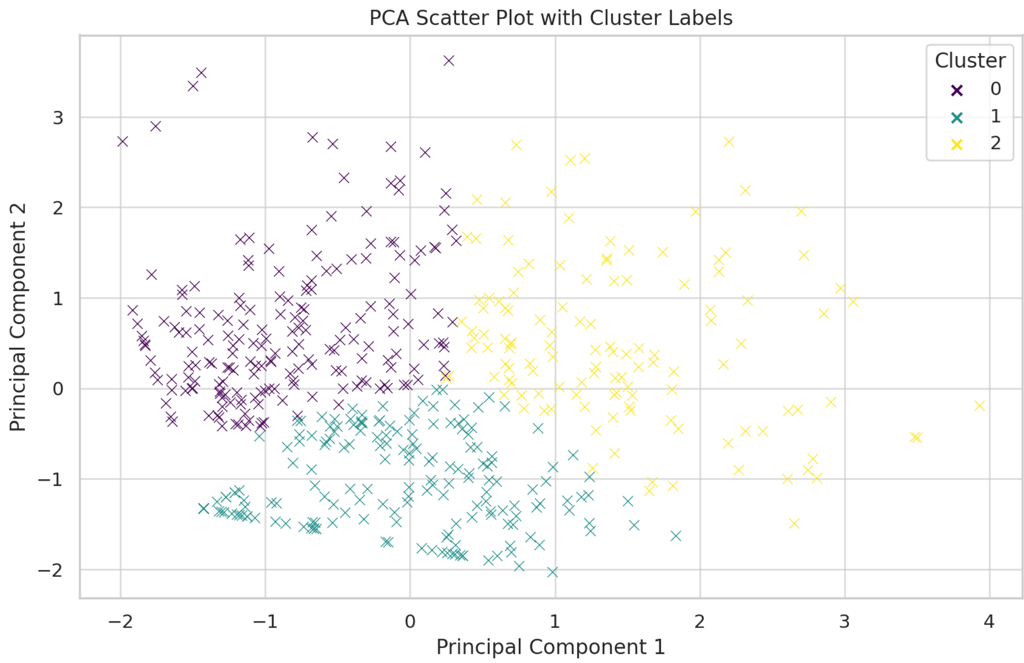


Figure 4.10: This PCA scatter plot shows the distribution of participants in the reduced two-dimensional space defined by the first two principal components.

Cluster 1: Participants in this cluster tend to start actions earlier, stop actions later, and have moderate angles at the start. This cluster is characterized by a lower Onset Index, higher Stop Index From End, and moderate Angle Start Index. Cluster 2: Participants in this cluster tend to start actions later, stop actions earlier, and have the highest angles at the start. This cluster is characterized by a higher Onset Index, moderate Stop Index From End, and the highest Angle Start Index. Cluster 3: Participants in this cluster show a balance between starting and stopping actions, with lower angles at the start. This cluster is characterized by a moderate Onset Index, lower Stop Index From End, and the lowest Angle Start Index (Table 4.5).

Variable	Cluster One	Cluster Two	Cluster Three
Onset Index Mean	41.78	80.92	65.41
Onset Index Median	33.0	88.0	69.5
Onset Index Std	36.05	39.91	43.16
Stop Index Mean	104.60	92.51	60.28
Stop Index Median	110.0	98.5	74.0
Stop Index Std	64.67	53.84	56.11
Angle Start Mean	18.48	31.15	12.96
Angle Start Median	14.5	29.5	7.0
Angle Start Std	18.12	22.35	16.57

Table 4.5: Summary statistics of cluster characteristics resulting from principal component analysis (PCA). The table presents the mean, median, and standard deviation of onset index, stop index from end, and angle start index for each cluster identified through PCA.

4.5 Data Analysis Summary

In summary, strong correlations were found between Onset Index, Stop Index From End, and Angle Start Index. A significant correlation between 'Early Starters' and 'Early Turners' indicates that participants who generally start their actions earlier also tend to complete their actions earlier. A moderate correlation for 'Late Starters' and 'Late Turners' suggests a similar but less pronounced relationship for those who start actions later. The regression analysis revealed significant trial and segment effects on both the onset and stop indices, highlighting specific trials and segments that significantly influence these indices. The positive correlation between Angle Start Index and Onset Index suggests that an increase in the angle start index results in a higher onset index.

Additionally, PCA and hierarchical clustering provided a nuanced view of different behavioural patterns, emphasizing the importance of considering multiple variables simultaneously. This multi-faceted approach not only provides a deeper understanding of participant behaviours but also offers a robust framework for future predictive modelling and analysis in similar contexts.

4.6 Key Contributions

- **Identification and Validation of Micro-Navigational Strategies:**
  - This study confirmed the existence of specific micro-navigational strategies, such as "Strafe then Move," "Turn Then Move," and "Turn during Move," which are crucial for realistic navigation in artificial agents.
- **Significant Correlations Between behavioural Indices:**
  - Discovered strong positive correlations between key indices: Onset Index and Stop Index From End ($r = 0.729$, $p = 0.026$), Onset Index and Angle Start Index ($r = 0.758$, $p = 0.018$), and Stop Index From End and Angle Start Index ($r = 0.763$, $p = 0.017$).
- **behavioural Pattern Classification:**
  - Classified participant behaviours into distinct patterns and identified predominant movement types. Notably, "Turn Then Move" was the most common strat-

egy, with variations observed in specific segments and participants.

- **Impact of Trial and Segment Variability:**
  - Demonstrated significant trial and segment effects on the onset and stop indices through mixed linear regression analysis, highlighting how specific trials and segments influence navigational behaviours.
- **Cluster Analysis of Navigational behaviours:**
  - Using PCA and hierarchical clustering, identified three distinct clusters of participant behaviours:
    * **Cluster 1:** Early starters with later stops and moderate starting angles.
    * **Cluster 2:** Late starters with earlier stops and highest starting angles.
    * **Cluster 3:** Balanced starters and stoppers with lower starting angles.
- **Framework for Future Research:**
  - As explained in the next section; established a robust framework combining traditional statistical methods with advanced machine learning techniques, offering a comprehensive approach for analysing and predicting human navigational behaviours in controlled environments.
- **Implications for Artificial Agent Design:**
  - Provided valuable insights for enhancing the realism of artificial agents, emphasizing the importance of integrating validated micro-navigational strategies to improve the immersion and functionality of virtual characters and autonomous systems.

4.7 Conclusion

In this chapter, micro-navigational strategies that enhance the realism of artificial social agents (ASAs), such as virtual characters in training simulations and non-player characters (NPCs) in video games, were investigated. This study aimed to bridge the gap in existing research by focusing on subtle human movement adjustments that contribute to the naturalness of navigation. By collecting detailed movement data from participants in a controlled environment, it was possible to capture and analyse these micro-movements, providing valuable insights into the strategies employed during human navigation.

The data analysis revealed significant correlations between key behavioural indices, such as the Onset Index, Stop Index From End, and Angle Start Index, highlighting the intricate relationships between different aspects of movement. Through mixed linear regression analysis, specific trial and segment effects that influence these indices were identified, further elucidating the factors that shape human navigational behaviour. The application of Principal Component Analysis (PCA) and hierarchical clustering allowed for the classification of participant behaviours into distinct patterns, providing a nuanced understanding of the variability in micro-navigational strategies.

The findings affirm the existence of micro-navigational strategies and their critical role in developing advanced locomotion models for artificial agents. By replicating these strategies, it is possible to significantly improve the authenticity of ASAs, thereby enhancing the quality of interactions in digital spaces. The insights gained from this study lay the groundwork for future research, which will focus on refining and validating these models through more complex experimental setups and broader participant samples.

4.8 Possible Framework for Future Research

The future of research in human navigational behaviours and their replication in artificial social agents (ASAs) necessitates an integrative approach as seen in this chapter, combining traditional statistical methods with advanced machine learning techniques. This section delves into the potential of such an approach, highlighting key studies and methodologies that have contributed to the field.

4.8.1 Combining Traditional Statistical Methods with Advanced Machine Learning

Traditional statistical methods have long been used to analyse human movement, providing foundational insights into patterns and behaviours. These methods include regression analysis, hypothesis testing, and various multivariate techniques. While powerful, these methods often lack the ability to handle the complexity and high dimensionality of human locomotion data effectively.

Advanced machine learning (ML) techniques, on the other hand, offer robust tools for modelling and predicting complex behaviours. Machine learning methods, including supervised learning, unsupervised learning, and reinforcement learning, can capture intricate patterns in large datasets that traditional methods might miss. The integration of these two approaches can enhance the predictive power and accuracy of models designed to replicate human navigational behaviours in ASAs.

Traditional Statistical Methods

Traditional statistical methods have provided significant insights into human locomotion. For instance, regression models have been used to predict walking speed and gait parameters based on various physiological factors Winter, 2009. Multivariate statistical techniques, such as principal component analysis (PCA), have been employed to reduce the dimensionality of movement data, facilitating easier interpretation and analysis Jolliffe, 2011.

These methods have also been instrumental in understanding the relationships between different movement variables. For example, studies have used correlation analysis to explore the link between joint angles and ground reaction forces during walking. Chang et al., 2012 investigated the association between joint kinematics and ground reaction forces during normal walking and found significant correlations between the joint angles and the loading rates of ground reaction forces. This research underscores the importance of understanding these biomechanical relationships in developing more effective gait analysis and rehabilitation strategies. Hypothesis testing has further allowed researchers to determine the statistical significance of observed movement patterns and their variations across different conditions Rosenbaum, 2010.

Advanced Machine Learning Techniques

Machine learning techniques have revolutionized the analysis and prediction of human movement behaviours. Supervised learning algorithms, such as support vector machines (SVMs) and neural networks, have been used to classify different types of gait and predict future movements based on historical data Bishop, 2006. Unsupervised learning methods, including clustering algorithms, have helped identify hidden patterns in movement data that are not apparent through traditional analysis Hastie et al., 2009.

Reinforcement learning, in particular, has shown promise in modelling the decision-making processes involved in human navigation. This approach involves training agents to make a series of decisions that maximize cumulative rewards, closely mimicking the trial-and-error learning process in humans Sutton and Barto, 2018. Reinforcement learning has been used to develop ASAs that can adapt their navigational strategies in response to dynamic environments, enhancing their realism and effectiveness Mnih et al., 2015.

Integrative Approaches

The integration of traditional statistical methods with advanced machine learning techniques offers significant advantages in the field of human movement analysis. Traditional statistical approaches provide a strong theoretical foundation for understanding the underlying mechanisms of human movement, such as biomechanics and motor control. These methods are essential for hypothesis testing and establishing causal relationships. However, they often fall short when it comes to handling the complex, high-dimensional data typically encountered in human movement studies. Machine learning, on the other hand, excels in processing and modelling such complex datasets, allowing for the identification of intricate patterns and the prediction of future behaviours with high accuracy. For example, a study on the use of machine learning in human movement biomechanics highlights how combining these methods can lead to more accurate predictions of joint torques and ground reaction forces, significantly reducing computation times compared to traditional optimization techniques Halilaj et al., 2018.

Applications in ASA Development

The integration of traditional statistical methods and machine learning has significant implications for the development of ASAs. By utilising these combined approaches, researchers can develop more sophisticated models that accurately replicate human navigational behaviours. This can lead to the creation of ASAs that move and interact in ways that are more natural and believable, enhancing user engagement and immersion in virtual environments.

For example, machine learning models trained on human locomotion data can be used to predict how ASAs should adjust their movements in response to environmental changes. These predictions can be fine-tuned using traditional statistical methods to ensure they are statistically valid and reliable Murphy, 2012. This iterative process can help create ASAs that not only mimic human movement but also adapt to new situations in a human-like manner.

4.8.2 Analysing and Predicting Human Navigational behaviours

The combination of traditional statistical methods and advanced machine learning provides a powerful framework for analysing and predicting human navigational behaviours. This integrative approach can uncover deeper insights into the complexities of human movement and inform the development of ASAs that exhibit high levels of realism and adaptability.

Research by Hicheur et al., 2005; Warren et al., 2001 underscores the importance of understanding both the biomechanical and cognitive aspects of navigation. By combining statistical analysis with machine learning, researchers can develop comprehensive models that account for these multifaceted influences. This holistic understanding is crucial for creating ASAs that can navigate and interact in complex environments with a high degree of realism.

Chapter 5

Realism Perception of Movement Strategies in Artificial Social Agents

This chapter aims to empirically evaluate the perception of realism in micro-movement strategies identified and developed in the preceding chapters. Utilising a structured questionnaire, the study gathers participants' feedback on the human-likeness, naturalness, performance, and overall realism of these movements. The questionnaire items are adapted from the well-established Artificial-Social-Agent (ASA) Questionnaire, ensuring the reliability and relevance of the measures. Data collection is conducted via the Gorilla platform, enabling efficient and diverse participant recruitment. The findings from this chapter will validate the effectiveness and realism of the micro-movement strategies, providing critical insights for refining these strategies and enhancing the realism of artificial social agents (ASAs).

5.1 Motivation

The motivation for Chapter 5 centres on obtaining empirical data through a structured questionnaire to evaluate the perception of realism in micro-movement strategies identified and developed in previous chapters. This chapter aims to validate the posited (in Chapter 3) and discovered (in Chapter 4) micro-movement strategies by assessing participants' perceptions of their realism and naturalness. This study specifically addresses the third research question: **What is the effect of the identified micro-movement strategies on the perceived realism of artificial social agents?** Gathering participants' feedback is crucial in understanding the effectiveness and realism of these micro-movement strategies in enhancing the realism of artificial social agents (ASAs).

Participant feedback plays a vital role in validating the theoretical and experimental findings related to micro-movement strategies. By collecting data on how real users perceive these movements, we can gauge the success of our proposed strategies in achieving realistic and human-like behaviour in ASAs. Previous research has shown that user perception is a critical factor in the acceptance and effectiveness of virtual agents. For instance, a study by Guadagno et al., 2007 has highlighted that the perceived behavioural realism of virtual agents significantly influences user engagement and interaction quality.

Participant feedback is also essential for identifying potential areas for improvement in the design of micro-movement strategies. By understanding the aspects of movement that users find most and least realistic, we can refine and enhance these strategies to better align with human expectations and experiences. This iterative process of feedback and refinement is crucial for developing ASAs that can effectively engage and interact with users in a variety of contexts.

The structured questionnaire developed for this study focuses on several key aspects of movement realism. These include the human-likeness of the movements, the naturalness and likelihood of these movements occurring in daily life, the performance of the movements, and the overall perceived realism. By evaluating these aspects, we aim to provide a comprehensive assessment of how well the micro-movement strategies enhance the realism of ASAs. This evaluation is crucial for refining these strategies and ensuring they meet the expectations and perceptions of real users.

The assessment of realism and naturalness is not only important for validating our findings but also for understanding the nuances of human-agent interaction. Realistic movements can significantly enhance the believability of ASAs, making them more effective in applications where social interaction and engagement are critical. By focusing on these key aspects, we can develop a deeper understanding of what constitutes realistic movement in virtual agents and how these movements impact user perception and interaction.

Understanding how users perceive the realism of ASAs' movements contributes to the broader field of virtual environment design. Realistic agent behaviours are essential for creating immersive and believable virtual experiences, whether in educational settings, therapeutic applications, or interactive entertainment. The insights gained from participant feedback will inform the design of more effective and engaging ASAs, ultimately leading to improved user experiences in various virtual environments.

The integration of realistic micro-movement strategies into virtual agents has the potential to transform the user experience in virtual environments. By creating agents that move in ways that are natural and believable, we can enhance the overall immersion and engagement of users. This is particularly important in applications such as virtual training and simulation, where the realism of the environment can significantly impact learning outcomes and user satisfaction.

The use of the Gorilla platform (https://gorilla.sc/) for conducting the questionnaire ensures methodological rigor and reliability in data collection. By leveraging this robust online tool, we can reach a diverse participant pool and collect data efficiently. The questionnaire items are adapted from the well-validated Artificial-Social-Agent (ASA) Questionnaire by Fitrianie et al., 2022, ensuring the relevance and reliability of the measures used.

Gorilla's platform allows for precise control over the experimental conditions, ensuring that the data collected is both reliable and valid. This platform also facilitates the inclusion of a wide range of participants, enhancing the generalizability of our findings. The adaptation of well-validated questionnaire items further strengthens the reliability of our measures, providing a solid foundation for evaluating the realism of micro-movement strategies in ASAs.

This chapter is structured as follows: Section 5.2 details the experimental design, focusing on the development and administration of the structured questionnaire. Participants' navigation and interaction with ASAs are captured and analysed to assess movement realism. Section 5.3 and 5.4 discuss the analytical techniques employed, including statistical analyses and qualitative assessments, to evaluate participants' feedback. As well as present the findings, interpreting the data to determine the effectiveness of the micro-movement strategies. 5.5 outlines key contributions from the chapter and finally, Section 5.6 concludes the chapter by summarizing the implications of the findings and suggesting directions for future research.

In summary, the motivation for Chapter 5 is driven by the need to empirically validate the micro-movement strategies through participant feedback. This validation process is essential for refining these strategies and enhancing the realism of ASAs, thereby contributing to the broader goal of creating more immersive and believable virtual environments.

5.2 Methodology

For this experiment into the perception of realism in ASA's; participants were recruited through the Gorilla platform, an online tool for conducting behavioural research. A total of

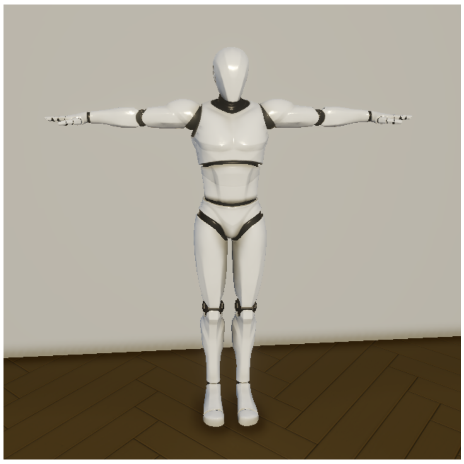
30 participants were selected for the study, ranging in age from 18 to 55. All participants had normal or corrected-to-normal vision and no history of photosensitivity, ensuring that visual impairments or sensitivities would not influence the results. The stimuli used in this study consisted of a series of videos showcasing various micro-movement strategies identified in Chapter 3 and evidenced in Chapter 4, these videos were created by taking the movement strategies from earlier chapters, and creating motion capture data that was turned into video animations in the Unity game engine, and then recorded into video files, with one complete set created for an agent with a humanoid aesthetic, and a complete set for an agent that looked similar to a crash test dummy, this was to investigate the role of aesthetics in perception. The micro-movement strategies included forward walk, backward step, strafe, turn and walk, backstep turn, and curved walk (see 5.2). These videos were created using high-quality motion capture techniques to ensure that the animation of movements was realistic and free from technical artifacts. The videos were presented to participants in a random order to control for any potential order effects. Each video displayed one of the micro-movement strategies, allowing participants to observe the movement in isolation. Participants were instructed to watch each video carefully and then rate five aspects of the movement:

1. **Perceived realism**: The agent's movements closely resemble human behaviour
2. **Likelihood of occurrence in real humans**: These movements are likely to be seen in your day-to-day life.
3. **Agent's Performance**: The agent performs its movements with efficiency.
4. **Perceived Realism Score**: The agent's movements are realistic.
5. **Overall Realism**: The agent is realistic.

These ratings were provided on a interval scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Data was collected through the Gorilla platform, which allowed participants to complete the study remotely. This method ensured an assumedly diverse participant pool and facilitated efficient data collection. The collected data was analysed to assess the perceived realism and likelihood of occurrence for each micro-movement strategy. Statistical analyses, including descriptive statistics and inferential tests, were conducted to identify significant differences between the movement strategies and to understand participants' perceptions. For how the questionnaire was adapted and reasons for doing so, please see appendix.

The data analysis process is detailed further in the next section of this chapter.

(a) Humanoid Agent



(b) Dummy Agent

Figure 5.1: Humanoid and Dummy visuals for social agent

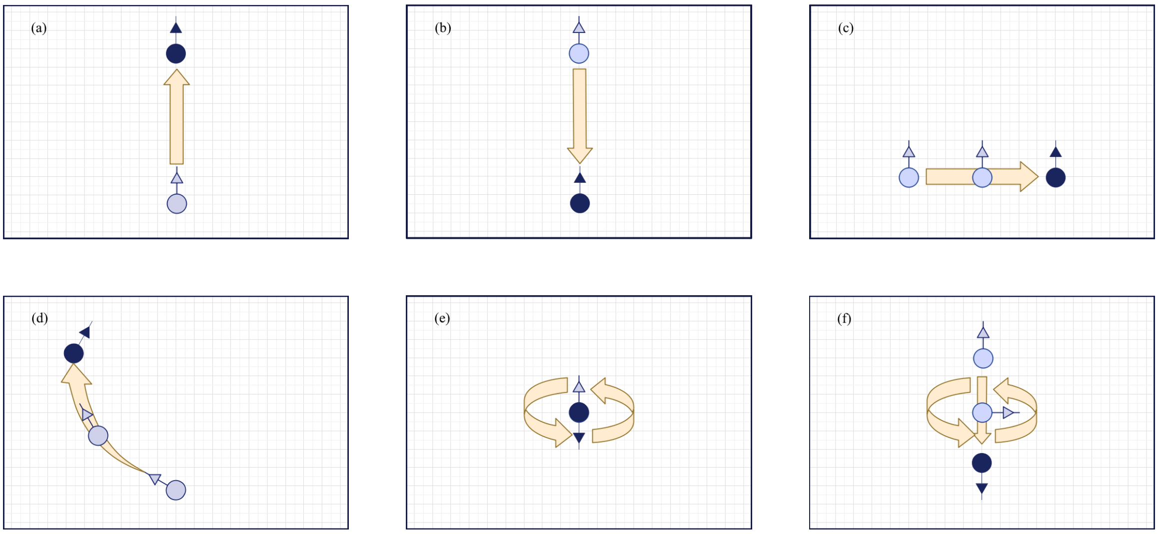


Figure 5.2: Proposed list of atomic micro-movements from chapter 3, The start location of the agent is the lighter blue circle, the darker blue circle denotes the end location of movement. The arrows on the circle show body orientation, the yellow arrows denote the displacement path irrespective of body orientation. (A) Linear walk in a direct line congruent with body orientation. (B) Linear back-step in a direct line. (C) Strafe (side-step) to the side while facing forward. (D) Curved walk with gradual body orientation along the curve. (E) Rotating in place with no translation of the centre of mass of the body, the original and final orientation differ by 180°. (F) Rotation during displacement along a path, the original and final orientation also differ by 180°.

5.3 Results

5.3.1 Descriptive Statistics

Descriptive statistics were calculated for various video files to provide a summary of the responses for different movements and agents. Having access to this data in a readable format was crucial for the next steps to more easily be accomplished. The preprocessing of the Gorilla export—selecting only the numeric "response" entries, extracting the Participant ID, VideoFile, and Question columns, pivoting into a wide format per participant and movement, and renaming each Question ID to a clear label (e.g. "resemblance," "efficiency," etc.) is what formed the basis for the dataset. Because participants rated each movement on a continuous 0–100 interval scale, the resulting data met the assumptions for parametric testing; this justifies our use of ANOVA in the later sections to robustly compare differences among movement strategies.

Descriptive Statistics Summary

The tables below provide an overview of the key descriptive statistics for the Turn Backward movements. For the full set of descriptive statistics, please refer to the appendix.

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Dummy_TurnBackwards					
Mean	67.73	62.57	71.43	75.57	44.30
Std	27.70	31.07	22.55	19.06	32.39
Humanoid_TurnBackwards					
Mean	66.33	61.27	67.77	70.67	69.67
Std	26.69	28.56	26.88	25.58	23.89

Table 5.1: Summary Table of Descriptive Statistics for TurnBackward Movements

Summary of Descriptive Statistics for Example Movements

The descriptive statistics for the TurnBackward movements illustrate the mean and standard deviation (SD) of various perception metrics for both the Dummy and Humanoid agents. For the "Dummy_TurnBackwards" movement, the mean Resemblance score was 67.73 (SD = 27.70), Day-to-day practicality scored 62.57 (SD = 31.07), Efficiency had a mean of 71.43 (SD = 22.55), Movement Realism was 75.57 (SD = 19.06), and Agent Realism was 44.30 (SD = 32.39). In contrast, the "Humanoid_TurnBackwards" movement had a mean Resemblance score of 66.33 (SD = 26.69), Day-to-day practicality scored 61.27 (SD = 28.56), Efficiency was 67.77 (SD = 26.88), Movement Realism was 70.67 (SD = 25.58), and Agent Realism was 69.67 (SD = 23.89). These results (a seen in figure 5.3 to figure 5.7 suggest that both agent types were perceived similarly in terms of movement realism and day-to-day practicality, with the Dummy agent scoring lower in Agent Realism. The Dummy agent negatively impacting Agent Realism is supported in later analysis of this chapter.

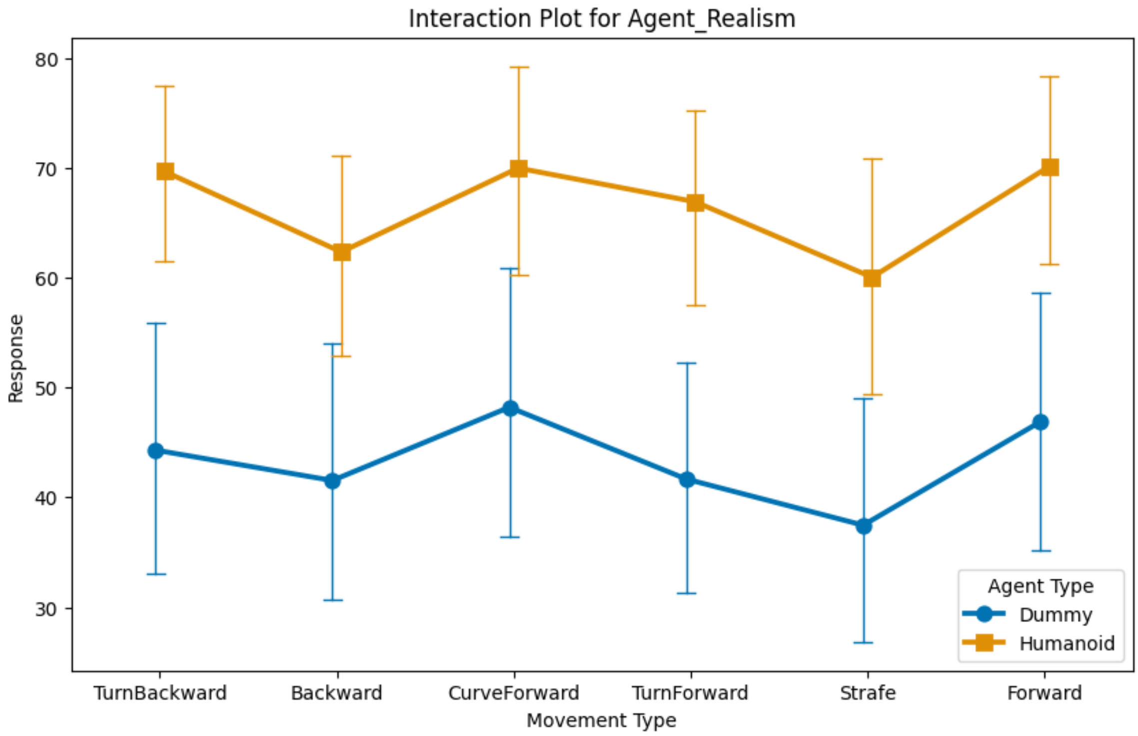


Figure 5.3: Interaction plot showing mean *Agent Realism* scores for each movement type by agent (Humanoid vs. Dummy).

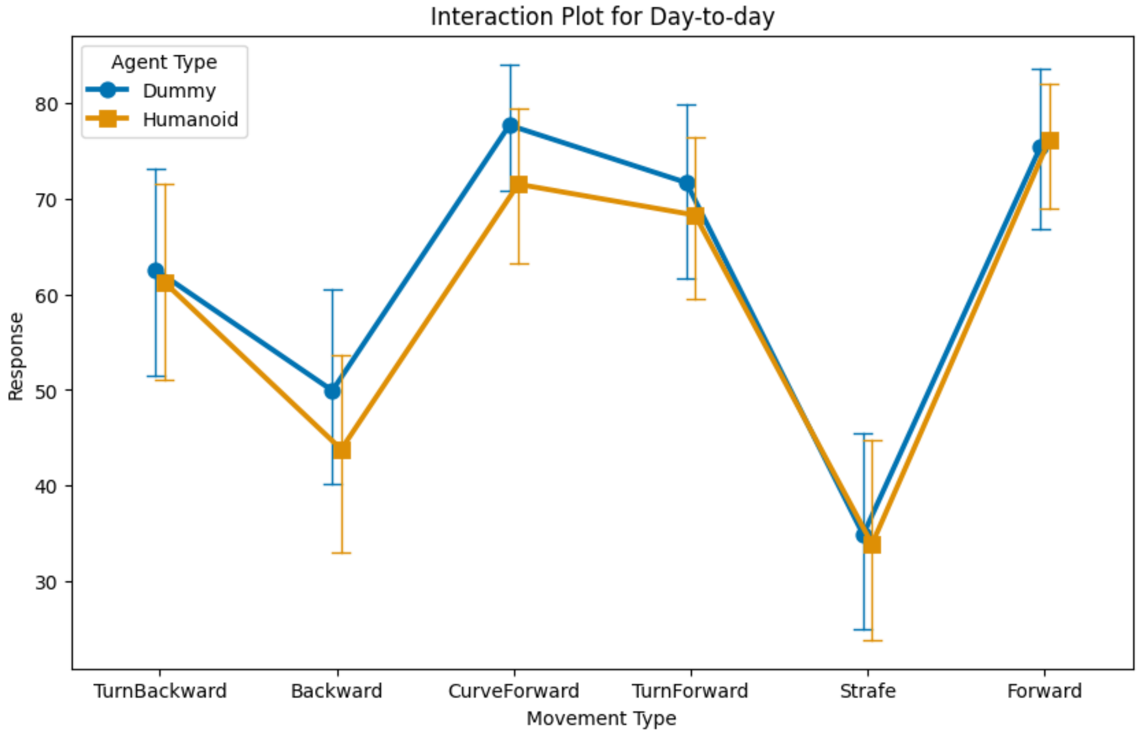


Figure 5.4: Interaction plot showing mean *Day-to-day Realism* scores for each movement type by agent (Humanoid vs. Dummy).

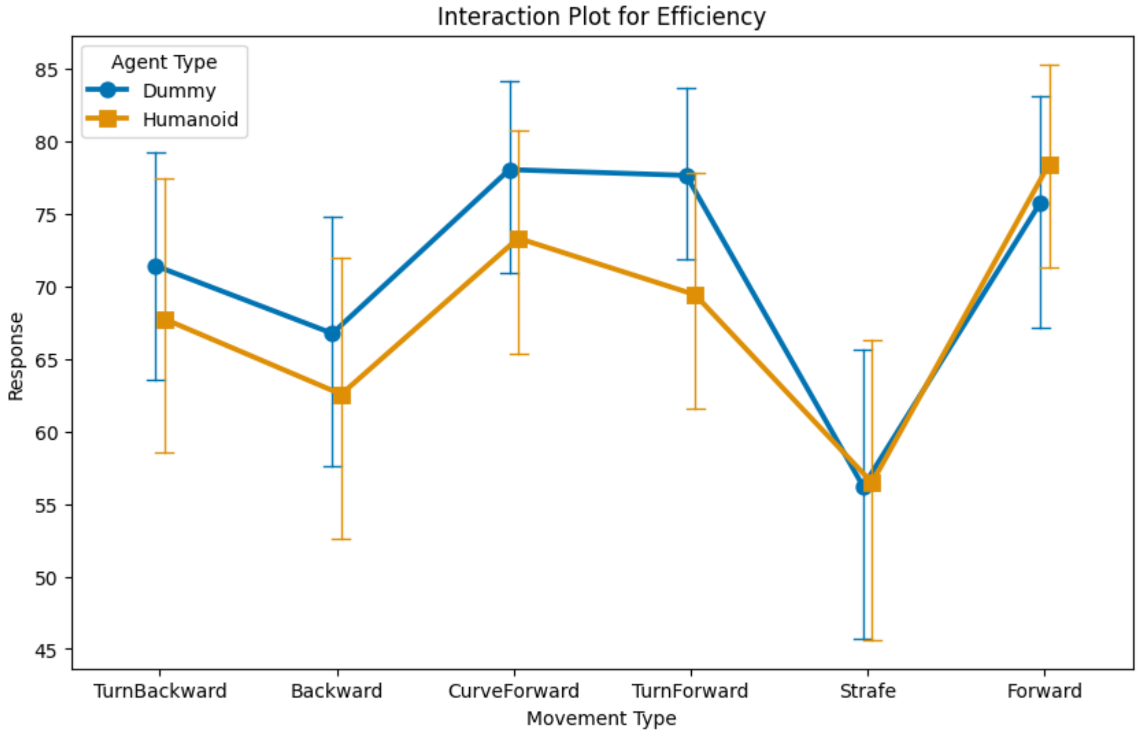


Figure 5.5: Interaction plot showing mean *Efficiency* scores for each movement type by agent (Humanoid vs. Dummy).

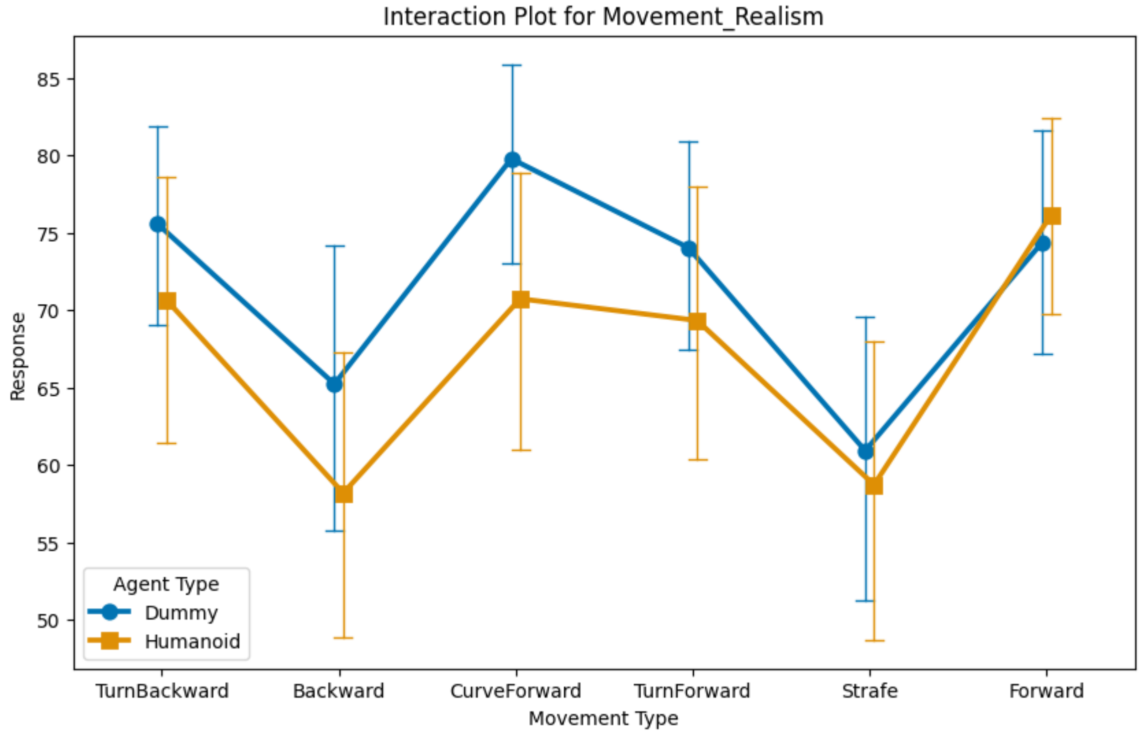


Figure 5.6: Interaction plot showing mean *Movement Realism* scores for each movement type by agent (Humanoid vs. Dummy).

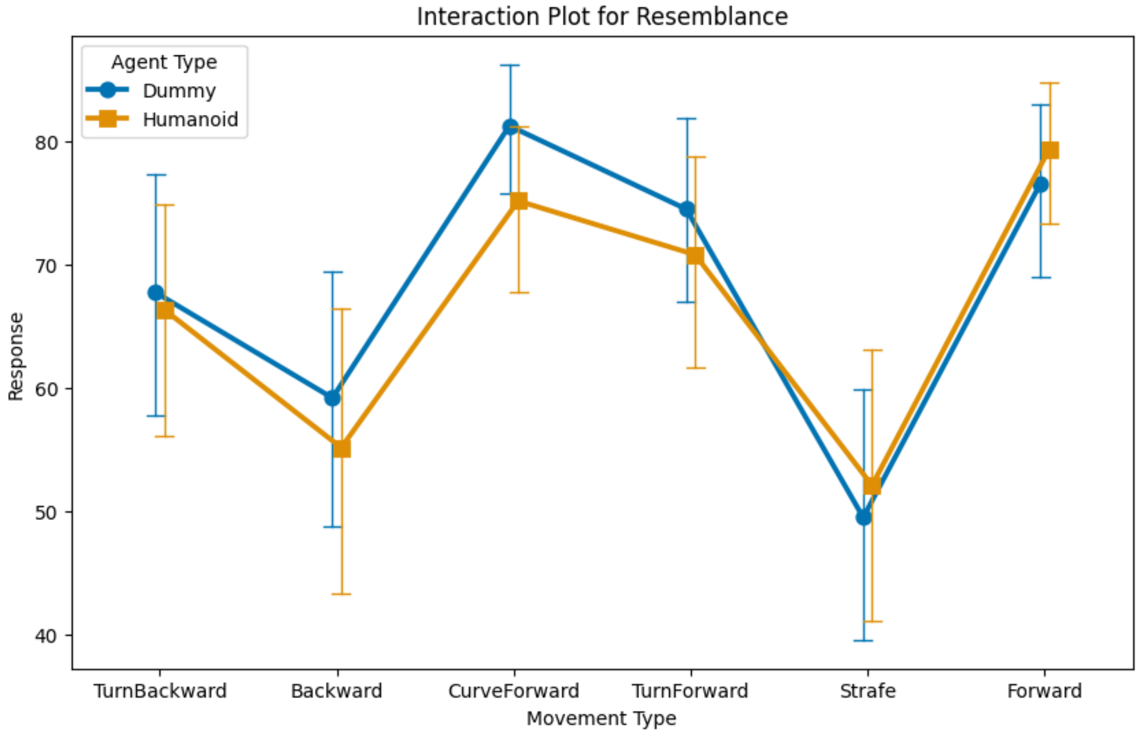


Figure 5.7: Interaction plot showing mean *Resemblance* scores for each movement type by agent (Humanoid vs. Dummy).

5.3.2 ANOVA Results

Because all responses were recorded on a 0–100 continuous interval scale—providing sufficient granularity and satisfying parametric assumptions—we employed a two-way ANOVA to assess how agent type (Dummy vs. Humanoid) and movement type influence each realism measure. This design tested both main effects and their interaction on perceived resemblance, day-to-day practicality, efficiency, movement realism, and overall agent realism. Where significant effects emerged, we followed up with Tukey's HSD post-hoc comparisons to pinpoint which specific movement strategies differed from one another.

Factor	df	sum_sq	mean_sq	F	PR(>F)
Resemblance					
C(Agent)	1.0	241.736	241.736	0.387	0.534
C(Movement)	5.0	38238.492	7647.698	12.232	<0.001
C(Agent):C(Movement)	5.0	1014.181	202.836	0.324	0.898
Residual	348.0	217579.967	625.230		
Day-to-day					
C(Agent)	1.0	742.469	742.469	1.053	0.306
C(Movement)	5.0	83335.447	16667.089	23.639	<0.001
C(Agent):C(Movement)	5.0	613.047	122.609	0.174	0.972
Residual	348.0	245361.300	705.061		
Efficiency					
C(Agent)	1.0	801.025	801.025	1.339	0.248
C(Movement)	5.0	18560.058	3712.012	6.203	<0.001
C(Agent):C(Movement)	5.0	1125.858	225.172	0.376	0.865
Residual	348.0	208253.033	598.428		
Movement Realism					
C(Agent)	1.0	1703.025	1703.025	3.025	0.083
C(Movement)	5.0	14279.592	2855.918	5.072	<0.001
C(Agent):C(Movement)	5.0	1073.925	214.785	0.381	0.861
Residual	348.0	195931.233	563.021		
Agent Realism					
C(Agent)	1.0	48279.336	48279.336	55.572	<0.001
C(Movement)	5.0	4900.947	980.189	1.128	0.345
C(Agent):C(Movement)	5.0	255.547	51.109	0.059	0.998
Residual	348.0	302332.833	868.773		

Table 5.2: ANOVA Results for Dependent Variables

5.3.3 Analysis and Interpretation

The ANOVA results provide valuable insights into how agent type and movement type influence participants' perceptions of realism in ASAs. For **Resemblance**, the agent type (Humanoid vs. Dummy) did not significantly impact how closely the movements resemble human behaviour ($F(1, 348) = 0.387$, $p = 0.534$). However, movement type significantly affected Resemblance ($F(5, 348) = 12.232$, $p < 0.001$), indicating that some movements are perceived as more human-like than others, with no significant interaction effect ($F(5, 348) = 0.324$, $p = 0.898$).

In **Day-to-day Realism**, agent type did not significantly influence the perception ($F(1, 348) = 1.053$, $p = 0.306$), while movement type had a highly significant effect ($F(5, 348) = 23.639$, $p < 0.001$), suggesting that certain movements are more commonly seen in daily life. The interaction effect was not significant ($F(5, 348) = 0.174$, $p = 0.972$).

For **Efficiency**, agent type was not a significant factor ($F(1, 348) = 1.339$, $p = 0.248$), but movement type significantly impacted perceptions ($F(5, 348) = 6.203$, $p < 0.001$), with no significant interaction effect ($F(5, 348) = 0.376$, $p = 0.865$).

In **Movement Realism**, the agent type showed a non-significant effect ($F(1, 348) =$

3.025, $p = 0.083$), whereas movement type significantly influenced Movement Realism ($F(5, 348) = 5.072$, $p < 0.001$), with no significant interaction effect ($F(5, 348) = 0.381$, $p = 0.861$).

Lastly, for **Agent Realism**, agent type had a highly significant effect ($F(1, 348) = 55.572$, $p < 0.001$), indicating that Humanoid agents are perceived as significantly more realistic than Dummy agents. Movement type ($F(5, 348) = 1.128$, $p = 0.345$) and the interaction effect ($F(5, 348) = 0.059$, $p = 0.998$) were not significant.

These findings align with the Mixed Linear Model (MLM) analysis in the next section, which also indicated that specific movement types, particularly CurveForward and Forward, positively impact perceived realism dimensions, while movements such as Strafe and Backward negatively impact Agent Realism. Interaction effects between agent type and movement were not found to be significant across the models. This consistency between ANOVA and MLM analyses reinforces the robustness of the findings regarding the perception of realism in ASAs.

Tukey Post-Hoc Analysis

Factor	df	sum_sq	mean_sq	F	PR(>F)
		Resemblance			
C(Movement)	5.0	38238.492	7647.698	12.232	<0.001
Residual	354.0	218835.883	625.230		

Table 5.3: ANOVA Results for Resemblance (see Appendix for full tables)

Group 1	Group 2	Mean Diff	p-adj	Lower	Upper	Reject
		Tukey HSD for Resemblance				
Backward	CurveForward	21.0667	0.0001	8.0595	34.0738	True
Backward	Forward	20.7833	0.0001	7.7762	33.7905	True
Backward	Strafe	-6.3833	0.7233	-19.3905	6.6238	False
Backward	TurnBackward	9.8833	0.251	-3.1238	22.8905	False
Backward	TurnForward	15.5000	0.0092	2.4928	28.5072	True
CurveForward	Forward	-0.2833	1.0	-13.2905	12.7238	False
CurveForward	Strafe	-27.4500	0.0	-40.4572	-14.4428	True
CurveForward	TurnBackward	-11.1833	0.1379	-24.1905	1.8238	False
CurveForward	TurnForward	-5.5667	0.8238	-18.5738	7.4405	False
Forward	Strafe	-27.1667	0.0	-40.1738	-14.1595	True
Forward	TurnBackward	-10.9000	0.1586	-23.9072	2.1072	False
Forward	TurnForward	-5.2833	0.8537	-18.2905	7.7238	False
Strafe	TurnBackward	16.2667	0.0052	3.2595	29.2738	True
Strafe	TurnForward	21.8833	0.0	8.8762	34.8905	True
TurnBackward	TurnForward	5.6167	0.8182	-7.3905	18.6238	False

Table 5.4: Tukey HSD Results for Resemblance (see Appendix for full tables)

The post-hoc Tukey HSD tests following the ANOVA provide detailed insights into the specific differences between movement types for each dependent variable. For Resemblance, CurveForward and Forward movements were significantly more human-like compared to Backward and Strafe movements. In terms of Day-to-day Realism, CurveForward and Forward movements were perceived as more realistic in daily life, whereas Strafe movements were seen as less realistic. For Efficiency, Strafe movements were viewed as significantly less efficient compared to other movements, such as CurveForward and Forward. Similarly, for Movement Realism, CurveForward and Forward movements were considered more realistic than Backward and Strafe movements. These results are consistent with the ANOVA and mixed linear model findings, underscoring the significant impact of specific movement types on various dimensions of perceived realism. The ANOVA results for Agent Realism with respect to movement type showed no significant differences, indicating that the type of movement does not impact perceived Agent Realism. However, the Tukey HSD test revealed that Humanoid agents are perceived as significantly more realistic than Dummy agents, a finding that also aligns with the ANOVA and mixed linear model analyses, which also highlighted significant differences in perceived agent realism based on agent type but not on movement type. Full tables for all dependent variables can be found in the appendix.

5.3.4 Mixed Linear Model Analysis

In this study, it was prudent to conduct both ANOVA (Analysis of Variance) and Mixed Linear Model (MLM) analyses to ensure a comprehensive understanding of the data. An ANOVA was utilised to identify the main effects and interactions between the agent type and movement type on perceived realism dimensions, offering a straightforward analysis of whether significant differences exist between the levels of these factors. However, an ANOVA is limited by its assumption of balanced data and inability to account for participant-specific variability. Therefore, a Mixed Linear Model was employed to address these limitations, providing a more nuanced analysis by incorporating random effects to account for variability between participants and handling unbalanced data structures. The MLM also allowed for detailed estimation of fixed effects, including the magnitude and direction of these effects. By using both methods, the study benefits from the strengths of each approach, ensuring robust and reliable findings. The consistency observed between the ANOVA and MLM results further validates the conclusions drawn.

The mixed linear model analysis was performed for each dependent variable separately: Resemblance, Day-to-day, Efficiency, Movement Realism, and Agent Realism. Each movement was included, with TurnForward being used as a reference movement. Below are the summarized findings for each model.

Resemblance

Variable	Coef.	Std.Err.	z	P>|z|
Intercept	67.292	3.090	21.775	0.000
C(Agent, Sum)[S.Dummy]	0.819	1.013	0.809	0.419
C(Movement, Sum)[S.Backward]	-10.142	2.265	-4.477	0.000
C(Movement, Sum)[S.CurveForward]	10.925	2.265	4.823	0.000
C(Movement, Sum)[S.Forward]	10.642	2.265	4.697	0.000
C(Movement, Sum)[S.Strafe]	-16.525	2.265	-7.294	0.000
C(Movement, Sum)[S.TurnBackward]	-0.258	2.265	-0.114	0.909
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Backward]	1.197	2.265	0.528	0.597
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.CurveForward]	2.231	2.265	0.985	0.325
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Forward]	-2.219	2.265	-0.980	0.327
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Strafe]	-2.119	2.265	-0.936	0.349
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.TurnBackward]	-0.119	2.265	-0.053	0.958
Group Var	255.715	4.088		

Table 5.5: Mixed Linear Model Summary for Resemblance

The results indicate that the intercept is 67.292, with significant positive effects of CurveForward (Coef. = 10.925, $p < 0.001$) and Forward (Coef. = 10.642, $p < 0.001$) movements on Resemblance. The Backward and Strafe movements have significant negative effects (Coef. = -10.142, $p < 0.001$ and Coef. = -16.525, $p < 0.001$, respectively). The interaction terms and the effect of the Dummy agent did not show evidence of significance.

Day-to-day

Variable	Coef.	Std.Err.	z	P>|z|
Intercept	60.569	3.337	18.149	0.000
C(Agent, Sum)[S.Dummy]	1.436	1.060	1.355	0.176
C(Movement, Sum)[S.Backward]	-13.703	2.371	-5.780	0.000
C(Movement, Sum)[S.CurveForward]	14.014	2.371	5.911	0.000
C(Movement, Sum)[S.Forward]	15.131	2.371	6.382	0.000
C(Movement, Sum)[S.Strafe]	-26.186	2.371	-11.046	0.000
C(Movement, Sum)[S.TurnBackward]	1.347	2.371	0.568	0.570
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Backward]	1.631	2.371	0.688	0.492
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.CurveForward]	1.647	2.371	0.695	0.487
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Forward]	-1.803	2.371	-0.760	0.447
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Strafe]	-0.953	2.371	-0.402	0.688
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.TurnBackward]	-0.786	2.371	-0.332	0.740
Group Var	300.405	4.556		

Table 5.6: Mixed Linear Model Summary for Day-to-day

The results show that the intercept is 60.569, with significant positive effects of CurveForward (Coef. = 14.014, $p < 0.001$) and Forward (Coef. = 15.131, $p < 0.001$) movements on

Day-to-day. The Backward and Strafe movements have significant negative effects (Coef. = -13.703, $p < 0.001$ and Coef. = -26.186, $p < 0.001$, respectively). The interaction terms and the effect of the Dummy agent did not have evidence of significance.

Efficiency

Variable	Coef.	Std.Err.	z	P>|z|
Intercept	69.492	3.065	22.670	0.000
C(Agent, Sum)[S.Dummy]	1.492	0.979	1.523	0.128
C(Movement, Sum)[S.Backward]	-4.825	2.190	-2.203	0.028
C(Movement, Sum)[S.CurveForward]	6.208	2.190	2.835	0.005
C(Movement, Sum)[S.Forward]	7.608	2.190	3.474	0.001
C(Movement, Sum)[S.Strafe]	-13.158	2.190	-6.009	0.000
C(Movement, Sum)[S.TurnBackward]	0.108	2.190	0.049	0.961
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Backward]	0.608	2.190	0.278	0.781
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.CurveForward]	0.875	2.190	0.400	0.689
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Forward]	-2.825	2.190	-1.290	0.197
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Strafe]	-1.625	2.190	-0.742	0.458
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.TurnBackward]	0.342	2.190	0.156	0.876
Group Var	253.126	4.161		

Table 5.7: Mixed Linear Model Summary for Efficiency

The results show that the intercept is 69.492, with significant positive effects of CurveForward (Coef. = 6.208, $p = 0.005$) and Forward (Coef. = 7.608, $p = 0.001$) movements on Efficiency. The Backward and Strafe movements have significant negative effects (Coef. = -4.825, $p = 0.028$ and Coef. = -13.158, $p < 0.001$, respectively). The interaction terms and the effect of the Dummy agent did not have evidence of significance.

Movement Realism

Variable	Coef.	Std.Err.	z	P>|z|
Intercept	69.475	3.098	22.426	0.000
C(Agent, Sum)[S.Dummy]	2.175	0.913	2.382	0.017
C(Movement, Sum)[S.Backward]	-7.758	2.042	-3.800	0.000
C(Movement, Sum)[S.CurveForward]	5.775	2.042	2.829	0.005
C(Movement, Sum)[S.Forward]	5.775	2.042	2.829	0.005
C(Movement, Sum)[S.Strafe]	-9.642	2.042	-4.723	0.000
C(Movement, Sum)[S.TurnBackward]	3.642	2.042	1.784	0.074
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Backward]	1.342	2.042	0.657	0.511
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.CurveForward]	2.342	2.042	1.147	0.251
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Forward]	-3.058	2.042	-1.498	0.134
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Strafe]	-1.075	2.042	-0.527	0.599
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.TurnBackward]	0.275	2.042	0.135	0.893
Group Var	262.906	4.559		

Table 5.8: Mixed Linear Model Summary for Movement Realism

The results show that the intercept is 69.475, with significant positive effects of the Dummy agent (Coef. = 2.175, p = 0.017), and positive effects of CurveForward (Coef. = 5.775, p = 0.005) and Forward (Coef. = 5.775, p = 0.005) movements on Movement Realism. The Backward and Strafe movements have significant negative effects (Coef. = -7.758, $p < 0.001$ and Coef. = -9.642, $p < 0.001$, respectively). The interaction terms did not have evidence of significance.

Agent Realism

Variable	Coef.	Std.Err.	z	P>|z|
Intercept	54.919	3.930	13.973	0.000
C(Agent, Sum)[S.Dummy]	-11.581	1.108	-10.449	0.000
C(Movement, Sum)[S.Backward]	-2.986	2.478	-1.205	0.228
C(Movement, Sum)[S.CurveForward]	4.164	2.478	1.680	0.093
C(Movement, Sum)[S.Forward]	3.564	2.478	1.438	0.150
C(Movement, Sum)[S.Strafe]	-6.169	2.478	-2.489	0.013
C(Movement, Sum)[S.TurnBackward]	2.064	2.478	0.833	0.405
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Backward]	1.181	2.478	0.476	0.634
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.CurveForward]	0.697	2.478	0.281	0.778
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Forward]	-0.036	2.478	-0.015	0.988
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.Strafe]	0.297	2.478	0.120	0.905
C(Agent, Sum)[S.Dummy]:C(Movement, Sum)[S.TurnBackward]	-1.103	2.478	-0.445	0.656
Group Var	426.559	6.045		

Table 5.9: Mixed Linear Model Summary for Agent Realism

The results indicate that the intercept is 54.919, with a significant negative effect of the Dummy agent (Coef. = -11.581, $p < 0.001$) on Agent Realism. The Strafe movement has a significant negative effect (Coef. = -6.169, p = 0.013). The CurveForward movement has a marginally significant positive effect (Coef. = 4.164, p = 0.093). The interaction terms and other movement types did not have evidence of significance.

5.3.5 Summary of Mixed Linear Model Findings

The mixed linear model analysis revealed several key findings regarding the perception of realism in artificial social agents (ASAs). For the Resemblance dimension, significant positive effects were observed for the CurveForward and Forward movements, while Backward and Strafe movements had significant negative effects. The agent type (Dummy vs. Humanoid) and interaction terms were not significant. Similarly, for Day-to-day Realism, CurveForward and Forward movements showed significant positive effects, whereas Backward and Strafe movements had significant negative impacts, with no significant effects from the agent type or interaction terms. Efficiency was positively influenced by CurveForward and Forward movements, and negatively impacted by Backward and Strafe movements, with the agent type and interaction terms again not showing significance. In contrast, Movement Realism showed significant positive effects for the Dummy agent, CurveForward, and Forward movements, while Backward and Strafe movements had significant negative effects, with non-significant interaction terms. Finally, for Agent Realism, the Dummy agent and Strafe movement had significant negative effects, whereas CurveForward had a marginally significant positive effect, with other movements and interaction terms being non-significant. These findings from the MLM align well with the ANOVA results, which similarly indicated that movement type significantly affects perceived realism dimensions, while the agent type predominantly impacts Agent Realism. Interaction effects between agent type and movement were not significant in both analyses, reinforcing the consistency and reliability of the conclusions drawn. Notably, TurnForward was used as a reference movement in the MLM analysis.

5.3.6 Correlation Analysis

In this section, we will examine the correlations between five dependent variables: Resemblance, Day-to-day Realism, Efficiency, Movement Realism, and Agent Realism across all movement types. By understanding these relationships, we can gain insights into how participants' perceptions of different aspects of agent realism are interrelated.

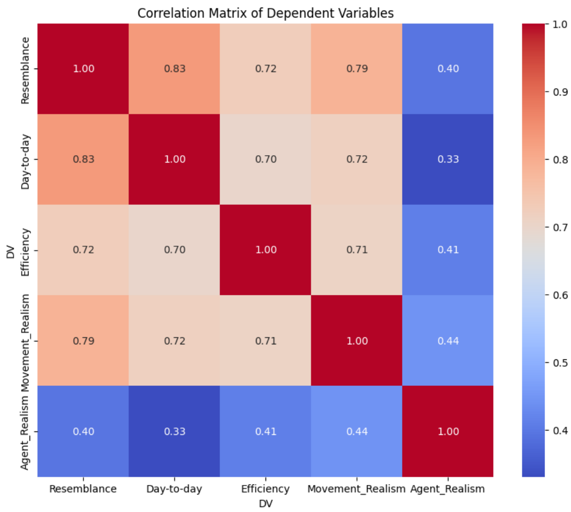


Figure 5.8: Correlation Matrix of Dependent Variables: The heatmap illustrates the strength and direction of the linear relationships between various dependent variables: Resemblance, Day-to-day Realism, Efficiency, Movement Realism, and Agent Realism across all movement types. The color intensity and numerical values indicate the correlation coefficients, ranging from -1 (perfect negative correlation) to 1 (perfect positive correlation).

The correlation matrix presented in figure 5.8 illustrates the relationships between five dependent variables: Resemblance, Day-to-day Realism, Efficiency, Movement Realism, and Agent Realism across all movement types.

Notably, there is a strong positive correlation between Resemblance and Day-to-day Realism (0.832), suggesting that agents perceived as resembling humans are also seen as performing actions common in daily life. Similarly, Resemblance is strongly correlated with Efficiency (0.725) and Movement Realism (0.786), indicating that agents with more human-like movements are also considered more efficient and realistic in their movements.

Day-to-day Realism shows a strong positive correlation with Movement Realism (0.716) and a moderate correlation with Efficiency (0.698), reinforcing the notion that realistic and efficient movements are perceived as typical human behaviours. Efficiency also correlates well with Movement Realism (0.708), demonstrating that these attributes are closely linked in participants' evaluations.

However, Agent Realism exhibits weaker correlations with the other variables. It has the highest correlation with Movement Realism (0.444) and Efficiency (0.410), but its correlations with Resemblance (0.396) and Day-to-day Realism (0.331) are notably lower. This suggests that while Agent Realism is related to the other aspects, it may be influenced by additional factors not captured by the other variables.

Correlation analysis of Pair Plots for Humanoid and Dummy Agents

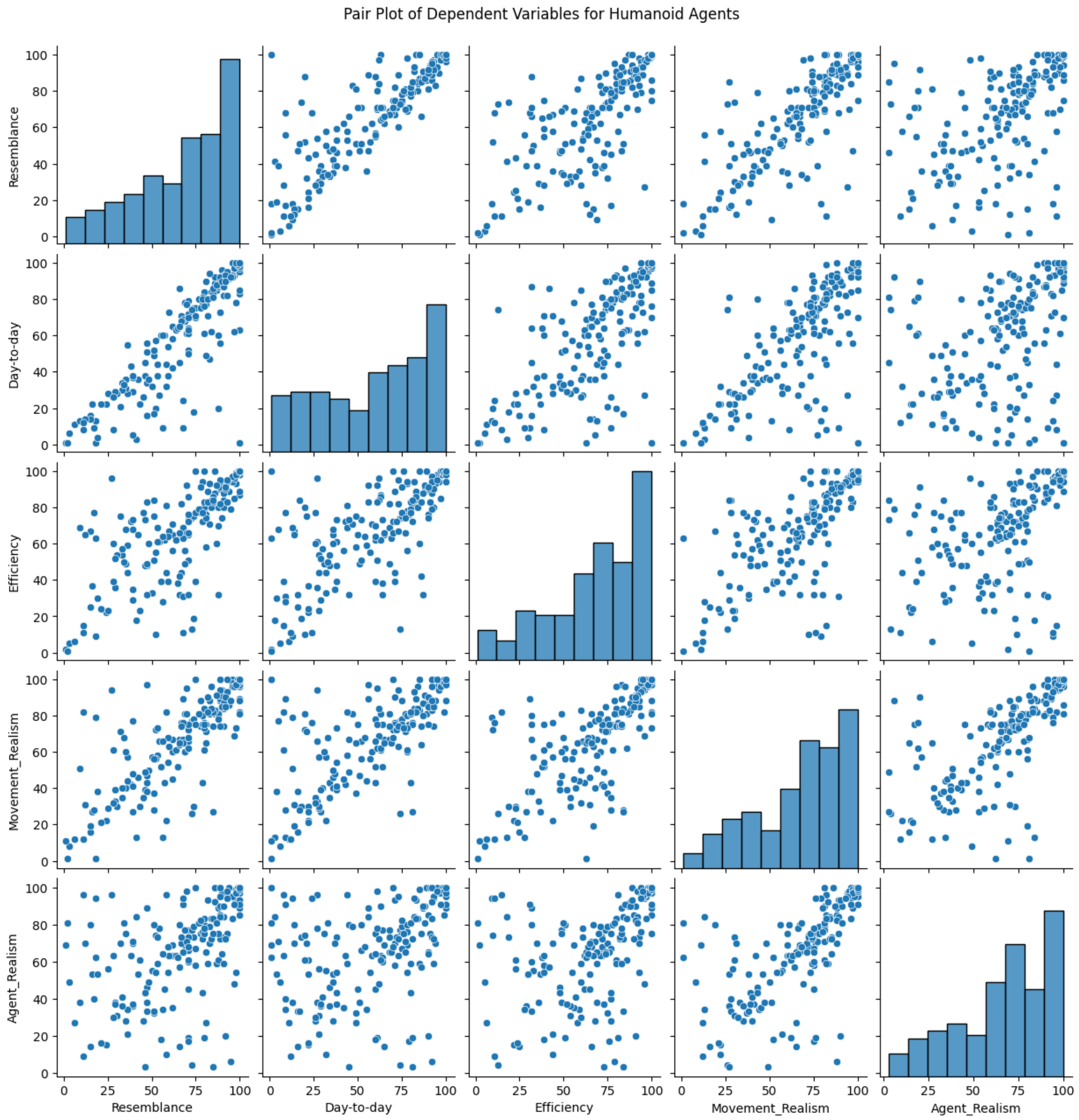


Figure 5.9: Pair plot illustrating the relationships between Resemblance, Day-to-day Realism, Efficiency, Movement Realism, and Agent Realism for Humanoid agents. The diagonal shows each variable's distribution, while off-diagonals show pairwise scatterplots.

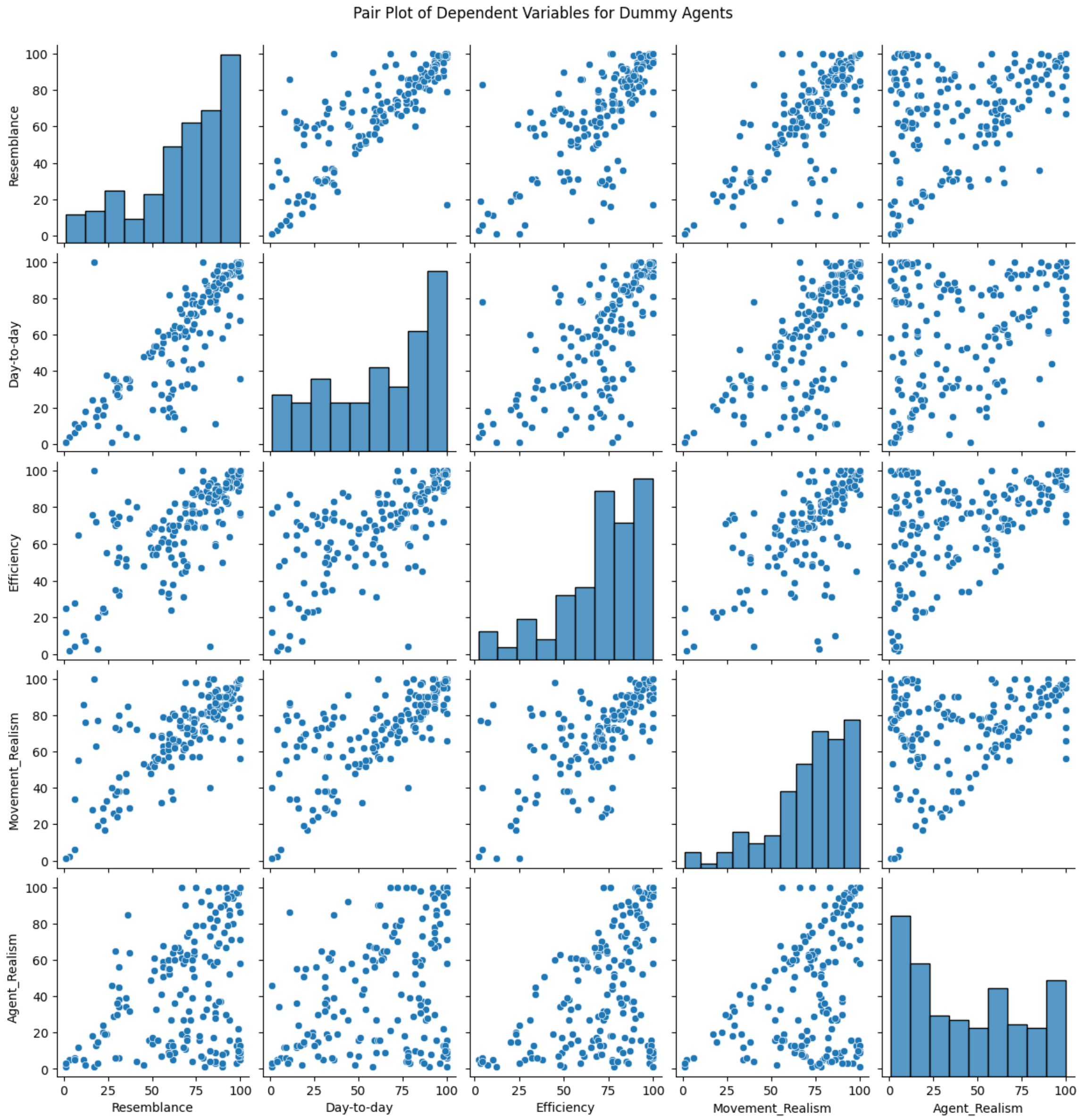


Figure 5.10: Pair plot illustrating the relationships between Resemblance, Day-to-day Realism, Efficiency, Movement Realism, and Agent Realism for Dummy agents. The diagonal shows each variable's distribution, while off-diagonals show pairwise scatterplots.

The pair plots in figure 5.9 and 5.10 provide an additional visual representation of the relationships between the dependent variables for both Humanoid and Dummy agents much the same as figure 5.8. Each plot on the diagonal shows the distribution of scores for a specific variable, summarizing how these scores are spread across participants.

In summary of this section; for both Humanoid and Dummy agents there are strong positive correlations between Resemblance, Day-to-day Realism, Efficiency, and Movement Realism. This indicates that higher scores in one dimension tend to be associated with higher scores in others. It also shows however that Overall Agent Realism isn't fully dependent on movement, as this has much lower correlation scores with the other variables. It is also important to note that the differences between the pair plots for Humanoid and Dummy agents are not substantial, highlighting that the aesthetic look of the agent (whether Humanoid or Dummy) is not as critical as the realism of the movements. This suggests that participants' perceptions of realism are more heavily influenced by how the agents move rather than their appearance. These findings reinforce the importance of movement realism in the overall perception of agent realism, aligning with previous analyses.

5.4 Key Contributions

- **Empirical Validation of Micro-Movement Strategies:**
  - This study empirically validated specific micro-movement strategies, such as "CurveForward," "Forward," "Backward," and "Strafe," confirming their impact on perceived realism in artificial social agents (ASAs).
- **Insights into User Perception of Realism:**
  - Provided valuable insights into how users perceive the realism, efficiency, and naturalness of different micro-movement strategies, highlighting the importance of specific movements in enhancing ASA realism.
- **Impact of Movement on Perceived Realism Dimensions:**
  - Demonstrated significant effects of movement type on perceived realism dimensions, such as resemblance, day-to-day practicality, efficiency, and movement realism, using both ANOVA and mixed linear model analyses.
- **Correlation Analysis of Realism Dimensions:**
  - Conducted correlation analysis revealing strong positive relationships between key realism dimensions (resemblance, day-to-day realism, efficiency, and movement realism), but weaker correlations with overall agent realism.
- **Methodological Rigor in Data Collection and Analysis:**

  - Employed rigorous methodological approaches, including the use of the Gorilla platform for data collection and well-validated questionnaire items from the ASA Questionnaire, ensuring reliability and relevance of measures.

- **Guidance for Future ASA Development:**
  - Provided critical guidance for refining micro-movement strategies, suggesting that movement realism has a greater impact on perceived realism than agent appearance, thus directing future efforts in ASA design.

- **Framework for Future Research:**
  - Established a robust framework for evaluating ASA realism, combining traditional statistical methods with advanced analytical techniques, offering a comprehensive approach for future studies in human-agent interaction.

- **Implications for Artificial Agent Design:**
  - Provided valuable insights for enhancing the realism of artificial agents, emphasizing the importance of integrating validated micro-movement strategies to improve the immersion and functionality of virtual characters and autonomous systems.

5.5 Conclusion

This study aimed to empirically evaluate the perception of realism in the micro-movement strategies of artificial social agents (ASAs). Utilising a structured questionnaire adapted from the Artificial-Social-Agent (ASA) Questionnaire, data was collected from participants via the Gorilla platform. The study focused on several key aspects of movement realism, including perceived resemblance, day-to-day practicality, efficiency, movement realism, and agent realism. This directly addresses the third research question: **What is the effect of the identified micro-movement strategies on the perceived realism of virtual agents?**

The descriptive statistics provided a comprehensive summary of the participants' responses across different video files showcasing various micro-movement strategies. The results indicated significant variability in how different movements and agents were perceived. Generally, movement realism and efficiency were rated higher than agent realism, suggesting that participants found the movements more realistic and efficient compared to the agents themselves. Notably, movements like "Dummy CurveForward" and "Humanoid Forward" received very positive ratings in terms of resemblance, day-to-day practicality, and efficiency, even though they had different agent types.

An ANOVA was conducted to further investigate the main and interaction effects of agent and movement on the response variable. The results revealed that the main effect of the movement factor was statistically significant, indicating that different types of movements have a significant impact on the response variable. However, the agent factor and the interaction effect between agent and movement were not statistically significant, suggesting that the type of agent and the combined effect of agent type and movement type do not significantly influence the response variable beyond their individual effects. These results were confirmed by post-hoc Tukeys HSD tests on the significant variables and factors.

The mixed linear regression analysis provided additional insights into the factors influencing the response variable across different agents, movements, and participants. The analysis revealed significant effects for the movement factors, particularly the CurveForward and Forward movements, which significantly increased the response. The agent factor showed a marginally non-significant effect, indicating a slight decrease in response compared to the overall mean.

The correlation analysis revealed very weak correlations between the key variables. The correlation between response and agent was slightly positive, while the correlation between response and movement was slightly negative. The correlation between agent and movement was effectively zero, indicating no linear relationship between these variables. However, with only 30 participants, our study was underpowered to detect small-to-moderate correlations. In such a small sample, even true correlations around $|r| \approx 0.3$ can easily appear near zero. Future work should use a power analysis (e.g. G*Power) to estimate the sample size needed—likely over 100 participants—to reliably detect correlations in the $r = 0.2$–0.3 range.

Overall, the findings from this study validate the effectiveness and believability of the micro-movement strategies in enhancing the realism of ASAs. The results suggest that while movements are generally perceived as realistic and efficient, there is room for improvement in the representation of agents, moreso in their movements, as the aesthetic of the agent seems to be less important to users. These insights provide critical guidance for refining micro-movement strategies and developing more realistic and believable ASAs.

Chapter 6

Conclusion

6.1 Summary of Findings

This thesis has investigated the importance of micro-movement strategies in enhancing the realism and effectiveness of artificial social agents (ASAs) within virtual environments. By focusing on the nuanced micro-movements and natural navigational behaviours that characterize human locomotion, this research addresses a critical gap in existing literature and contributes significantly to the field of human-computer interaction. Chapter 2 focused on the formalization of micro-movement strategies. This chapter began with a discussion on the hierarchy of navigational realism, positioning micro-movements as a critical component for enhancing ASA realism. The detailed analysis of human movement data emphasized the complexity of human navigational behaviour and the need for more nuanced data that captures orientation and micro-movements during locomotion. A comprehensive framework for categorizing and describing micro-movements was proposed, identifying six key micro-movement behaviours. These findings underscored the necessity of incorporating micro-movements into ASA navigation systems to improve their believability, social presence, and overall user experience. Chapter 3 delved into recording human locomotion data in the context of a waypoint-based task. The motivation behind this data collection was explained, particularly its relevance to tasks involving navigation to specific waypoints. Detailed analysis of the recorded data included differential and inferential analysis to identify patterns and correlations in human movement. The application of machine learning techniques to analyse and predict human locomotion patterns was explored, providing insights into the development of more sophisticated ASA control systems. Key findings included the identification of significant correlations between behavioural indices and the successful application of a Recurrent Neural Network (RNN) model, which significantly improved predictive accuracy. Chapter 4 utilised a structured questionnaire adapted from the Artificial-Social-Agent (ASA) Questionnaire, to collect data from participants via the Gorilla platform. This chapter focused on evaluating several key aspects of movement realism, including perceived resemblance, day-to-day practicality, efficiency, movement realism, and agent realism. Key findings indicated significant variability in the perception of different movements and agents. Movements were generally rated higher for realism and efficiency compared to agent realism, with "D_CurveForward" and "H_Forward" being particularly well-received. The nonparametric analyses revealed that the movement factor exerts a significant effect on the response variable, as evidenced by the Friedman tests conducted for each perceived realism measure. In contrast, neither the agent factor nor the interaction between agent type and movement type reached significance. Subsequent pairwise Wilcoxon signed-rank tests (with Bonferroni adjustments) confirmed that specific movement strategies—particularly CurveForward and Forward—yielded significantly different perceptions compared to other strategies. Complementing these findings, the mixed linear regression analyses further underscored significant positive effects for CurveForward and Forward movements on perceived realism, while the agent factor contributed little additional variance. Moreover, the correlation analyses indicated only very weak linear relationships among the key variables. Together, these results validate the effectiveness of the micro-movement strategies in enhancing the realism of Artificial Social Agents (ASAs) and highlight potential avenues for improving agent representation.

6.2 Research Questions Revisited

In revisiting the research questions posed at the outset of this thesis, each has been addressed through the studies and analyses presented in the preceding chapters. The findings provide insights into the structures and strategies that enhance the realism of virtual agent movements, the prevalence of specific micro-movement strategies in human navigation, and the perception of these strategies when implemented in virtual agents.

What factors increase the realism of virtual agent movements?

This was addressed in Chapter 3, where the research identified and formalized six key micro-movement strategies: linear walk, backwards walk, strafe walk, curved walk, rotate in place, and rotate while walking. A comprehensive framework for categorizing and describing these micro-movements was developed, emphasizing their importance in enhancing navigational realism in ASAs.

Which movement strategies are most commonly used by humans during navigation?

This was explored in Chapter 4, where detailed recording and analysis of human locomotion data were conducted in a waypoint-based task. The study identified prevalent movement patterns and their contexts, using machine learning techniques to analyse and predict these patterns, thus providing empirical data on common micro-movements in human navigation.

What is the effect of the identified micro-movement strategies on the perceived realism of virtual agents?

This was the focus of Chapter 5. A structured questionnaire was used to gather participant feedback on the realism of various micro-movement strategies implemented in virtual agents. The findings from the questionnaire validated the effectiveness and believability of these strategies, with participants generally rating movement realism and efficiency higher than agent realism.

6.3 Contributions Revisited

This thesis has made significant strides in the understanding and formalization of human micro-movement strategies, with implications for enhancing the realism of artificial social agents (ASAs) in virtual environments. The primary contributions can be revisited under several key thematic areas, reflecting the comprehensive nature of this research and its potential to inform future studies.

6.3.1 Formalization and Classification of Micro-Movement Strategies

- **Identification and Structured Analysis**: This research has systematically identified and classified micro-movement behaviours crucial for realistic human navigation. By formalizing these behaviours into six fundamental categories—linear walk, backwards walk, strafe walk, curved walk, rotate in place, and rotate while walking—this work provides a structured framework for understanding and describing the subtle movements that humans make during navigation.
- **Hierarchical Framework**: The hierarchical framework developed for these micro-movements positions them within the broader context of navigational realism, emphasizing their critical role in enhancing the believability of ASAs. This framework serves as a foundation for future research aimed at further refining and expanding the repertoire of micro-movement behaviours in ASAs.

6.3.2 Empirical Study of Human Movement

- **Data Collection and Analysis**: The detailed recording and analysis of human locomotion data in a waypoint-based task have yielded valuable insights into the patterns and correlations in human movement. By employing advanced motion capture techniques and comprehensive data analysis, this research provides a robust methodology for studying human movement in detail.
- **behavioural Correlations and Cluster Analysis**: Statistical analyses revealed significant correlations between key behavioural indices, such as Onset Index, Stop Index From End, and Angle Start Index. The cluster analysis further classified participant behaviours into distinct patterns, highlighting the diversity and complexity of human navigational strategies.

6.3.3 Framework for Enhancing ASA Realism

- **Application of Machine Learning**: The use of Recurrent Neural Networks (RNNs) to analyse and predict human locomotion patterns demonstrated substantial improvements in predictive accuracy. This integration of machine learning techniques with traditional statistical methods underscores the potential for developing more sophisticated and responsive ASA control systems.

- **Recommendations for ASA Design**: The findings provide valuable recommendations for the design of ASAs, emphasizing the importance of incorporating validated micro-movement strategies to improve the realism and immersion of virtual characters and autonomous systems. This has direct implications for applications in virtual training, education, and therapy.

6.3.4 Perception of Realism in ASAs

- **User Studies on Realism**: The user studies conducted in Chapter 4 provided empirical evidence on how participants perceive the realism of various micro-movement strategies in ASAs. The results indicated that while the movements were generally perceived as realistic and efficient, the agents themselves were often rated lower in terms of realism. This suggests that further improvements are needed in the overall representation of agents to enhance their believability. The insights gained from these user studies are critical for refining micro-movement strategies and improving the design of ASAs to meet user expectations.

6.3.5 Implications for Virtual Environments

- **Enhanced Social Presence and User Experience**: By improving the believability and immersion of ASAs, this research contributes to the development of more engaging and effective virtual environments. The detailed understanding of human micro-movement strategies allows for the creation of ASAs that can interact more naturally and intuitively with human users, enhancing the overall user experience.

- **Foundation for Future Research**: This thesis identifies several research gaps, particularly in the formalization and comprehensive study of micro-movements in ASAs. By addressing these gaps, it provides a clear direction for future research aimed at further enhancing the realism of virtual human interactions and the effectiveness of ASAs in various applications.

6.4 Limitations

While this study has made significant strides in understanding and replicating human micro-movement strategies in ASAs, there are several limitations to consider:

- **Data Collection Constraints**: The accuracy of the motion capture and tracking systems used may vary, potentially introducing noise or occasional dropout in the skeletal data. This measurement error can obscure subtle micro-movements, leading to under- or over-estimation of onset, turn, and stop indices, and thus affecting the internal validity of our findings.

- **Sample Size**: The user studies conducted involved a limited number of participants, which reduces statistical power and makes it harder to detect small-to-moderate effects. Consequently, some true movement patterns or perceived realism differences may have gone undetected, limiting the generalizability of our results to broader populations.

- **Technological Limitations**: Implementing advanced movement strategies in ASAs in real time is constrained by current hardware and computational resources. Simplifications or lower sampling rates required for performance may smooth out fine-grained behaviours, reducing ecological validity when agents operate in live, interactive environments.

Implications for Validity and Future Work Each of these limitations carries implications for the study's validity. Measurement noise can bias the estimation of micro-movement parameters, while a small sample size increases the risk of both TypeI and TypeII errors. Technological constraints may prevent a full realization of the movement strategies in practical ASA systems. To address these concerns, future research should:

- Use higher-precision capture systems and multi-sensor fusion to reduce data noise and improve the detection of subtle movements.

- Recruit larger and more diverse participant samples—guided by formal power analyses—to bolster statistical robustness and external validity.

- Optimize algorithms and leverage GPU or edge-computing solutions to implement richer movement strategies without sacrificing real-time performance, thereby enhancing ecological validity in deployed ASAs.

6.5 Future Research Directions

The investigation into micro-movement strategies and the realism of artificial social agents (ASAs) within virtual environments has yielded significant insights. However, there are several avenues for future research that can expand on these findings, address existing gaps, and explore new frontiers in the field.

1. **Advanced Integration of Psychological Theories and Human-ASA Interaction**

   The current research has laid a foundation by integrating proxemics, social cues, and psychological theories into the design and function of ASAs. Future research could further explore these areas by delving deeper into the cognitive and emotional processes that govern human interactions with ASAs. This could include more sophisticated modelling of human emotional responses, cognitive load, and theory of mind (ToM) in ASAs, potentially enhancing their ability to engage with users in even more nuanced and human-like ways. Studies could investigate how these psychological theories can be implemented in real-time interaction scenarios, thus providing more dynamic and adaptive ASA behaviours.

2. **Enhancing Realism through Machine Learning and AI**

   While this thesis has explored the application of Recurrent Neural Networks (RNNs) and other machine learning techniques in enhancing movement realism, future research could focus on the development and testing of more advanced AI models. For instance, Generative Adversarial Networks (GANs) could be explored for creating even more lifelike movement patterns and behaviours in ASAs. Additionally, research could examine the use of deep reinforcement learning for improving the adaptability and autonomy of ASAs, allowing them to learn and refine their movement strategies based on continuous interaction with their environment and users.

3. **Cross-Cultural Adaptation of ASA behaviour**

   The current research emphasizes the importance of cultural differences in proxemics and interpersonal distance. Future studies should explore how ASAs can be designed to adapt to different cultural norms automatically. This could involve developing algorithms that allow ASAs to recognize cultural cues in real-time and adjust their behaviours accordingly, ensuring that interactions are culturally appropriate and respectful. Cross-cultural studies involving diverse user groups could be conducted to validate the effectiveness of these adaptive behaviours.

4. **Ethical Considerations and Privacy Concerns**
   As ASAs become more advanced and integrated into daily life, the ethical implications of their use will become increasingly important. Future research should explore the ethical boundaries of ASA interaction, particularly in sensitive areas such as healthcare, education, and law enforcement. This could include the development of ethical guidelines for the design and deployment of ASAs, as well as studies on user trust, consent, and privacy. Investigating the potential for bias in AI-driven ASAs and ensuring that these systems operate transparently and fairly should be key priorities.

5. **Longitudinal Studies on User Interaction and Engagement**
   While this thesis has provided valuable insights into the immediate perceptions of realism and engagement, there is a need for longitudinal studies that explore how these perceptions evolve over time. Future research could involve long-term user studies that track how interactions with ASAs influence user behaviour, satisfaction, and emotional well-being over extended periods. These studies could also investigate the long-term impact of ASAs on social relationships, work efficiency, and learning outcomes.

6. **Expanding the Application Domains of ASAs**
   The findings of this research have broad implications across multiple domains, including education, healthcare, and social robotics. Future research could explore new and emerging application areas for ASAs, such as mental health support, personalized education, and virtual team collaboration. Studies could also examine how ASAs can be integrated into new technologies, such as augmented reality (AR) and mixed reality (MR), to create more immersive and interactive experiences.

7. **Real-Time Adaptation and Context-Aware behaviours**
   Developing ASAs that can adapt in real-time to changes in their environment and the behaviour of users is a critical next step. Future research could focus on creating context-aware systems that enable ASAs to recognize and respond to complex environmental cues, such as changes in user mood or shifts in group dynamics. This could

involve the integration of advanced sensors and real-time data processing techniques, allowing ASAs to adjust their behaviours dynamically to maintain engagement and realism.

8. **Improving Data Collection and Analysis Techniques**
   The methodologies for data collection and analysis in this research have been robust, but there is always room for improvement. Future studies could explore new technologies for capturing more detailed and comprehensive data on human movement and interaction, such as advanced motion capture systems or wearable sensors. Additionally, the development of more sophisticated data analysis techniques, such as machine learning-based pattern recognition, could enhance the accuracy and depth of insights gained from movement data.

9. **Collaboration with Interdisciplinary Fields**
   Finally, the continued advancement of ASA realism will benefit from collaboration across multiple disciplines, including psychology, neuroscience, computer science, and design. Future research should seek to integrate insights and methods from these fields to create more holistic and comprehensive models of human behaviour and ASA interaction. Interdisciplinary projects that combine expertise in AI, human-computer interaction, and social sciences could lead to groundbreaking innovations in the development of lifelike and socially intelligent ASAs.

6.6 Final Remarks

As this research draws to a close, it is essential to reflect on the journey undertaken and the insights gained. This thesis has explored the intricacies of micro-movement strategies and the realism of artificial social agents (ASAs) within virtual environments, contributing to the growing body of knowledge in this field. By integrating psychological theories, machine learning techniques, and cultural considerations, this work has sought to advance our understanding of how ASAs can more closely mimic human behaviour, thereby enhancing user interaction and engagement.

The findings presented in this thesis offer valuable contributions to both academia and industry. The integration of proxemics and social cues into ASA design has been shown to significantly improve the perceived realism and effectiveness of these agents in various applications. Moreover, the exploration of machine learning techniques, such as Recurrent Neural Networks (RNNs), has provided a solid foundation for future advancements in the field of human movement modelling.

However, it is important to acknowledge the limitations of this research. While the methodologies employed have been robust, the complexity of human behaviour means that there are still many aspects of ASA interaction that require further investigation. The reliance on specific cultural contexts, the challenges in achieving real-time adaptability, and the need for more sophisticated ethical frameworks are areas that warrant continued exploration.

The broader implications of this work extend beyond the immediate applications of ASAs. As virtual environments become more prevalent in education, healthcare, and social interaction, the principles and models developed in this research have the potential to influence a wide range of technologies and platforms. By fostering more natural and human-like interactions, this research contributes to the ongoing effort to create digital agents that are not only functional but also socially and culturally aware.

In conclusion, this thesis has made significant strides in enhancing the realism and effectiveness of ASAs within virtual environments. While much has been achieved, the field remains dynamic, with many opportunities for further innovation and discovery.

List of References

Abro, A. H., Manzoor, A., Tabatabaei, S. A., & Treur, J. (2015). A computational cognitive model integrating different emotion regulation strategies [6th Annual International Conference on Biologically Inspired Cognitive Architectures, BICA 2015, 6-8 November Lyon, France]. *Procedia Computer Science*, *71*, 157–168. https://doi.org/https://doi.org/10.1016/j.procs.2015.12.187

Adkins, D. L., et al. (2006). Motor training induces experience-specific patterns of plasticity across motor cortex and spinal cord. *Journal of Neurophysiology*, *96*(4), 1809–1818.

Ahrens, J. P., Istipliler, B., Isaak, A., & Steininger, D. M. (2019). The star citizen phenomenon & the "ultimate dream management" technique in crowdfunding. *40th International Conference on Information Systems, ICIS 2019*.

Amadou, N., Haque, K. I., & Yumak, Z. (2023). Effect of appearance and animation realism on the perception of emotionally expressive virtual humans. *Proceedings of the 2023 Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3570945.3607307

Animal Crossing World (@ACWorldBlog). (2020, March 4). *Screenshot of animal crossing character* [Accessed: 2025-05-07]. https://x.com/ACWorldBlog/status/1223736337452298240

Anthes, C., Garcia-Hernandez, R. J., Wiedemann, M., & Kranzlmüller, D. (2016). State of the art of virtual reality technology. *IEEE Aerospace Conference*. https://doi.org/10.1109/AERO.2016.7500674

Bailenson, J. N., Blascovich, J., Beall, A. C., & Loomis, J. M. (2003). Interpersonal distance in immersive virtual environments. *Personality and Social Psychology Bulletin*, *29*(7), 819–833.

Bailenson, J. N., Blascovich, J., & Guadagno, R. E. (2008). Self-representations in immersive virtual environments. *Journal of Applied Social Psychology*, *38*(11), 2673–2690. https://doi.org/https://doi.org/10.1111/j.1559-1816.2008.00409.x

Bartle, R. A. (2004). Designing Virtual Worlds.

Bartneck, C., Kulic, D., Croft, E., & Zoghbi, S. (2007). Measurement instruments for the anthropomorphism, animacy, likeability, perceived intelligence, and perceived safety of robots. *International journal of social robotics*, *1*(1), 71–81.

Baylor, A., & Kim, Y. (2004). Pedagogical agent design: The impact of agent realism, gender, ethnicity, and instructional role. *3220*, 592–603. https://doi.org/10.1007/978-3-540-30139-4_56

Bernardet, U., Kanq, S. H., Feng, A. W., DiPaola, S., & Shapiro, A. (2019). Speech breathing in virtual humans: An interactive model and empirical study. *2019 IEEE Virtual Humans and Crowds for Immersive Environments (VHCIE)*, 1–9. https://api.semanticscholar.org/CorpusID:155094886

Besset, D. H. (2015). *Object-oriented implementation of numerical methods: An introduction with smalltalk* [Maintained by Stéphane Ducasse and Serge Stinckwich]. Square Bracket Associates. https://files.pharo.org/books-pdfs/numerical-methods/2015-NumericalMethods-EN.pdf

Bhanu, A., Sharma, H., Piratla, K., & Madathil, K. C. (2022). Application of augmented reality for remote collaborative work in architecture, engineering, and construction – a systematic review. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, *66*(1), 1829–1833. https://doi.org/10.1177/1071181322661167

Bickmore, T. W., Pfeifer, L. M., & Paasche-Orlow, M. K. (2009). Using computer agents to explain medical documents to patients with low health literacy. *Patient Education and Counseling*, *75*(3), 315–320.

Bickmore, T. W., & Picard, R. W. (2005a). Establishing and maintaining long-term human–computer relationships. *ACM Transactions on Computer–Human Interaction*, *12*(2), 293–327. https://doi.org/10.1145/1067860.1067867

Bickmore, T. W., & Picard, R. W. (2005b). Establishing and maintaining long-term human-computer relationships. *ACM Transactions on Computer-Human Interaction (TOCHI)*, *12*(2), 293–327.

Biocca, F., & Delaney, B. (1995). Immersive virtual reality technology [(Reprinted in modified form from "Journal of Communication," Autumn 1992)]. In F. Biocca & M. R. Levy (Eds.), *Communication in the age of virtual reality* (pp. 57–124). Lawrence Erlbaum Associates, Inc.

Biocca, F., Harms, C., & Burgoon, J. (2003). Towards a more robust theory and measure of social presence: Review and suggested criteria. *Presence*, *12*, 456–480. https://doi.org/10.1162/105474603322761270

Bishop, C. M. (2006). *Pattern recognition and machine learning*. Springer.

Blascovich, J., & Bailenson, J. (2011). *Infinite reality: Avatars, eternal life, new worlds, and the dawn of the virtual revolution*. William Morrow.

Blascovich, J., Loomis, J., Beall, A., Swinth, K., Hoyt, C., & Bailenson, J. (2002). Immersive virtual environment technology as a methodological tool for social psychology. *Psychol. Inq*, *13*.

Borenstein, J., & Arkin, R. (2015). Robotic nudges: The ethics of engineering a more socially just human being. *Science and engineering ethics*, *22*. https://doi.org/10.1007/s11948-015-9636-2

Boucaud, F., Tafiani, Q., Pelachaud, C., & Thouvenin, I. (2019). Social touch in human-agent interactions in an immersive virtual environment. *International Conference on Human-Computer Interaction*. https://doi.org/10.5220/0007397001290136

Breazeal, C. (2003). Emotion and sociable humanoid robots. *International journal of human-computer studies*, *59*(1-2), 119–155.

Brilli, E., Birkenkampf, P., Laich, L., & Mariani, R. (2021). Deep reinforcement learning for end-to-end vehicle navigation using radar sensor data. *Journal of Intelligent & Robotic Systems*, *101*(3), 1–16.

Broadbent, E., Stafford, R., & Macdonald, B. (2009). Acceptance of healthcare robots for the older population: Review and future directions. *I. J. Social Robotics*, *1*, 319–330. https://doi.org/10.1007/s12369-009-0030-6

Bulu, S. T. (2012). Place presence, social presence, co-presence, and satisfaction in virtual worlds. *Computers & Education*, *58*(1), 154–161.

Burgoon, J. K., & Kendon, A. (1992). Conducting Interaction: Patterns of Behavior in Focused Encounters. *Contemporary Sociology*. https://doi.org/10.2307/2075490

Castermans, T., & Duvinage, M. (2013). Corticomuscular coherence revealed during treadmill walking: Further evidence of supraspinal control in human locomotion. *The Journal of Physiology*. https://doi.org/10.1113/JPHYSIOL.2012.247593

Cha, I., Kim, S.-I., Hong, H., Yoo, H., & Lim, Y.-k. (2021). Exploring the use of a voice-based conversational agent to empower adolescents with autism spectrum disorder. *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3411764.3445116

Chalmers, A., Debattista, K., & Ramic-Brkic, B. (2009). Towards high-fidelity multi-sensory virtual environments. *The Visual Computer*, *25*(2), 179–190. https://doi.org/10.1007/s00371-009-0389-2

Chang, C.-F., Shih, K.-S., Wang, T.-M., Huang, C.-H., Huang, S.-C., & Lu, T.-W. (2012). Correlations between heelstrike impulsive loading and joint kinematics of the lower extremities during normal level walking. *Journal of Mechanics*. https://doi.org/10.1017/JMECH.2012.37

Dautenhahn, K. (2007). Socially intelligent robots: Dimensions of human-robot interaction. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *362*(1480), 679–704.

Davison, A. K., Lansley, C., Costen, N., Tan, K., & Yap, M. H. (2018). SAMM: A Spontaneous Micro-Facial Movement Dataset. *IEEE Transactions on Affective Computing*. https://doi.org/10.1109/TAFFC.2016.2573832

de Graaf, M., Ben Allouch, S., & van Dijk, J. (2016). Long-term acceptance of social robots in domestic environments: Insights from a user's perspective [2016 AAAI Spring Symposium on Enabling Computing Research in Socially Intelligent Human-Robot Interaction ; Conference date: 21-03-2016 Through 23-03-2016]. *The 2016 AAAI Spring Symposium Series*, 96–103.

Djerroud, H., & Ali-Chérif, A. (2021). VICA: A vicarious cognitive architecture environment model for navigation among movable obstacles. *ICAART 2021 - Proceedings of the 13th International Conference on Agents and Artificial Intelligence*, *2*(Icaart), 298–305. https://doi.org/10.5220/0010269602980305

England, E. M., & Petro, K. D. (1998). Middle school students' perceptions of peer groups relative judgments about group characteristics. *Journal of Early Adolescence*. https://doi.org/10.1177/0272431698018004002

Evers, E., de Vries, H., Spruijt, B. M., & Sterck, E. H. M. (2014). The emo-model: An agent-based model of primate social behavior regulated by two emotional dimensions, anxiety-fear and satisfaction-like. *PLOS ONE*, *9*(2), 1–25. https://doi.org/10.1371/journal.pone.0087955

Fitrianie, S., Bruijnes, M., Li, F., Abdulrahman, A., & Brinkman, W.-P. (2022). The artificial-social-agent questionnaire: Establishing the long and short questionnaire versions. *Proceedings of the 22nd ACM International Conference on Intelligent Virtual Agents*. https://doi.org/10.1145/3514197.3549612

Fong, T., Nourbakhsh, I., & Dautenhahn, K. (2003). A survey of socially interactive robots. *Robotics and Autonomous Systems*, *42*(3-4), 143–166.

Friedman, B., & Hendry, D. G. (2019, May). *Value Sensitive Design: Shaping Technology with Moral Imagination*. The MIT Press. https://doi.org/10.7551/mitpress/7585.001.0001

Gayle, R., & Manocha, D. (2008). Navigating virtual agents in online virtual worlds. *Proceedings of the 13th International Symposium on 3D Web Technology*, 53–56. https://doi.org/10.1145/1394209.1394223

Ghazali, A. S., Ham, J., Barakova, E., & Markopoulos, P. (2019). Assessing the effect of persuasive robots interactive social cues on users' psychological reactance, liking, trusting beliefs and compliance. *Advanced Robotics*. https://doi.org/10.1080/01691864.2019.1589570

Gockley, R., Forlizzi, J., & Simmons, R. (2005). Designing robots for long-term social interaction. *2005 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 1338–1343.

Gong, L. (2008). How social is social responses to computers? the function of the degree of anthropomorphism in computer representations [Including the Special Issue: Integration of Human Factors in Networked Computing]. *Computers in Human Behavior*, *24*(4), 1494–1509. https://doi.org/https://doi.org/10.1016/j.chb.2007.05.007

Gratch, J., Rickel, J., Andre, E., Cassell, J., Petajan, E., & Badler, N. (2002). Creating Interactive Virtual Humans: Some Assembly Required. *IEEE Intelligent Systems*. https://doi.org/10.1109/MIS.2002.1024753

Guadagno, R., Blascovich, J., Bailenson, J., & McCall, C. (2007). Virtual humans and persuasion: The effects of agency and behavioral realism. *Media Psychology*, *10*, 1–22. https://doi.org/10.1080/15213260701300865

Guadagno, R., Swinth, K., & Blascovich, J. (2011). Social evaluations of embodied agents and avatars. *Computers in Human Behavior*, *27*, 2380–2385. https://doi.org/10.1016/j.chb.2011.07.017

Halilaj, E., Rajagopal, A., Fiterau, M., Hicks, J. L., Hastie, T., & Delp, S. L. (2018). Machine learning in human movement biomechanics: Best practices, common pitfalls, and new opportunities. *Journal of Biomechanics*. https://doi.org/10.1016/J.JBIOMECH.2018.09.009

Hall, E. T. (1966). *The hidden dimension*. Anchor Books.

Hancock, P. A., Billings, D. R., Schaefer, K. E., Chen, J. Y., de Visser, E. J., & Parasuraman, R. (2011). A meta-analysis of factors affecting trust in human–robot interaction. *Human Factors*, *53*(5), 517–527.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning*. Springer.

Hebb, D. O. (1949). *The organization of behavior: A neuropsychological theory*. John Wiley & Sons.

Heerink, M., Krose, B., Wielinga, B., & Evers, V. (2010). Assessing acceptance of assistive social agent technology by older adults: The almere model. *International Journal of Social Robotics*, *2*(4), 361–375.

Helbing, D., & Molnár, P. (1995). Social force model for pedestrian dynamics. *Physical review E*, *51*(5), 4282.

Herrera, F., Oh, S. Y., & Bailenson, J. N. (2020). Effect of behavioral realism on social interactions inside collaborative virtual environments. *Presence: Teleoperators and Virtual Environments*. https://doi.org/10.1162/PRES_A_00324

Hicheur, H., Pham, Q. C., Arechavaleta, G., Laumond, J. P., & Berthoz, A. (2005). The formation of trajectories during goal-oriented locomotion in humans. ii. a maximum smoothness model. *European Journal of Neuroscience*, *22*(4), 871–888.

Holden, M. K. (2005). Virtual environments for motor rehabilitation: Review. *CyberPsychology & Behavior*, *8*(3), 187–211. https://doi.org/10.1089/cpb.2005.8.187

Holt-Lunstad, J., Smith, T. B., Baker, M., Harris, T., & Stephenson, D. (2015). Loneliness and social isolation as risk factors for mortality: A meta-analytic review. *Perspectives on Psychological Science*, *10*(2), 227–237.

Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: A meta-analytic review. *PLOS Medicine*, *7*(7), e1000316.

Jolliffe, I. T. (2011). *Principal component analysis*. Springer.

Jung, Y.-K., & Lindeman, R. W. (2021). Perspective: Does realism improve presence in vr? suggesting a model and metric for vr experience evaluation. *Frontiers in Virtual Reality*, *2*, 693327. https://doi.org/10.3389/frvir.2021.693327

Kagami, S., Mochimaru, M., Ehara, Y., Miyata, N., Nishiwaki, K., Kanade, T., & Inoue, H. (2003). Measurement and comparison of human and humanoid walking. *Proceedings of IEEE International Symposium on Computational Intelligence in Robotics and Automation, CIRA*. https://doi.org/10.1109/CIRA.2003.1222302

Karamouzas, I., Skinner, B., & Guy, S. J. (2017). Universal power law governing pedestrian interactions. *Physical review letters*, *113*(23), 238701.

Khan, A. Y., & Kamal, A. (2010). Exploring reactions to invasion of personal space in university students. *Journal of Behavioural Sciences*. https://typeset.io/papers/exploring-reactions-to-invasion-of-personal-space-in-5bqbh39prd

Kotlarek, J., Lin, I.-C., & Ma, K.-L. (2018). Improving spatial orientation in immersive environments. *Symposium on Spatial User Interaction*. https://doi.org/10.1145/3267782.3267792

Kuffner, J., Chestnutt, J., Kagami, S., Latombe, J. C., Nishiwaki, K., Hodgins, J., LaValle, S., Inaba, M., Yamane, K., & Inoue, H. (2003). Motion planning for digital humans. *Proceedings of IEEE International Symposium on Computational Intelligence in Robotics and Automation, CIRA*, *2*, 912–917. https://doi.org/10.1109/CIRA.2003.1222301

Kulms, P., & Kopp, S. (2016). The effect of embodiment and competence on trust and cooperation in human–agent interaction. In *Intelligent virtual agents* (pp. 107–116). Springer. https://doi.org/10.1007/978-3-319-47665-0_7

Kyrlitsias, C., & Michael-Grigoriou, D. (2022). Social interaction with agents and avatars in immersive virtual environments: A survey. *Frontiers in Virtual Reality*. https://doi.org/10.3389/frvir.2021.786665

Lanier, J. (2017). *Dawn of the new everything: Encounters with reality and virtual reality*. Henry Holt; Company.

Latoschik, M. E., Roth, D., Gall, D., Achenbach, J., Waltemate, T., & Botsch, M. (2017). The effect of avatar realism in immersive social virtual realities. *Proceedings of the ACM Symposium on Virtual Reality Software and Technology, VRST*, *Part F1319*. https://doi.org/10.1145/3139131.3139156

Latoschik, M. E., Wienrich, C., & Botsch, M. (2017). A systematic review on the definition and measurement of virtual reality concepts: Concepts and measures for immersive technologies. *Frontiers in Robotics and AI*, *4*, 25.

LaValle, S. M. (2006). *Planning algorithms*. Cambridge University Press.

Lavigne, G., Gutiérrez, G., McAnally-Salas, L., & Organista, J. S. (2015). Log analysis in a virtual learning environment for engineering students. *RUSC. Universities and Knowledge Society Journal*, *12*(3), 113–128. https://doi.org/http://dx.doi.org/10.7238/rusc.v12i3.2162

LaViola, J. J. (2001). 3d user interfaces for virtual reality and games. *Proceedings of the ACM SIGGRAPH 2001 Courses*, 112–118.

Lee, J., Won, J., & Lee, J. (2018). Crowd simulation by deep reinforcement learning. *Proceedings of the 11th ACM SIGGRAPH Conference on Motion, Interaction and Games*. https://doi.org/10.1145/3274247.3274510

Lele, A. (2013). Virtual reality and its military utility. *Journal of Ambient Intelligence and Humanized Computing*, *4*(1), 17–26. https://doi.org/10.1007/s12652-011-0052-4

Lemoine, B. (2022). Chatbot ai has a mind of its own, google engineer claims. *Axios*. https://www.axios.com/2022/06/13/google-engineer-ai-sentient-lamda-chatbot

Li, R., Van Almkerk, M., Van Waveren, S., Carter, E., & Leite, I. (2019). Comparing Human-Robot Proxemics between Virtual Reality and the Real World. *ACM/IEEE International Conference on Human-Robot Interaction*, *2019-March*, 431–439. https://doi.org/10.1109/HRI.2019.8673116

Lin, X., Liu, Z., Liu, T., & Chai, Y. (2022). A personalized and emotion-based virtual simulation model for pedestrian-vehicle collision avoidance. *Computer Animation and Virtual Worlds*. https://doi.org/10.1002/cav.2089

Liu, P., Glas, D. F., Kanda, T., & Ishiguro, H. (2018). Learning proactive behavior for interactive social robots. *Autonomous Robots*. https://doi.org/10.1007/s10514-017-9671-8

Llorens, R., Noé, E., Naranjo, V., Borrego, A., Latorre, J., & Alcañiz, M. (2015). Tracking systems for virtual rehabilitation: Objective performance vs. subjective experience. *Sensors*. https://doi.org/10.3390/S150306586

Lombard, M., & Ditton, T. (1997). At the Heart of It All: The Concept of Presence. *Journal of Computer-Mediated Communication*, *3*(2), JCMC321. https://doi.org/10.1111/j.1083-6101.1997.tb00072.x

Lu, T.-W., & Chang, C. (2012). Biomechanics of human movement and its clinical applications. *Kaohsiung Journal of Medical Sciences*, *28*(2), S13–S25. https://doi.org/10.1016/J.KJMS.2011.08.004

Luckmann, T. (2008). *Social interaction and communicative construction of personal identity*. Guilford Press.

Maslow, A. H. (1943). A theory of human motivation. *Psychological Review*. https://doi.org/10.1037/h0054346

McNeill Alexander, R. (2002). Energetics and optimization of human walking and running: The 2000 raymond pearl memorial lecture. *American Journal of Human Biology*, *14*(5), 641–648.

Merchant, Z., Goetz, E., Cifuentes, L., Keeney-Kennicutt, W., & Davis, T. (2014). Effectiveness of virtual reality-based instruction on students' learning outcomes in k-12 and higher education: A meta-analysis. *Computers & Education*.

Microsoft Agent Plays Wiki community. (n.d.). *Dr. sbaitso* [Accessed: 2025-05-07]. https://microsoft-agent-plays.fandom.com/wiki/Dr._Sbaitso

Miles, L. K., Lumsden, J., Richardson, M. J., & Neil Macrae, C. (2011). Do birds of a feather move together? group membership and behavioral synchrony. *Experimental brain research*, *211*, 495–503.

Miyawaki, K., & Sano, M. (2008). A virtual agent for a cooking navigation system using augmented reality. In H. Prendinger, J. Lester, & M. Ishizuka (Eds.), *Intelligent virtual agents* (pp. 97–103). Springer Berlin Heidelberg.

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., Graves, A., Riedmiller, M., Fidjeland, A. K., & Ostrovski, G. (2015). Human-level control through deep reinforcement learning. *Nature*, *518*(7540), 529–533.

Mori, M. (1970). The uncanny valley [Original in Japanese, translation by MacDorman & Minato, 2005]. In *Energy* (pp. 33–35, Vol. 7). Energy.

Moussaïd, M., Helbing, D., & Theraulaz, G. (2011). How simple rules determine pedestrian behavior and crowd disasters. *Proceedings of the National Academy of Sciences*, *108*(17), 6884–6888.

Murphy, K. P. (2012). *Machine learning: A probabilistic perspective*. MIT Press.

Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues*, *56*(1), 81–103.

Newn, J., Singh, R., Allison, F., Madumal, P., Velloso, E., & Vetere, F. (2019). Designing interactions with intention-aware gaze-enabled artificial agents. In D. Lamas, F. Loizides, L. Nacke, H. Petrie, M. Winckler, & P. Zaphiris (Eds.), *Human-computer interaction – interact 2019* (pp. 255–281). Springer International Publishing.

Nielsen, J. (1994). *Usability engineering*. Morgan Kaufmann.

Norman, D. (2012). *The design of everyday things: Revised and expanded edition*. Basic Books.

Nowak, K., & Biocca, F. (2003). The effect of the agency and anthropomorphism on users' sense of telepresence, copresence, and social presence in virtual environments. *Presence Teleoperators & Virtual Environments*, *12*, 481–494. https://doi.org/10.1162/105474603322761289

Nowak, K. L., & Fox, J. (2018). Avatars and computer-mediated communication: A review of the definitions, uses, and effects of digital representations. *Review of Communication Research*, *6*, 30–53. https://doi.org/10.12840/issn.2255-4165.2018.06.01.015

Nudo, R. J. (2013). Recovery after brain injury: Mechanisms of neural plasticity and behavioral recovery. *Nature Reviews Neuroscience*, *14*(5), 255–267.

O'Callaghan, S., Singh, S. P. N., Alempijevic, A., & Ramos, F. (2011). Learning navigational maps by observing human motion patterns. *International Conference on Robotics and Automation*. https://doi.org/10.1109/ICRA.2011.5980478

Okada, K., Kojima, M., Nakadai, K., Hirukawa, H., & Inaba, M. (2005). Integrated system software for hrp-2 humanoid. *Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems*, 3207–3212.

Olcay, E., Schuhmann, F., & Lohmann, B. (2020). Collective navigation of a multi-robot system in an unknown environment. *Robotics and Autonomous Systems*, *132*, 103604. https://doi.org/10.1016/j.robot.2020.103604

Onishi, M., Odashima, T., Asano, F., & Luo, Z. (2003). Development of PC-based 3D dynamic human interactive robot simulator. *Proceedings of IEEE International Symposium on Computational Intelligence in Robotics and Automation, CIRA*. https://doi.org/10.1109/CIRA.2003.1222170

Patla, A. E., & Vickers, J. N. (2003). How far ahead do we look when required to step on specific locations in the travel path during locomotion? *Experimental Brain Research*, *148*(1), 133–138. https://doi.org/10.1007/s00221-002-1246-y

Pedica, C., & Vilhjálmsson, H. (2008). Social perception and steering for online avatars. *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, *5208 LNAI*, 104–116. https://doi.org/10.1007/978-3-540-85483-8_11

Pelechano, N., Allbeck, J. M., & Badler, N. I. (2008). Controlling individual agents in high–density crowd simulation. *Proceedings of the 2008 Symposium on Computer Animation*, 99–108.

Pham, H., Kawanishi, M., & Narikiyo, T. (2015). A lle-hmm-based framework for recognizing human gait movement from emg. *International Conference on Robotics and Automation*. https://doi.org/10.1109/ICRA.2015.7139610

Pincus, A. L., Lukowitsky, M. R., Wright, A. G. C., & Eichler, W. C. (2009). The interpersonal nexus of persons, situations, and psychopathology. *Journal of Research in Personality*, *43*(2), 264–265. https://doi.org/10.1016/J.JRP.2008.12.029

Powers, A., Kiesler, S., Fussell, S. R., & Torrey, C. (2007). Comparing a computer agent with a humanoid robot. *Computers in Human Behavior*, *23*(4), 1822–1840.

Premack, D., & Woodruff, G. (1978). Does the chimpanzee have a theory of mind? *Behavioral and brain sciences*, *1*(4), 515–526.

Pütten, A. M. V. D., Krämer, N. C., & Gratch, J. (2009). Who's there? Can a Virtual Agent Really Elicit Social Presence? *Design*, 1–7.

Raees, M., & Ullah, S. (2021). RUN: rational ubiquitous navigation, a model for automated navigation and searching in virtual environments. *Virtual Reality*, *25*(2), 511–521. https://doi.org/10.1007/s10055-020-00468-0

Ramezani, F., Ghasem-Aghaee, N., & Kazemifard, M. (2011). Modeling of emotional-social negotiator agents. *2011 11th International Conference on Intelligent Systems Design and Applications*, 42–46. https://doi.org/10.1109/ISDA.2011.6121628

Reeves, B., & Nass, C. (1996). *The media equation: How people treat computers, television, and new media like real people and places*. Cambridge University Press.

Rickel, J. W., Johnson, W. L., & Lester, J. C. (2000). Animated pedagogical agents: Face-to-face interaction in interactive learning environments. In *Artificial intelligence in education* (pp. 21–30). IOS Press.

Rizzo, A., Requejo, P., Winstein, C., Lange, B., Ragusa, G., Merians, A., Patton, J., Banerjee, P., & Aisen, M. (2011). Virtual reality applications for addressing the needs of those aging with disability. *Studies in health technology and informatics*, *163*, 510–6. https://doi.org/10.3233/978-1-60750-706-2-510

Rodriguez-Criado, D., Bachiller, P., Vogiatzis, G., & Manso, L. J. (2024). Multi-person 3d pose estimation from unlabelled data. *Machine Vision and Applications*, *35*(46), 1–18. https://doi.org/https://doi.org/10.1007/s00138-024-01530-6

Rodriguez-Criado, D., & Manso, L. J. (2020). A skeletal tracking system for real-time motion analysis. *Sensors*, *20*(15), 4085.

Rosenbaum, D. A. (2010). *Human motor control*. Academic Press.

Saberi, M., DiPaola, S., & Bernardet, U. (2021). Expressing personality through non-verbal behaviour in real-time interaction. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.660895

Salem, M., Ziadee, M., & Sakr, M. (2014). Marhaba, how may i help you?: Effects of politeness and culture on robot acceptance and anthropomorphization. *Proceedings of the Human-Robot Interaction Conference*. https://doi.org/10.1145/2559636.2559683

Samperi, K. (2021). Representing and generating maps of large-scale virtual environments for intelligent mobile agents. *Proceedings of the AAAI Conference on Artificial Intelligence and Interactive Digital Entertainment*, *8*(6), 34–36. https://doi.org/10.1609/aiide.v8i6.12488

Schubert, T., Friedmann, F., & Regenbrecht, H. (2001). The experience of presence: Factor analytic insights. *Presence*, *10*, 266–281. https://doi.org/10.1162/105474601300343603

Sharkey, A., & Sharkey, N. (2010). Children, the elderly, and interactive robots: Anthropomorphism and deception in robotics. *IEEE Robotics & Automation Magazine*, *18*(1), 32–38.

Sharp, J., & Bernardet, U. (2023). The missing tip: Lack of micro-movements impairs navigation realism in artificial social agents. *15th International Conference on Agents and Artificial Intelligence*, 380–386. https://doi.org/10.5220/0011798300003393

Sheridan, T. B. (1992). Musings on telepresence and virtual presence. *Presence: Teleoperators & Virtual Environments*, *1*(1), 120–126.

Short, J., Williams, E., & Christie, B. (1976). *The social psychology of telecommunications*. John Wiley & Sons.

Slater, M., & Wilbur, S. (1997). *Framework for immersive virtual environments (five): Speculations on the role of presence in virtual environments*. ACM.

Slater, M. (2009). Place illusion and plausibility can lead to realistic behavior in immersive virtual environments. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *364*(1535), 3549–3557.

Sorokowska, A., Sorokowski, P., Hilpert, P., Cantarero, K., Frackowiak, T., Ahmadi, K., Alghraibeh, A., Aryeetey, R., Bertoni, A., Bettache, K., Blumen, S., Błażejewska, M., Soares Bortolini, T., Butovskaya, M., Castro, F., Cetinkaya, H., Cunha, D., David, D., David, O., & Pierce, J. (2017). Preferred interpersonal distances: A global comparison. *Journal of Cross-Cultural Psychology*, *48*, 002202211769803. https://doi.org/10.1177/0022022117698039

Sparrow, R. (2007). Killer robots. *Journal of Applied Philosophy*, *24*(1), 62–77.

Steuer, J. (2006). Defining Virtual Reality: Dimensions Determining Telepresence. *Journal of Communication*, *42*(4), 73–93. https://doi.org/10.1111/j.1460-2466.1992.tb00812.x

Strait, M., Floerke, V. A., Ju, W., Maddox, K. B., Remedios, J. D., Jung, M. F., & Urry, H. L. (2017). Understanding the uncanny: Both atypical features and category ambiguity provoke aversion toward humanlike robots. *Frontiers in Psychology*. https://doi.org/10.3389/FPSYG.2017.01366

Suo, X., Tang, W., & Li, Z. (2024). Motion capture technology in sports scenarios: A survey. *Sensors*, *24*(9), 2947. https://doi.org/10.3390/s24092947

Sutera, E., Mazzia, V., Salvetti, F., Fantin, G., & Chiaberge, M. (2021). Indoor point-to-point navigation with deep reinforcement learning and ultra-wideband. *ICAART 2021 - Proceedings of the 13th International Conference on Agents and Artificial Intelligence*. https://doi.org/10.5220/0010202600380047

Sutton, R. S., & Barto, A. G. (2018). *Reinforcement learning: An introduction*. MIT Press.

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive science*, *12*(2), 257–285.

Takayama, L., & Pantofaru, C. (2009). Influences on proxemic behaviors in human-robot interaction. *2009 IEEE/RSJ International Conference on Intelligent Robots and Systems*, 5495–5502.

Traum, D., & Rickel, J. (2002). Embodied agents for multi-party dialogue in immersive virtual worlds. *Proceedings of the First International Joint Conference on Autonomous Agents and Multiagent Systems: Part 2*, 766–773. https://doi.org/10.1145/544862.544922

Triandis, H. C. (2004). The many dimensions of culture. *The Academy of Management Executive (1993-2005)*, *18*(1), 88–93. http://www.jstor.org/stable/4166039

Turkle, S. (2011). *Alone together: Why we expect more from technology and less from each other*. Basic Books.

van Luin, J., op den Akker, R., & Nijholt, A. (2001). A dialogue agent for navigation support in virtual reality. *ACM SIGCHI Bulletin*, 117. https://doi.org/10.1145/634133.634138

Vicon. (2020). Vicon motion capture systems. https://www.vicon.com/

Vinayagamoorthy, V., Gillies, M., Steed, A., Tanguy, E., Pan, X., Loscos, C., & Slater, M. (2006). Building Expression into Virtual Characters. In B. Wyvill & A. Wilkie (Eds.), *Eurographics 2006 - state of the art reports*. The Eurographics Association. https://doi.org/10.2312/egst.20061052

Walters, M., Dautenhahn, K., Boekhorst, R., Koay, K., Kaouri, C., Woods, S., Nehaniv, C., Lee, D., & Werry, I. (2005). The influence of subjects' personality traits on personal spatial zones in a human-robot interaction experiment. *2005*, 347–352. https://doi.org/10.1109/ROMAN.2005.1513803

Wang, Y., Dubey, R., Magnenat-Thalmann, N., & Thalmann, D. (2013). An immersive multi-agent system for interactive applications. *Visual Computer*, *29*(5), 323–332. https://doi.org/10.1007/s00371-012-0735-7

Warren, W. H., Kay, B. A., Zosh, W. D., Duchon, A. P., & Sahuc, S. (2001). Optic flow is used to control human walking. *Nature Neuroscience*, *4*(2), 213–216.

Watson, O. M., & Graves, T. D. (1966). Quantitative research in proxemic behavior. *American Anthropologist*, *68*(4), 971–985. https://doi.org/https://doi.org/10.1525/aa.1966.68.4.02a00070

Weber, S., Weibel, D., & Mast, F. W. (2021). How to get there when you are there already? defining presence in virtual reality and the importance of perceived realism. *Frontiers in Psychology*, *12*, 628298. https://doi.org/10.3389/fpsyg.2021.628298

Wenmackers, S., Vanpoucke, D. E., & Douven, I. (2014). Rationality: A social-epistemology perspective. *Frontiers in Psychology*, *5*. https://doi.org/10.3389/fpsyg.2014.00581

Wikiquote contributors. (n.d.). *“sophia (robot)”* [Accessed: 2025-05-07]. https://en.wikiquote.org/wiki/Sophia_(robot)

Wiltermuth, S. S., & Heath, C. (2009). Synchrony and cooperation. *Psychological Science*, *20*(1), 1–5.

Winter, D. A. (1995). Human balance and posture control during standing and walking. *Gait & Posture*, *3*(4), 193–214. https://doi.org/10.1016/0966-6362(96)82849-9

Winter, D. A. (2009). *Biomechanics and motor control of human movement*. John Wiley & Sons.

Witmer, B. G., & Singer, M. J. (1998). Measuring presence in virtual environments: A presence questionnaire. *Presence: Teleoperators & Virtual Environments*, *7*(3), 225–240.

Xie, B., Liu, H., Alghofaili, R., Zhang, Y., Jiang, Y., Lobo, F. D., Li, C., Li, W., Huang, H., Akdere, M., Mousas, C., & Yu, L.-F. (2021). A review on virtual reality skill training applications. *Frontiers in Virtual Reality*, *2*. https://doi.org/10.3389/frvir.2021.645153

Yee, N., & Bailenson, J. (2007). The proteus effect: The effect of transformed self-representation on behavior. *Human Communication Research*, *33*, 271–290. https://doi.org/10.1111/j.1468-2958.2007.00299.x

Zarsky, T. (2016). The trouble with algorithmic decisions: An analytic road map to examine efficiency and fairness in automated and opaque decision making. *Science, Technology, & Human Values*, *41*(1), 118–132. https://doi.org/10.1177/0162243915605575

Zeltzer, D. (1990). Task-level graphic simulation: Abstraction, representation, and control. *Making Them Move*, 3–33.

Zhukov, S., & Iones, A. (2000). Building the navigational maps for intelligent agents. *Computers and Graphics (Pergamon)*, *24*(1), 79–89. https://doi.org/10.1016/S0097-8493(99)00139-9

Appendices

Appendix A

Questionnaire Development for Perception of Realism in ASA Movements

To evaluate the perception of realism in the micro-movement strategies of Artificial Social Agents (ASAs), we developed a questionnaire adapted from the well-established Artificial-Social-Agent (ASA) Questionnaire by Fitrianie et al., 2022. This questionnaire has been refined through multi-year efforts and extensive validation, ensuring its relevance and reliability for assessing human interaction with ASAs.

The questions selected for this study aim to specifically gauge participants' perceptions of movement realism and its impact on the overall realism of the ASAs. The adaptations made to the original questions are as follows:

A.1 Human-Like Behaviour

Original Question: A human would behave like [the agent]. (C01D02Q7)
Adapted Question: The agent's movements closely resemble human behaviour
Rationale: Simplified to focus specifically on the movement aspect, ensuring clarity and relevance to ASA movements.

A.2 Natural Behaviour

Original Question: [The agent] acts naturally. (C01D04Q13)
Adapted Question: These movements are likely to be seen in your day-to-day life.
Rationale: Adapted to focus on the participant's perception of how likely they are to encounter such movements in their daily life, emphasizing the realism and naturalness of the movements.

A.3 Agent's Performance

Original Question: [The agent] does its task well. (C03D01Q7)
Adapted Question: The agent performs its movements with efficiency.

Rationale: Adapted to specifically assess the efficiency of movements rather than task performance in general.

A.4 Perceived Realism Score

Original Question: How [the agent] is represented is realistic. (C01D03Q12)
Adapted Question: The agent's movements are realistic.
Rationale: Generalized to capture the overall perception of realism, focusing on movements.

A.5 Overall Realism

Original Question: This question is an original question.
Adapted Question: The agent is realistic.
Rationale: This original question was added to directly assess the overall realism of the agent.

These questions will be rated on a Likert scale:

- Strongly Disagree
- Disagree
- Neutral
- Agree
- Strongly Agree

Appendix B

CHAPTER 4 DESCRIPTIVE ANALYSIS TABLES

B.1 Video File: D_TurnBackward.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	67.73	62.57	71.43	75.57	44.30
Std	27.70	31.07	22.55	19.06	32.39
Min	6.00	10.00	3.00	28.00	1.00
25%	59.25	37.25	65.00	67.00	13.00
50%	72.00	64.50	70.50	77.50	43.00
75%	90.75	91.75	87.25	89.25	73.00
Max	100.00	100.00	100.00	100.00	100.00

Table B.1: Descriptive Statistics for Video File: D_TurnBackward.mp4

B.2 Video File: D_Backward.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	59.17	49.93	66.77	65.23	41.53
Std	29.72	27.87	25.99	26.01	33.52
Min	1.00	1.00	2.00	1.00	1.00
25%	39.75	32.50	58.00	55.25	13.75
50%	60.50	47.00	71.50	69.50	32.50
75%	77.75	71.75	83.25	80.75	69.25
Max	100.00	100.00	100.00	100.00	100.00

Table B.2: Descriptive Statistics for Video File: D_Backward.mp4

B.3 Video File: H_Backward.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	55.13	43.80	62.57	58.20	62.33
Std	32.18	30.73	29.45	26.81	26.27
Min	1.00	1.00	2.00	8.00	3.00
25%	30.50	15.50	42.00	38.00	50.25
50%	56.00	43.50	72.50	64.00	64.00
75%	81.25	67.00	80.75	79.50	80.00
Max	100.00	100.00	100.00	100.00	100.00

Table B.3: Descriptive Statistics for Video File: H_Backward.mp4

B.4 Video File: H_CurveForward.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	75.17	71.50	73.33	70.73	69.97
Std	19.15	24.19	23.40	25.67	26.67
Min	33.00	9.00	13.00	13.00	4.00
25%	60.50	60.50	62.75	50.50	59.00
50%	80.50	77.50	77.00	76.50	71.50
75%	88.25	89.75	93.25	94.75	93.50
Max	100.00	100.00	100.00	100.00	100.00

Table B.4: Descriptive Statistics for Video File: H_CurveForward.mp4

B.5 Video File: H_TurnForward.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	70.80	68.27	69.43	69.33	66.90
Std	23.62	25.67	23.27	24.35	25.01
Min	16.00	17.00	23.00	27.00	6.00
25%	56.75	56.50	53.25	54.50	54.50
50%	77.00	72.50	77.00	75.00	67.50
75%	89.50	90.75	84.75	87.25	87.50
Max	100.00	100.00	100.00	100.00	100.00

Table B.5: Descriptive Statistics for Video File: H_TurnForward.mp4

B.6 Video File: D_Strafe.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	49.47	34.87	56.20	60.93	37.47
Std	29.54	29.23	28.66	27.87	31.12
Min	1.00	1.00	4.00	1.00	2.00
25%	24.75	12.25	32.25	48.00	12.25
50%	49.50	25.50	53.50	70.50	25.50
75%	69.75	47.00	81.50	79.50	59.00
Max	100.00	100.00	100.00	100.00	100.00

Table B.6: Descriptive Statistics for Video File: D_Strafe.mp4

B.7 Video File: D_Forward.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	76.53	75.33	75.77	74.37	46.87
Std	20.01	24.52	23.08	19.18	34.70
Min	27.00	1.00	4.00	32.00	2.00
25%	64.00	60.50	64.50	66.25	11.75
50%	81.50	82.00	83.00	78.50	43.50
75%	91.75	93.75	93.75	90.00	77.50
Max	100.00	100.00	100.00	100.00	100.00

Table B.7: Descriptive Statistics for Video File: D_Forward.mp4

B.8 Video File: D_CurveForward.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	81.27	77.67	78.07	79.77	48.20
Std	15.17	18.93	18.81	18.18	34.18
Min	37.00	27.00	24.00	29.00	1.00
25%	72.25	69.00	73.25	73.00	15.25
50%	84.50	83.00	83.00	85.50	46.50
75%	92.00	89.75	90.75	92.25	77.75
Max	100.00	100.00	100.00	100.00	100.00

Table B.8: Descriptive Statistics for Video File: D_CurveForward.mp4

B.9 Video File: H_Strafe.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	52.07	33.90	56.47	58.73	60.03
Std	31.00	29.65	30.42	29.35	30.55
Min	9.00	1.00	9.00	1.00	9.00
25%	27.75	13.00	30.25	38.00	31.50
50%	44.00	24.50	60.50	65.00	69.00
75%	79.25	52.75	85.50	84.25	89.25
Max	100.00	100.00	100.00	100.00	100.00

Table B.9: Descriptive Statistics for Video File: H_Strafe.mp4

B.10 Video File: H_Forward.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	79.33	76.07	78.43	76.13	70.10
Std	17.16	18.67	19.57	18.71	24.34
Min	33.00	30.00	32.00	27.00	3.00
25%	71.00	65.75	66.75	71.25	61.00
50%	80.50	77.50	83.00	75.00	73.00
75%	90.75	90.00	94.00	88.00	89.75
Max	100.00	100.00	100.00	100.00	100.00

Table B.10: Descriptive Statistics for Video File: H_Forward.mp4

B.11 Video File: D_TurnForward.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	74.50	71.67	77.67	74.03	41.67
Std	20.52	25.93	17.36	20.13	28.07
Min	29.00	15.00	34.00	24.00	3.00
25%	63.00	58.50	68.25	63.25	16.25
50%	75.50	78.50	81.00	78.50	40.00
75%	89.75	92.25	91.25	89.75	62.25
Max	100.00	100.00	100.00	100.00	98.00

Table B.11: Descriptive Statistics for Video File: D_TurnForward.mp4

B.12 Video File: H_TurnBackward.mp4

	Resemblance	Day-to-day	Efficiency	Movement Realism	Agent Realism
Mean	66.33	61.27	67.77	70.67	69.67
Std	26.69	28.56	26.88	25.58	23.89
Min	2.00	1.00	1.00	1.00	18.00
25%	49.00	36.50	52.75	53.00	55.25
50%	72.00	68.50	73.00	79.50	76.00
75%	89.75	84.25	91.00	89.75	82.75
Max	100.00	100.00	100.00	100.00	100.00

Table B.12: Descriptive Statistics for Video File: H_TurnBackward.mp4

Appendix C

CHAPTER 4 DESCRIPTIVE ANALYSIS SUMMARIES

C.1 Video File: D_TurnBackward.mp4

For the video file "D_TurnBackward.mp4", the mean Resemblance score was 67.73, with a standard deviation (SD) of 27.70, indicating considerable variability in how similar the movements were perceived to be. Day-to-day practicality had a mean of 62.57 (SD = 31.07), while Efficiency was rated higher with a mean of 71.43 (SD = 22.55). Movement Realism was also rated relatively high (M = 75.57, SD = 19.06), whereas Agent Realism had a lower mean of 44.30 (SD = 32.39), suggesting that participants found the agent less realistic compared to the movements.

C.2 Video File: D_Backward.mp4

The descriptive statistics for "D_Backward.mp4" revealed a mean Resemblance score of 59.17 (SD = 29.72). Day-to-day practicality was rated lower (M = 49.93, SD = 27.87) compared to Efficiency (M = 66.77, SD = 25.99). Movement Realism had a mean of 65.23 (SD = 26.01), and Agent Realism was again on the lower end (M = 41.53, SD = 33.52).

C.3 Video File: H_Backward.mp4

For "H_Backward.mp4", the mean Resemblance score was 55.13 (SD = 32.18). Day-to-day practicality scored a mean of 43.80 (SD = 30.73), and Efficiency had a mean of 62.57 (SD = 29.45). Movement Realism was rated with a mean of 58.20 (SD = 26.81), while Agent Realism was notably higher than previous files (M = 62.33, SD = 26.27).

C.4 Video File: H_CurveForward.mp4

In "H_CurveForward.mp4", the mean Resemblance score was 75.17 (SD = 19.15), indicating higher perceived similarity. Day-to-day practicality scored 71.50 (SD = 24.19), and Efficiency had a mean of 73.33 (SD = 23.40). Movement Realism and Agent Realism were rated at 70.73 (SD = 25.67) and 69.97 (SD = 26.67), respectively.

C.5 Video File: H_TurnForward.mp4

The mean Resemblance score for "H_TurnForward.mp4" was 70.80 (SD = 23.62). Day-to-day practicality had a mean of 68.27 (SD = 25.67), while Efficiency was rated 69.43 (SD = 23.27). Movement Realism was 69.33 (SD = 24.35), and Agent Realism was 66.90 (SD = 25.01).

C.6 Video File: D_Strafe.mp4

For "D_Strafe.mp4", the mean Resemblance score was 49.47 (SD = 29.54), indicating lower perceived similarity. Day-to-day practicality was even lower (M = 34.87, SD = 29.23). Efficiency had a mean of 56.20 (SD = 28.66), Movement Realism was rated 60.93 (SD = 27.87), and Agent Realism was the lowest among the files (M = 37.47, SD = 31.12).

C.7 Video File: D_Forward.mp4

The mean Resemblance score for "D_Forward.mp4" was 76.53 (SD = 20.01). Day-to-day practicality scored higher with a mean of 75.33 (SD = 24.52), and Efficiency was rated 75.77 (SD = 23.08). Movement Realism had a mean of 74.37 (SD = 19.18), while Agent Realism was 46.87 (SD = 34.70).

C.8 Video File: D_CurveForward.mp4

In "D_CurveForward.mp4", the mean Resemblance score was 81.27 (SD = 15.17), indicating a high perceived similarity. Day-to-day practicality had a mean of 77.67 (SD = 18.93), and Efficiency was rated 78.07 (SD = 18.81). Movement Realism and Agent Realism were rated 79.77 (SD = 18.18) and 48.20 (SD = 34.18), respectively.

C.9 Video File: H_Strafe.mp4

For "H_Strafe.mp4", the mean Resemblance score was 52.07 (SD = 31.00), indicating moderate perceived similarity. Day-to-day practicality was 33.90 (SD = 29.65), and Efficiency had a mean of 56.47 (SD = 30.42). Movement Realism was rated 58.73 (SD = 29.35), and Agent Realism was 60.03 (SD = 30.55).

C.10 Video File: H_Forward.mp4

The mean Resemblance score for "H_Forward.mp4" was 79.33 (SD = 17.16), indicating high perceived similarity. Day-to-day practicality had a mean of 76.07 (SD = 18.67), and Efficiency was rated 78.43 (SD = 19.57). Movement Realism was 76.13 (SD = 18.71), and Agent Realism was 70.10 (SD = 24.34).

C.11 Video File: D_TurnForward.mp4

For "D_TurnForward.mp4", the mean Resemblance score was 74.50 (SD = 20.52). Day-to-day practicality scored 71.67 (SD = 25.93), and Efficiency had a mean of 77.67 (SD =

17.36). Movement Realism was rated 74.03 (SD = 20.13), while Agent Realism was 41.67 (SD = 28.07).

C.12 Video File: H_TurnBackward.mp4

The mean Resemblance score for "H_TurnBackward.mp4" was 66.33 (SD = 26.69). Day-to-day practicality had a mean of 61.27 (SD = 28.56), and Efficiency was rated 67.77 (SD = 26.88). Movement Realism was 70.67 (SD = 25.58), and Agent Realism was 69.67 (SD = 23.89).

C.13 Summary

The descriptive statistics reveal variability in how different movements and agents were perceived across various dimensions. Generally, Movement Realism and Efficiency tend to be rated higher than Agent Realism, indicating that participants found the movements more realistic and efficient than the agents. The standard deviations indicate substantial variability in responses, suggesting differences in individual perceptions. Agent realism was notably lower in several videos, highlighting a potential area for improvement in the representation of agents. Movements like "D_CurveForward.mp4" and "H_Forward.mp4" were perceived very positively in terms of Resemblance, Day-to-day practicality, and Efficiency.

Appendix D

Tukey Post-Hoc Table Results

Factor	df	sum_sq	mean_sq	F	PR(>F)
		Resemblance			
C(Movement)	5.0	38238.492	7647.698	12.232	<0.001
Residual	354.0	218835.883	625.230		
		Day-to-day			
C(Movement)	5.0	83335.447	16667.089	23.914	<0.001
Residual	354.0	246716.817	705.061		
		Efficiency			
C(Movement)	5.0	18560.058	3712.012	6.252	0.000014
Residual	354.0	210179.917	598.428		
		Movement Realism			
C(Movement)	5.0	14279.592	2855.918	5.088	0.000161
Residual	354.0	198708.183	563.021		

Table D.1: ANOVA Results for Different Dependent Variables

Group 1	Group 2	Mean Diff	p-adj	Lower	Upper	Reject
Tukey HSD for Resemblance						
Backward	CurveForward	21.0667	0.0001	8.0595	34.0738	True
Backward	Forward	20.7833	0.0001	7.7762	33.7905	True
Backward	Strafe	-6.3833	0.7233	-19.3905	6.6238	False
Backward	TurnBackward	9.8833	0.251	-3.1238	22.8905	False
Backward	TurnForward	15.5000	0.0092	2.4928	28.5072	True
CurveForward	Forward	-0.2833	1.0	-13.2905	12.7238	False
CurveForward	Strafe	-27.4500	0.0	-40.4572	-14.4428	True
CurveForward	TurnBackward	-11.1833	0.1379	-24.1905	1.8238	False
CurveForward	TurnForward	-5.5667	0.8238	-18.5738	7.4405	False
Forward	Strafe	-27.1667	0.0	-40.1738	-14.1595	True
Forward	TurnBackward	-10.9000	0.1586	-23.9072	2.1072	False
Forward	TurnForward	-5.2833	0.8537	-18.2905	7.7238	False
Strafe	TurnBackward	16.2667	0.0052	3.2595	29.2738	True
Strafe	TurnForward	21.8833	0.0	8.8762	34.8905	True
TurnBackward	TurnForward	5.6167	0.8182	-7.3905	18.6238	False
Tukey HSD for Day-to-day						
Backward	CurveForward	27.7167	0.0	13.9058	41.5276	True
Backward	Forward	28.8333	0.0	15.0224	42.6442	True
Backward	Strafe	-12.4833	0.1024	-26.2942	1.3276	False
Backward	TurnBackward	15.0500	0.0236	1.2391	28.8609	True
Backward	TurnForward	23.1000	0.0	9.2891	36.9109	True
CurveForward	Forward	1.1167	0.9999	-12.6942	14.9276	False
CurveForward	Strafe	-40.2000	0.0	-54.0109	-26.3891	True
CurveForward	TurnBackward	-12.6667	0.0933	-26.4776	1.1442	False
CurveForward	TurnForward	-4.6167	0.9308	-18.4276	9.1942	False
Forward	Strafe	-41.3167	0.0	-55.1276	-27.5058	True
Forward	TurnBackward	-13.7833	0.0508	-27.5942	0.0276	False
Forward	TurnForward	-5.7333	0.8418	-19.5442	8.0776	False
Strafe	TurnBackward	27.5333	0.0	13.7224	41.3442	True
Strafe	TurnForward	35.5833	0.0	21.7724	49.3942	True
TurnBackward	TurnForward	8.0500	0.5525	-5.7609	21.8609	False
Tukey HSD for Efficiency						
Backward	CurveForward	11.0333	0.1328	-1.7140	23.7806	False
Backward	Forward	12.4333	0.0606	-0.3140	25.1806	False
Backward	Strafe	-8.3333	0.4204	-21.0806	4.4140	False
Backward	TurnBackward	4.9333	0.8775	-7.8140	17.6806	False
Backward	TurnForward	8.8833	0.3462	-3.8640	21.6306	False
CurveForward	Forward	1.4000	0.9996	-11.3473	14.1473	False
CurveForward	Strafe	-19.3667	0.0003	-32.1140	-6.6194	True
CurveForward	TurnBackward	-6.1000	0.7443	-18.8473	6.6473	False
CurveForward	TurnForward	-2.1500	0.9967	-14.8973	10.5973	False
Forward	Strafe	-20.7667	0.0001	-33.5140	-8.0194	True
Forward	TurnBackward	-7.5000	0.5420	-20.2473	5.2473	False
Forward	TurnForward	-3.5500	0.9677	-16.2973	9.1973	False
Strafe	TurnBackward	13.2667	0.0359	0.5194	26.0140	True
Strafe	TurnForward	17.2167	0.0018	4.4694	29.9640	True
TurnBackward	TurnForward	3.9500	0.9493	-8.7973	16.6973	False
Tukey HSD for Movement Realism						
Backward	CurveForward	13.5333	0.0232	1.1388	25.9279	True
Backward	Forward	13.5333	0.0232	1.1388	25.9279	True
Backward	Strafe	-1.8833	0.9980	-14.2779	10.5112	False
Backward	TurnBackward	11.4000	0.0915	-0.9946	23.7946	False
Backward	TurnForward	9.9667	0.1951	-2.4279	22.3612	False
CurveForward	Forward	0.0000	1.0	-12.3946	12.3946	False
CurveForward	Strafe	-15.4167	0.0055	-27.8112	-3.0221	True
CurveForward	TurnBackward	-2.1333	0.9964	-14.5279	10.2612	False
CurveForward	TurnForward	-3.5667	0.9629	-15.9612	8.8279	False
Forward	Strafe	-15.4167	0.0055	-27.8112	-3.0221	True
Forward	TurnBackward	-2.1333	0.9964	-14.5279	10.2612	False
Forward	TurnForward	-3.5667	0.9629	-15.9612	8.8279	False
Strafe	TurnBackward	13.2833	0.0276	0.8888	25.6779	True
Strafe	TurnForward	11.8500	0.0702	-0.5446	24.2446	False
TurnBackward	TurnForward	-1.4333	0.9995	-13.8279	10.9612	False

Table D.2: Tukey HSD Results for Significant ANOVA Effects

D.1 ANOVA Results for Agent Realism with respect to Movement

Factor	df	sum_sq	mean_sq	F	PR(>F)
C(Movement)	5.0	4900.947	980.189	0.989	0.424
Residual	354.0	350867.717	991.732		

Table D.3: ANOVA results for Agent Realism with respect to Movement

D.2 ANOVA Results for Agent Realism with respect to Agent

Factor	df	sum_sq	mean_sq	F	PR(>F)
C(Agent)	1.0	48279.336	48279.336	56.210	<0.001
Residual	358.0	307489.328	858.521		

Table D.4: ANOVA results for Agent Realism with respect to Agent

D.3 Tukey HSD Results for Agent Realism with respect to Agent

Group 1	Group 2	Mean Diff	p-adj	Lower	Upper	Reject
Dummy	Humanoid	23.1611	0.000	17.0858	29.2365	True

Table D.5: Tukey HSD results for Agent Realism with respect to Agent