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COGNITIVE AUGMENTATION SYSTEMS THROUGH EXTENDED REALITY, ARTIFICIAL INTELLIGENCE, AND SENSORS: A HUMAN-COMPUTER INTERACTION PERSPECTIVE

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Abstract

In an era increasingly shaped by digital and immersive technologies, this thesis explores how Extended Reality (XR), Artificial Intelligence (AI), and sensor integration are transforming cognitive augmentation from a Human-Computer Interaction (HCI) perspective.

Through case studies in education, physical activity, and collaboration, this work demonstrates how these technologies address diverse user needs in everyday life. In education, an AI-powered Augmented Reality (AR) application supports language learning for dyslexic students with adaptive feedback, while an XR application strengthens spatial reasoning by teaching Rubik's Cube notation. XR further demonstrates its potential by evaluating the effectiveness of embodied and audio-only virtual assistant guides in a puzzle-solving task. Beyond education, case studies extend to physical activity, where an AR application provides real-time feedback to optimize workouts, and Virtual Reality (VR) interfaces improve bi-manual interaction for individuals with limb loss. In everyday settings, a VR smart home study examines AI assistant engagement, while an AR family album application overlays metadata onto physical photos, enriching individual interactions with personal history. An Internet of Things (IoT)-integrated VR environment introduces real-time feedback that dynamically responds to user environmental changes. Collaboration is another key focus, with virtual office studies analyzing how communication quality affects teamwork and an AR experience facilitating family memory sharing. These case studies also highlight technological and usability challenges, providing insights that inform future improvements. The thesis adopts a mixed-method evaluation, combining quantitative performance metrics with qualitative user insights while exploring ethical considerations to inform responsible future research. In addition, a comparative analysis identifies universal design principles for creating effective XR, AI, and sensor-driven cognitive augmentation systems.

In conclusion, the findings highlight the transformative potential of HCI-driven case studies in developing immersive, user-centered solutions. By integrating advanced technologies with interdisciplinary approaches, this research aims to address cognitive and social challenges while promoting responsible and ethical practices.

Keywords: Cognitive Augmentation Systems (CAS), Human-Computer Interaction (HCI), Extended Reality (XR), Artificial Intelligence (AI), Sensor Technologies

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Chapter 1

Introduction

1.1 Cognitive Augmentation Systems

In an era characterized by rapid technological advancements, the pursuit of improving human cognitive capabilities has gained considerable attention across diverse fields. Cognitive augmentation involves methods that actively support and expand mental processes and capabilities. These augmentations can be achieved through interventions that actively assist cognitive functions through real-time technology support [154]. The motivation behind cognitive augmentation is often linked to the desire to support and improve performance in both professional and personal contexts, as well as to promote overall mental well-being [1099]. Researchers have explored cognitive augmentation not only as a tool for addressing cognitive decline or disorders but also as a means of augmenting everyday cognitive performance in healthy individuals [361]. The growing interest in this area reflects broader societal trends toward self-optimization and the augmentation of human potential. This focus on cognitive augmentation highlights the increasing recognition of human cognition as a dynamic capacity that can be influenced and improved through intentional efforts [565].

The integration of technology plays a pivotal role in this domain, introducing cognitive augmentation systems (CAS) that harness the synergy of advanced tools and environments [154, 777, 330]. In practical applications, a variety of technologies have been developed to actively augment cognitive functions. Nootropic substances and pharmaceuticals, such as modafinil, are utilized to support concentration, memory, and alertness [96]. Brain-computer interfaces (BCIs) facilitate direct communication between the brain and external devices, thereby extending cognitive capabilities or aiding in neurorehabilitation [717]. Non-invasive brain stimulation techniques, such as transcranial magnetic stimulation (TMS) and transcranial direct current stimulation (tDCS), are employed to modulate neural activity, potentially supporting memory and attention in real time [546]. Finally, cognitive training software provides a more accessible and personalized approach to cognitive augmentation, using targeted exercises and games to actively support specific cognitive skills, such as memory, attention, and problem-solving [1186]. The latest advancements in this field involve the integration of extended reality (XR), artificial intelligence (AI), and sensor technologies to create more immersive and adaptive experiences. These sensor technologies can be both embedded within XR devices, such as headsets and gloves, and external, interfacing with the environment to capture a wider range of user interactions and physiological data, thereby providing responsive, context-sensitive support.

CAS technologies have been applied across diverse fields, including education, psychology, healthcare, and industry, demonstrating their broad impact on cognitive augmentation. In education, CAS play a transformative role by personalizing learning experiences, adapting instructional content, and enhancing student engagement. XR-based educational tools create immersive learning environments that enable experiential learning [135, 40, 221], allowing students to engage with complex concepts in science, engineering, and medicine [1415, 1109, 200]. AI-driven intelligent tutoring systems provide real-time feedback, assess learner progress, and tailor instruction based on individual cognitive needs [482, 239, 1335]. Sensor-based adaptive learning platforms track physiological and behavioral responses, adjusting difficulty levels or instructional strategies to optimize learning efficiency [768, 740]. These advancements enhance learning experiences for all students, including those with disabilities, by providing personalized, adaptive learning environments that improve engagement and knowledge retention. Additionally, they bridge accessibility gaps by offering customized support for students with learning disabilities, such as dyslexia, ensuring a more inclusive and equitable education system [1427, 1381, 21]. In healthcare, CAS have been used for cognitive rehabilitation, such as XR-based therapies for stroke recovery and AI-driven cognitive training for patients with neurodegenerative disorders [59, 183]. In industrial settings, CAS enhance human performance in complex work environments, supporting tasks like AR-guided assembly in manufacturing [68, 1330, 307], AI-powered decision support in high-risk operations, and real-time cognitive assistance in safety-critical tasks [1406, 16, 36]. By leveraging wearable biosensors, motion tracking, and haptic feedback, these systems dynamically adapt to users' cognitive load and physical state, enhancing efficiency, accuracy, and safety in demanding work conditions [942].

The theoretical foundation for CAS emerges from interdisciplinary research in cognitive science, computer science (CS), and human-computer interaction (HCI) [386]. From a cognitive science perspective, CAS are inspired by models of *brain plasticity* and *cognitive load theory*. These models suggest that the human brain is not static but can adapt and rewire itself based on external stimuli and interactive training [154, 660]. Cognitive load theory posits that humans have limited working memory capacity, and CAS are designed to provide direct, real-time assistance that reduces cognitive overload and augments executive functions [1254, 660, 858]. From a computer science perspective, CAS are powered by algorithms that can trace and learn from user behavior, identify patterns, and adapt over time [668]. Additionally, from an HCI perspective, CAS are designed to be user-centric, focusing on creating intuitive, accessible, and engaging systems that support cognitive augmentation through interaction. HCI principles underscore the importance of usability and user experience in the design of CAS. They emphasize how users interact with technology and how these interactions can be designed to improve cognitive outcomes [924]. These interdisciplinary insights ensure that CAS are technologically robust and deeply attuned to human cognition and user experience complexities. This, in turn, paves the way for effective and equitable cognitive augmentations.

This thesis centers on the role of the HCI perspective in designing CAS that supports cognitive augmentation through user-centered interaction design and experience evaluation.

This chapter outlines the research approach adopted in this study, presents the key research questions, objectives, and contributions of the thesis, and concludes with an overview of its structure.

1.2 Research Approach

The research methodology in this thesis follows a structured, multi-phase approach grounded in HCI principles, designed to systematically explore the integration of XR, AI, and sensor technologies in cognitive augmentation systems. This approach prioritizes user-centered design and evaluation to create intuitive and accessible systems that actively assist personal or collaborative cognitive experiences in everyday contexts.

The study begins with an initial exploration phase focusing on a theoretical and practical analysis of applied technologies and the supporting infrastructure framework. It establishes foundational criteria for implementing and evaluating cognitive augmentation systems explored in this thesis. Building on these insights, the design and development phase creates case studies that apply these technologies in diverse scenarios to address specific cognitive augmentation goals. In the evaluation phase, each case study is assessed using qualitative and quantitative methods to examine its usability, effectiveness, and impact on user performance and experience. Additionally, each case study identifies technical and usability challenges and proposes potential solutions to mitigate them. Beyond technical and usability considerations, this thesis also explores ethical concerns associated with the deployment of cognitive augmentation technologies. Ethical challenges related to the case studies, including data privacy, user autonomy, and responsible AI deployment, are systematically identified, analyzed, and discussed within their specific contexts. In the conclusion chapter, a comparative analysis of the case studies informs the development of universal design guidelines and best practices, enhancing usability and effectiveness across similar applications, while a systematic comparison of technical and usability challenges reveals key insights that guide future improvements and research directions.

1.3 Research Questions and Objectives

- **How can XR, AI, and sensor technologies be effectively integrated to develop and evaluate immersive and adaptive CAS for diverse daily scenarios?**
  - **Objective:** To examine the potential of XR, AI, and sensor technologies in cognitive augmentation for everyday scenarios by analyzing their individual and combined capabilities based on existing technological advancements.
- **In what ways do CAS applications, developed through the integration of XR, AI, and sensor technologies, impact cognitive augmentation at both personal and collaborative levels in real-world contexts?**

1. **Personal Context:** How do cognitive augmentation systems impact individual learning, skill development, and cognitive processes?
2. **Collaborative Context:** How do cognitive augmentation systems enhance social dynamics, teamwork, and collaborative experiences in shared virtual environments?

   – **Objective:** To develop and assess the influence of CAS on cognitive augmentation by differentiating their impacts at personal and collaborative levels. Additionally, this research aims to identify universal design principles and best practices for CAS applications similar to the developed case studies, analyze technical and usability challenges, and propose future directions for improvement.

- **What ethical considerations arise from the deployment of XR, AI, and sensor-based CAS in personal and collaborative environments?**
  – **Objective:** To identify and examine ethical challenges such as data privacy, user autonomy, and inclusivity, drawing insights from case studies. This includes suggesting directions for future research to develop responsible and equitable approaches to CAS deployment.

1.4 Contributions

While XR, AI, and sensor technologies offer significant potential, their integration into everyday personal skill-building and collaborative experiences remains limited, highlighting a gap in practical application. To address this gap, the contributions of this thesis include:

- Comprehensive analysis of selected XR, AI, and sensor technologies, integrated with an infrastructure framework and A systematic evaluation method, aimed at advancing the development of CAS across diverse real-world scenarios.
- Demonstrate through the design and evaluation of case studies the practical integration of XR, AI, and sensor technologies in CAS to support learning, skill acquisition, and social interaction in everyday contexts. A comparative analysis of these case studies shapes universal design guidelines, suggesting more accessible and effective CAS implementations, while a systematic analysis of technical and usability barriers informs strategies to optimize design, enhance usability, and improve system performance.
- Conduct a preliminary review and outline directions for future ethical analyses of CAS applications, with a focus on key considerations such as data privacy, user autonomy, and the responsible use of XR, AI, and sensor technologies across personal and collaborative environments. Case studies serve as a critical foundation for identifying ethical challenges and assessing deployment implications.

1.5 Outline

This thesis is organized into six chapters.

Chapter 2 investigates the potential of XR, AI, and sensor technologies for cognitive augmentation by assessing their individual and synergistic capabilities based on current advancements. It introduces the **core technologies, frameworks, and evaluation methods** that underpin the development of the subsequent case studies.

Chapter 3 focuses on the development and assessment of CAS in real-world contexts, emphasizing **personal cognitive augmentation**. The chapter presents a series of case studies demonstrating the application of these technologies, highlighting their role in skill acquisition, learning, accessibility, and interactive engagement. The first case study (N1) introduces an AI and AR-powered mobile application designed to assist students with dyslexia in learning Spanish as a foreign language. This application leverages the unique cognitive strengths of dyslexic learners, providing personalized and accessible learning experiences. The second case study (N2) investigates how mixed reality (MR), in conjunction with a rule-based virtual assistant, can enhance puzzle-solving tasks, comparing the effectiveness of audio-only versus embodied virtual assistants. Similarly, the third case study (N3) focuses on using MR to teach complex notations required for solving a Rubik's Cube, illustrating how immersive environments can support skill acquisition in challenging cognitive tasks. The fourth case study (N4) explores how AR technologies can augment physical workout routines by offering real-time AI-powered assistance and feedback during outdoor exercises. The fifth case study (N5) focuses on the development of Virtual Reality (VR) applications designed to assist individuals with upper limb differences in performing VR bi-manual tasks. These applications employ VR's immersive capabilities to provide users with tools that accommodate their specific physical needs. The study showcases how VR can foster inclusivity by creating accessible environments where users can practice and refine their skills with customized support. Preserving Family Album Photos (Case study N6) explores an augmented reality application that enhances user interaction by overlaying metadata onto physical family photos, enriching personal engagement with historical and contextual information. Another case study (N7) explores how users interact with and experiment in various daily scenarios in a smart home setting supported by an AI assistant. Finally, the next case study (N8) explores the integration of Internet of Things (IoT) sensors with XR environments. In this study, real-time environmental feedback is provided to users, enhancing their interaction with virtual environments. By integrating sensor data with the immersive capabilities of XR, the system dynamically adjusts the virtual environment based on real-world inputs, demonstrating the potential for IoT and XR to create highly responsive and adaptive virtual spaces.

In Chapter 4, the thesis turns to the development and impact of these technologies on **interpersonal augmentation**. It examines how integrating XR, AI, and sensors can improve communication, and shared experiences in virtual spaces. The first case study (N9) investigates a virtual office environment where users interact under different levels of uncertainty. The study explores how participants respond to varying degrees of uncertainty in communication while engaging in collaborative tasks within a virtual office. By manipulating elements such as incomplete information or ambiguous cues, the study aims to understand how uncertainty influences group dynamics, decision-making processes, and overall task performance. This case study highlights the critical role of XR in simulating real-world challenges in a controlled environment, allowing users to experiment with and adapt to uncertain situations. The second case study (N10) expands on this. The study analyzes how uncertainty affects social presence and interaction dynamics using a shared virtual environment. It provides valuable insights into how XR can enhance communication and collaboration skills. The third case study (N11) focuses on collaborative memory sharing in AR environments. In this study, participants use AR applications to share family memories by interacting with digital recreations of family photo albums. The study emphasizes the emotional and cultural dimensions of technology use, exploring how AR can support collaborative memory creation and sharing.

Chapter 5 explores the **ethical implications of applying XR, AI, and sensor technologies**, focusing on issues such as privacy, data security, autonomy, and inclusivity in different contexts. These ethical concerns are analyzed in both personal and collaborative settings, with a particular emphasis on the proposed case studies.

Chapter 6 **concludes** the thesis with a comparative analysis of the case studies, identifying universal design principles and best practices for CAS. It also systematically categorizes the technical and usability challenges observed across these studies, proposing potential solutions to enhance system design and user experience. Additionally, it reflects on the research questions, synthesizing key insights before outlining future research directions and highlighting pathways for advancing XR, AI, and sensor-based cognitive augmentation technologies.

Chapter 2

Infrastructure and Evaluation Framework

This chapter begins with an overview of the criteria for case study selection followed by a detailed look at the foundational technologies, software development kits, and evaluation methods applied in the case studies.

In this chapter we aim to answer to this key research question:

- RQ: How can Extended Reality (XR), Artificial Intelligence (AI), and sensor technologies be effectively integrated to develop and evaluate immersive and adaptive Cognitive Augmentation Systems (CAS) for diverse daily scenarios?

2.1 Case Study Selection

The research includes ***eleven case studies***, each selected based on the following criteria:

- Relevance to Cognitive Augmentation: Case studies were chosen to reflect different aspects of cognitive augmentation, including personal and interpersonal cognitive augmentation in virtual environments.

- Technological Integration: Each case study incorporated XR, AI, and sensor technologies to varying degrees. However, some case studies may not have included AI or sensor technologies explicitly.

- Diversity of Applications: The case studies span a range of domains, from educational tools (e.g., AR language learning) to social interaction environments (e.g., virtual office collaboration). This variety enables a broad evaluation across different contexts, with attention to both individual and collaborative cognitive augmentation.

2.2 Infrastructure Technologies Behind Developed Case Studies

The following sections examine the role of core technologies and highlight the features that support the development of cognitive augmentation systems in this research.

2.2.1 Extended Reality for Cognitive Augmentation

This section examines XR's contributions to cognitive augmentation, setting the stage for understanding its integration with AI and sensor technologies in subsequent sections.

The Role of Extended Reality Technologies

XR encompasses a range of technologies that blend the physical and digital worlds to create immersive experiences. The main types of XR technologies are Virtual Reality (VR), Augmented Reality (AR), and Mixed Reality (MR). Each of these technologies offers unique capabilities and applications.

VR is a technology that immerses users in a completely digital environment, effectively replacing their real-world surroundings with a simulated one. This immersive experience is typically achieved through the use of VR headsets, which provide a 360-degree view of the virtual environment. Tracking systems are essential in VR as they monitor the user's body movements to ensure accurate representation in the virtual world. By fully immersing users in a virtual space, VR offers a powerful tool for creating realistic and impactful experiences [218, 314, 723, 1068]. AR enhances the user's perception of the real world by overlaying digital information onto their physical surroundings. Unlike VR, which creates a completely separate environment, AR integrates digital elements into the user's view of the real world, enhancing their interaction with both digital and physical objects. The available devices use cameras and sensors to capture the real-world environment and accurately place digital overlays within it [287, 1150, 1320, 856]. MR merges elements of both VR and AR to create environments where physical and digital objects coexist and interact in real time. This technology allows users to interact with digital elements as if they were part of the real world, seamlessly blending physical and virtual experiences. MR headsets support this integration by providing advanced tracking and environmental mapping capabilities [588, 329, 464].

One of the key features of XR technologies is their ability to create immersive environments that deeply engage users. Immersiveness refers to the degree to which users feel present within a virtual environment, and this sense of presence plays a critical role in enhancing cognitive processes [1151]. Presence, or the sensation of 'being there' in the virtual space, helps anchor users, making the experience more impactful [555]. However, it is essential to manage simulation sickness, a common issue where users experience discomfort due to discrepancies between visual and physical motion cues [671]. When well-balanced, these immersive environments allow users to experience realistic scenarios in a controlled setting, making the experience more impactful and engaging [1418], where users can practice and reinforce cognitive skills in a low-risk environment [1365]. This heightened engagement is particularly valuable for individuals with cognitive impairments, where repetitive, immersive tasks can stimulate neuroplasticity and promote cognitive recovery [97].

Selected Extended Reality Devices: Features and Applications

In this section, we review the XR devices utilized throughout the case studies, focusing on their core technical features. The key features of the selected devices, including their experience type, resolution, field of view (FOV), interaction modalities, mobility, indoor/outdoor suitability, and battery life, are summarized in Table 2.1 and elaborated upon in greater detail in the following subsections.

Device	**Experience Type**	**Resolution (Per eye)**	**FOV (Diagonal)**	**Interaction Modalities**	**Mobility**	**Indoor/Outdoor Suitability**	**Battery Life (Hours, Active Use)**
HoloLens 2	MR/AR	2048x1080	≈ 52°	Hand, eye, voice tracking	Untethered	Indoor use; limited visibility outdoors (suitable in shaded areas only)	2-3
Magic Leap 1	MR/AR	1280x960	≈ 50°	Hand, eye, voice tracking, controllers	Untethered	Suitable for both indoor and moderate outdoor use (requires indirect sunlight or shaded areas)	3
Varjo XR-3	MR/AR/VR	2880×2720 ("Human-eye" resolution)	≈ 134°	Hand, eye tracking	Tethered	Indoor only; tracking and display depend on stable indoor lighting	N/A (Tethered)
HTC Vive Pro	VR	1440×1600	≈ 110°	Controllers	Tethered	Indoor only; tracking and display depend on stable indoor lighting	N/A (Tethered)
Oculus Quest 2	MR/AR/VR	1832x1920	≈ 90°	Hand tracking, controllers	Untethered	Primarily indoor; usable outdoors in indirect sunlight or shaded areas	2-3
Oculus Quest 3	MR/AR/VR	2064x2208	≈ 120°	Hand tracking, controllers	Untethered	Primarily indoor; usable outdoors in indirect sunlight or shaded areas	2-3
Smartphone (e.g., Samsung Galaxy S22)	Mobile AR	2400x1080	N/A (Device-based AR)	Touch, voice input, motion tracking	Untethered	Indoor and outdoor use (AR visibility depends on lighting conditions)	4-6

Table 2.1: Features of XR Devices for CAS.

Device

The devices selected for this research—HoloLens 2, Magic Leap 1, Varjo XR-3, HTC Vive Pro, Oculus Quest 2 and 3, and a mobile device (e.g., Samsung Galaxy S22)—were chosen based on their availability in the lab and their proven suitability in previous research within similar contexts. Each device offers a distinctive combination of hardware and software features, making them suitable for diverse cognitive augmentation use cases.

Experience Type

The "Experience Type" column specifies the kind of immersive experience each device offers by indicating how it blends real and virtual elements. This includes AR, where digital content is overlaid onto the physical world; Mobile AR, which delivers augmented reality experiences through mobile devices using built-in cameras and sensors for spatial awareness and interaction; MR, where virtual and physical objects interact in real-time; and VR, which fully immerses users in a completely digital environment.

Resolution (per eye)

Resolution is the number of pixels displayed per eye in the device's headset. Higher resolution translates to sharper, clearer visuals, which is essential for detailed tasks in XR environments.

- **2048x1080 (HoloLens 2)**: The **HoloLens 2** features this resolution, offering a well-balanced display optimized for seamlessly overlaying digital content onto the real world. It ensures clarity while maintaining smooth performance, preventing visual fatigue during extended use.
- **1280×960 (Magic Leap 1)**: Though lower than newer devices, this resolution is well-optimized for 3D visualization, making **Magic Leap 1** suitable for applications in design, creative fields, and enterprise use.
- **2880×2720 (Varjo XR-3)**: The **Varjo XR-3** features a bionic display that achieves what is often called "human-eye resolution," with approximately 70 pixels per degree. This allows for exceptionally sharp visuals, making details nearly indistinguishable from real-life perception.
- **1440×1600 (HTC Vive Pro)**: Designed for immersive VR applications, this resolution delivers crisp and detailed visuals, improving depth perception and object clarity in virtual environments.
- **1832×1920 (Oculus Quest 2)**: The **Quest 2** delivers a high-resolution display, providing clear and immersive visuals for VR experiences. While it lacks some of the enhancements of its successor, it remains a versatile and widely used headset for both consumer and research applications.
- **2064×2208 (Oculus Quest 3)**: The **Quest 3** introduces significant improvements in resolution, offering crisp, vibrant visuals for both VR and MR experiences to enhance realism.
- **2400×1080 (Mobile AR - Samsung Galaxy S22)**: The **Galaxy S22** provides a high-resolution display optimized for Mobile AR, ensuring sharp and clear visuals for augmented reality applications, with reliable color accuracy and brightness for both indoor and outdoor use.

Field of View (FOV)

The Field of View (FOV) determines how much of the virtual or augmented environment is visible at any given moment. A wider FOV enhances immersion by covering a larger portion of the user's natural vision, reducing the feeling of looking through a restricted window.

- $\approx$ **52° diagonal**: **HoloLens 2** provides a moderate FOV for AR/MR applications, allowing users to see a meaningful portion of the real and digital environment simultaneously.

- $\approx$ **50° diagonal**: **Magic Leap 1** offers a slightly narrower FOV than HoloLens 2 but still enables interactive mixed-reality experiences with spatially anchored digital content.

- $\approx$ **134° diagonal**: **Varjo XR-3** provides an exceptionally wide FOV, enhancing realism in detailed simulations and professional applications where situational awareness and high-fidelity visuals are crucial.

- $\approx$ **110° diagonal**: **HTC Vive Pro** features a wide FOV, improving immersion in VR environments by closely matching the human visual field.

- $\approx$ **90° diagonal**: **Oculus Quest 2** offers a balanced FOV, delivering an immersive VR experience while maintaining a compact and lightweight design. Though narrower than its successor, it remains effective for a wide range of applications.

- $\approx$ **120° diagonal**: **Oculus Quest 3** expands upon its predecessor's FOV, providing a more natural and immersive VR/MR experience.

Interaction Modalities

Interaction modalities describe the methods users employ to interact with the virtual or augmented environment.

- **Hand tracking:** Hand-tracking technology allows users to interact with virtual environments using natural hand gestures without needing controllers, enabling users to manipulate objects, navigate menus, or perform tasks simply by moving their hands. This is particularly useful in applications like virtual training or education, where intuitive interaction enhances the learning experience.

- **Eye tracking:** Eye-tracking technology enables the system to detect where the user is looking, allowing for more precise interaction and reduced cognitive load. For instance, in high-stakes simulations or medical training, eye-tracking can adjust the focus or depth of the display based on the user's gaze, ensuring that critical information is always in view.

- **Voice commands:** Voice interaction allows users to control the virtual environment using spoken commands. This hands-free operation is particularly beneficial in scenarios like remote assistance or industrial training, where the user's hands may be occupied, and quick, efficient control is required.

- **Controllers:** Many VR devices use handheld controllers for precise input, offering haptic feedback and buttons to enhance interaction. Controllers are especially valuable in gaming or detailed virtual tasks where fine-tuned control is necessary, such as navigating complex environments or manipulating virtual tools.

- **Touch:** Mobile AR devices rely on touch-based interaction, enabling users to interact with augmented content through taps, swipes, and gestures on the touchscreen. This intuitive input method allows for direct manipulation of virtual objects, making it well-suited for navigation, object placement, and interactive learning applications.

- **Motion Tracking:** Mobile AR devices utilize camera-based motion tracking combined with sensor fusion (accelerometers, gyroscopes, and, in some models, LiDAR) to enable precise spatial awareness and real-time interaction with augmented content. This allows users to physically move their device to explore virtual objects from different angles and interact with AR elements through natural hand gestures.

Mobility

Mobility determines whether a device operates tethered (requiring a connection to an external computer) or untethered (wireless operation).

- **Untethered**: These devices operate without cables, providing users with greater freedom to move in real-world environments. This is particularly important for mobile applications and field training scenarios.

- **Tethered**: These devices require a connection to an external computer to handle their demanding graphics and processing. This tethering allows for higher resolution and more complex simulations but at the cost of mobility.

Indoor/Outdoor Suitability

The suitability of XR devices for indoor or outdoor use is an important consideration in their application for cognitive augmentation, influencing both user experience and performance outcomes. This aspect depends on factors such as display brightness, portability, durability, and tracking accuracy in varying lighting conditions. For indoor use, most XR devices are designed to perform optimally in controlled lighting environments. Indoors, lighting conditions are generally stable, reducing issues like glare and enhancing the visibility of digital content, which is essential for tasks that demand precise detail or prolonged interaction. Furthermore, tethered devices, which offer higher computational power, are generally restricted to indoor settings, making them ideal for high-fidelity simulations, professional training, or collaborative applications within fixed spaces. Outdoor suitability, on the other hand, requires that devices handle variable lighting, from shade to direct sunlight. Untethered, portable devices with displays that can adapt to different lighting intensities are better suited for outdoor applications. For outdoor cognitive augmentation experiences—such as augmented reality training scenarios or interactive learning in open spaces—these devices need to mitigate issues like glare and maintain high visibility even in bright sunlight. Additionally, outdoor-compatible devices must have stable tracking in dynamic lighting and environmental conditions, ensuring responsive and accurate user interactions.

Battery Life (Active Use)

This feature indicates the estimated battery life of untethered XR devices during continuous active use. Battery performance depends on factors such as display brightness, processing load, sensor usage, and wireless connectivity. Devices like the HoloLens 2, Magic Leap 1, and Oculus Quest 2 and 3 typically provide 2-3 hours of operation before requiring a recharge. For Mobile AR, smartphones like the Samsung Galaxy S22 offer a battery life of approximately 4-6 hours during AR applications, depending on screen brightness, processing demands, and sensor activity. In contrast, tethered devices such as the Varjo XR-3 and HTC Vive Pro do not have a standalone battery, as they rely on a constant power source from a connected PC. Users should consider battery life when planning extended XR sessions, especially for mobile applications or fieldwork.

2.2.2 Artificial Intelligence for Cognitive Augmentation

This section explores the integration of Artificial Intelligence (AI) assistants within Cognitive Augmentation Systems across various domains.

The Role of Artificial Intelligence Assistants

Personalization stands as a core strength of AI assistants in CAS, empowering them to autonomously adapt and evolve based on real-time user behaviors and interactions, thereby delivering increasingly customized support [207, 604]. These systems achieve this by continuously gathering and analyzing a diverse range of user data—from behavioral patterns and expressed preferences to the specific context of each interaction. This data enables the AI to interpret not only individual actions but also broader situational contexts, cultivating a profound understanding of each user's unique needs. Beyond personalization, AI assistants' ability to process vast amounts of information rapidly allows them to complement human expertise, particularly in environments where timely, data-driven responses are critical. AI assistants can provide real-time analysis and pattern recognition, which are invaluable in supporting cognitive functions, particularly in high-pressure situations [563, 1216]. Moreover, AI assistants are highly effective in content generation and task automation. They possess advanced capabilities for understanding and producing human-like content, including conversation analysis and synthesis, allowing them to simulate nuanced interactions [737]. In CAS, this conversational capability allows AI to offer guidance in a natural, human-centered way, such as generating insightful responses, clarifying concepts, or even engaging users in interactive learning dialogues. By analyzing speech patterns, tone, and content, AI assistants can adapt their conversational style, creating a responsive and personalized experience that feels both supportive and engaging [235]. They can also automate repetitive, time-consuming tasks, such as data entry, scheduling, or report generation, allowing users to focus on higher-order cognitive tasks. For example, in professional settings, AI assistants can draft documents, generate summaries, or even write code based on natural language inputs, streamlining workflows and boosting productivity [913, 819, 57].

Technology Enablers of Artificial Intelligence Assistants

AI assistants leverage Computer Vision (CV) and Image Recognition (IR) technologies to process and interpret visual information, thereby enhancing their interaction with users and their environment. CV enables AI systems to "see" and understand the physical world by analyzing images and videos in real-time, which is essential in contexts where visual interpretation is critical [309]. For instance, AI assistants can analyze visual inputs, recognize objects, and provide feedback based on identified patterns in the environment [211, 915]. Through the use of deep learning and convolutional neural networks (CNNs), AI assistants in CAS can recognize complex visual patterns, such as identifying objects, faces, or even emotions from images [433, 1248]. This capability is particularly valuable in dynamic environments where real-time interpretation of visual data is essential. Reinforcement learning and generative models further enhance the capabilities of computer vision systems within AI assistants, allowing them to improve their performance through interactions with their environment and generate new visual content when necessary [1038, 246]. These advanced learning techniques enable AI assistants to continuously evolve and adapt, ensuring that CAS remain effective and responsive to the changing needs of users.

Another fundamental enabler of AI assistants' effectiveness in CAS is Natural Language Processing (NLP), which facilitates seamless and intuitive interactions between users and AI systems. Through NLP, AI assistants can interpret and respond to user queries in natural, conversational language, making interactions more user-friendly and efficient [1336, 1031]. The ability to engage in meaningful dialogue ensures that AI assistants can provide relevant and accurate responses, thereby enhancing the overall user experience and effectiveness of CAS [553]. Beyond interaction, AI assistants play a significant role in content generation and task automation. Technologies such as Generative Pretrained Transformers (GPT) enable AI assistants to produce human-like text, summaries, and translations in response to user prompts [1038, 1201]. This capability not only streamlines workflows but also enhances productivity by automating repetitive or complex tasks, allowing users to focus on higher-level cognitive activities.

2.2.3 Sensor Technologies for Cognitive Augmentation

Sensor technologies are fundamental to the effectiveness of cognitive augmentation systems, playing a key role in capturing real-world data to create immersive, interactive, and responsive experiences. Both internal sensors, embedded within XR devices, and external sensors, which extend beyond the immediate XR hardware, contribute to creating effective and engaging cognitive environments.

Internal sensors, such as Inertial Measurement Units (IMUs), optical sensors, and eye-tracking sensors, are often embedded within XR devices like headsets and controllers. IMUs, which include accelerometers and gyroscopes, monitor the user's motion and orientation, providing immediate feedback on movements. These are critical in environments where precise motion control is required, such as when manipulating virtual tools or interacting with objects in a 3D environment [373]. Optical sensors, including cameras and depth sensors, further enhance this by capturing the user's environment and enabling inside-out tracking, which allows the XR device to orient itself in space without external markers or cameras. This ensures that virtual objects are spatially aligned with the user's real-world surroundings, maintaining immersion and accuracy. Eye-tracking sensors, which are increasingly integrated into advanced XR headsets, monitor the user's gaze, enabling adaptive interactions by focusing processing power on the areas of interest. This capability is particularly useful in applications that require attention to detail, as the system can adjust the display and interaction mechanisms based on where the user is looking, ensuring optimal performance while saving computational resources through techniques like foveated rendering [1007, 1189]. Beyond optimizing rendering efficiency and interaction, eye-tracking technology also plays a crucial role in behavioral studies, offering insights into user engagement, attention allocation, and cognitive processing in immersive environments. By analyzing gaze patterns, researchers can assess decision-making processes, learning strategies, and cognitive workload, making eye-tracking a valuable tool in domains such as psychology, human-computer interaction, and neuroscience [708, 876].

On the other hand, external sensors augment the system by providing broader spatial data or physiological monitoring. Wearable sensors, such as Electromyography (EMG) sensors, such as the EMG Trigno system [304], capture detailed physiological responses, including muscle contractions. These sensors enable real-time adaptation of XR systems based on the user's physical state. For instance, EMG sensors monitor muscle movements, allowing users to control virtual elements through gestures or muscle contractions. This hands-free interaction is particularly valuable in scenarios where traditional controllers are impractical, such as in rehabilitation or industrial training contexts [457, 616]. External environmental sensors, such as motion-tracking cameras, play a crucial role in mapping physical spaces and enhancing interactions between users and virtual objects in XR environments. Devices like the Qualisys Miqus M1 [1025] provide high-precision motion tracking, capturing real-time movement data to ensure accurate alignment of virtual objects with the real world. These cameras scan the surroundings to generate precise 3D models, which are vital for maintaining spatial consistency and interaction fidelity. In collaborative settings and industrial simulations, motion-tracking cameras help maintain the correct spatial relationships between virtual tools and real-world structures, improving task precision and ensuring user safety. By monitoring users' movements in real-time, these sensors provide additional data on how users physically interact with virtual elements, enabling more immersive and responsive experiences [22, 272]. Microcontrollers and temperature sensors further extend the adaptability and responsiveness of XR systems by providing critical environmental data. Microcontrollers, such as those used in Arduino-based setups or the Espressif Systems Platform 32-bit (ESP32), act as the central processing unit for various external sensors, collecting and transmitting real-time data to the XR system [782]. The ESP32 is particularly valuable in XR applications due to its built-in Wi-Fi and Bluetooth capabilities, which facilitate seamless communication between devices and support real-time monitoring. These devices are especially useful for managing multiple sensor inputs, as they can simultaneously handle data from temperature, humidity, or other environmental sensors, ensuring efficient data flow and processing [899]. Temperature sensors, like the Digital Humidity and Temperature sensor, model 22 (DHT22), play a unique role by capturing ambient conditions that can influence a user's comfort and overall experience within XR applications [865]. The DHT22 measures both temperature and humidity, making it ideal for XR environments where multiple environmental factors must be monitored. For instance, in prolonged usage scenarios, temperature sensors can monitor environmental conditions, allowing the system to make adjustments to maintain user comfort, such as altering visual or interaction intensity levels in response to rising temperatures [862]. This information becomes crucial in settings that simulate physical environments or involve physical exertion, such as rehabilitation exercises or outdoor simulations, where temperature can directly impact performance and safety [899].

By combining the precise, close-range data from internal sensors with the broader spatial and physiological insights provided by external sensors, XR systems are able to offer tailored, real-time responses that assist both individual and collaborative experiences.

2.2.4 Synergy of Extended Reality, Artificial Intelligence, and Sensors for Cognitive Augmentation

XR, AI, and sensor technologies each offer significant potential to advance Cognitive Augmentation Systems. However, it is their synergy that truly unlocks their potential in creating adaptive, immersive, and highly personalized environments. The integration of XR technologies provides the immersive layer, simulating real-world scenarios where cognitive exercises can be practiced in safe, controlled settings. These environments allow users to interact dynamically with virtual elements, fostering deeper engagement and cognitive reinforcement. AI amplifies this experience by providing personalization through adaptive algorithms that continuously monitor user performance. Additionally, it supports users in problem-solving, decision-making, and engaging in natural, human-like conversations. In addition, AI automates routine tasks and facilitates content creation, freeing up cognitive resources for more complex and creative activities, thus allowing users to focus on higher-order cognitive tasks. Sensors, whether embedded within XR devices or external, such as standalone motion capture systems or environmental monitors, are the third critical component in this trio. By gathering physiological data, tracking user movements, monitoring cognitive states, and assessing environmental conditions, sensors provide valuable real-time feedback and enhance environmental awareness. This feedback enables the AI to make data-driven adjustments to the XR environment. Together, these technologies create a closed-loop system where user performance and physiological states continuously inform the adaptation of the environment, enhancing learning outcomes and overall system effectiveness.

2.3 Infrastructure Framework of Developed Case Studies

The development and deployment of case studies in this thesis rely on robust frameworks that integrate essential tools and platforms, ensuring seamless interaction between virtual environments and users.

2.3.1 Development and Programming Frameworks

In this thesis, most of the case studies utilize Unity 3D [1287] as the primary development environment for creating immersive experiences. Unity's versatility enables the customization and scalability needed to develop complex, interactive systems across multiple platforms. C# is the predominant programming language used within Unity, providing the flexibility and control necessary to create sophisticated real-time interactions, manage physics, and handle 3D asset manipulation efficiently.

For mobile-based case studies, Android Studio [452] acts as the primary integrated development environment (IDE) for developing Android-specific experiences. It offers a comprehensive set of tools for creating and deploying native Android apps that utilize the full capabilities of ARCore, which provides key augmented reality functionalities such as motion tracking, environmental understanding, and light estimation. Through Java or Kotlin programming, developers can customize how the app handles device-specific configurations and optimize performance for a broad range of Android devices. In addition to Java/Kotlin, JavaScript can be integrated into Android Studio to support interactive web-based components. WebView can be used to embed and display dynamic content, such as interactive visual elements, directly within the mobile application. JavaScript facilitates seamless communication between WebView and the native Android framework, allowing for enhanced user interaction between web-based and native components.

For hardware interfacing and real-world data acquisition, the Arduino Integrated Development Environment (IDE) [58] plays an instrumental role in connecting physical devices with virtual environments. Arduino IDE provides an accessible platform to program microcontrollers, allowing developers to gather sensor data and send commands to actuators. This IDE is compatible with various sensors that can measure environmental parameters like temperature, humidity, and light, or capture physiological data, adding depth to XR applications. Arduino's straightforward programming language simplifies coding, while its extensive library support ensures compatibility with numerous sensor modules. By integrating with Unity or other backend systems through serial communication, Arduino can enable real-time data flow from the physical to the digital realm, supporting dynamic XR experiences that respond to environmental or user-driven changes.

2.3.2 Software Development Kits

A range of Software Development Kits (SDKs) extends Unity's functionality, enabling platform-specific features like image recognition, motion tracking, and environmental mapping.

SDKs such as Vuforia [1020] and ARCore [453] streamline the development process by offering components and Application Programming Interfaces (APIs) that manage user interaction tracking, spatial mapping, and real-time data processing. For instance, Vuforia leverages built-in cameras and depth sensors to enable accurate object detection and tracking in real-time AR environments, while ARCore supports motion-tracking and environmental understanding through the device's internal sensors. Additionally, sensor-specific SDKs, such as those designed for EMG devices like the EMG Trigno system, enable developers to integrate external sensors for capturing users' physiological data. Similarly, motion-tracking systems, like external cameras, wearable trackers, and specialized motion capture solutions, such as the Qualisys Miqus M1, utilize their respective SDKs to deliver precise movement data, further enhancing the system's ability to offer immersive, real-time feedback. In addition to these, SDKs like MRTK (Mixed Reality Toolkit) [855], OpenXR [646], OpenVR [1295], [851], and the Magic Leap Unity SDK [714] further enhance Unity's capability to support a wide range of XR devices and experiences. MRTK provides tools for building mixed-reality applications across different platforms. OpenXR and OpenVR offer cross-platform development capabilities, enabling XR experiences to run on various headsets with minimal changes to the codebase, ensuring compatibility and performance consistency across multiple devices. The Oculus SDK is essential for building applications for Oculus devices, providing APIs for handling device-specific features such as hand tracking, rendering optimizations, and spatial audio. The Magic Leap Unity SDK facilitates the development of applications for Magic Leap devices within Unity, providing access to key features such as spatial computing, meshing, hand tracking, and gesture recognition, enabling immersive and interactive MR experiences tailored to Magic Leap's hardware.

Another crucial component in the infrastructure is the OpenAI API [945], which provides advanced NLP capabilities. This API enables the system to generate human-like text, analyze language, and respond to complex queries, enhancing interactive user experiences within XR environments. By connecting with Unity and other platforms, the OpenAI API supports real-time language-based interactions that adapt based on user input. This can be particularly beneficial for conversational agents, enabling them to provide context-sensitive guidance, answer questions, or offer assistance in learning tasks. The OpenAI API's capacity for language comprehension and generation allows it to serve as a flexible tool for automating responses, enriching the realism of virtual assistants, and fostering more intuitive communication within case studies.

2.3.3 Client-Server Architecture

The client-server architecture facilitates distributed computing by managing real-time data exchange, ensuring low-latency interactions and efficient resource allocation between client devices and centralized servers. In this architecture, the server handles central processing, data synchronization, and logic, while the clients—whether XR headsets or mobile devices—serve as the user interface, rendering the virtual environment and processing local interactions. The server typically runs on backend frameworks such as Node.js [947] or Python, which handle concurrent user sessions and manage data traffic efficiently. Communication between clients and servers is often implemented using WebSockets or RESTful APIs, providing robust real-time data exchange.

2.3.4 Backend and Data Management Solutions

For backend operations, the Parse Platform SDK [974] and Back4App (a Backend-as-a-Service solution) [70] provide robust support for data management, user authentication, and real-time database interactions. The Parse SDK simplifies data operations through an abstraction layer, allowing efficient creation, retrieval, and modification of data objects without extensive backend development. With Back4App's cloud-hosted Parse platform, developers can leverage scalable infrastructure, which manages backend tasks, ensuring applications can efficiently handle features like session management, notifications, and multi-device data synchronization.

Python-based servers could play a key role in backend processing and real-time data handling, particularly for motion tracking, sensor integration, and AI-driven computations. These servers have the potential to facilitate efficient communication between XR applications and external data sources, ensuring low-latency interactions and adaptive system responses. By leveraging Python's extensive ecosystem for networking, machine learning, and database management, such backend solutions could enable seamless integration of AI-driven analysis, real-time updates, and optimized data processing pipelines.

Parse SDK, Back4App, and Python-based servers could provide a flexible and scalable solution for applications requiring dynamic, real-time data handling, ultimately enhancing user experience and system performance across platforms.

2.4 Evaluation Framework of Developed Case studies

This section outlines the participant selection criteria, data collection methods, analysis techniques, and ethical considerations that guided the evaluation of each case study.

2.4.1 Participant Selection Criteria

The participant selection criteria for each case study were carefully designed to align with the study objectives, ensuring a relevant and representative sample. Depending on the specific research goals, participants were selected based on factors such as age, expertise, familiarity with XR technologies, and cognitive or physical abilities. In cases where user studies were not conducted, future recruitment plans target specific demographics to evaluate usability and system effectiveness comprehensively. This structured approach ensured that the case studies captured a wide range of user experiences, enhancing the validity and applicability of the findings.

2.4.2 Data Collection Methods

To capture a comprehensive understanding of system usability and user experience, a mixed-methods approach was employed, including:

- User Performance Metrics: Data such as task completion times, accuracy rates, and error counts were collected to evaluate user performance through the use of the developed systems.

- Questionnaires and Surveys: Standardized questionnaires, including the System Usability Scale (SUS) [171], NASA-TLX for cognitive workload [506], and the Technology Acceptance Model (TAM) [292], as well as the Intolerance of Uncertainty Scale (IUS) [181], Motion Sickness Assessment Questionnaire

(MSAQ) [428], Immersive Experience Questionnaire (IEQ) [1067], the Networked Minds Social Presence Inventory [502], and Slater–Usoh–Steed Presence Questionnaire (SUS) [1291], were administered to collect comprehensive user feedback on system usability, cognitive load, acceptance, social presence, and overall user experience. Additionally, in the Collaborative Shared Memory Photo Album case study, custom-designed constructs were used to assess user perceptions of the system, including:

  - Perceived Ease and Enjoyment of Use (PEEU): Evaluated through a 5-point Likert scale, focusing on ease of understanding, user preference for augmented over traditional photo albums, and overall enjoyment.
  - Deep Learning Gain (DLG): Measured the perceived utility of AI-based features, such as automatic picture identification, date estimation, and socio-historical context recognition.
  - HoloLens Perspective (HLP) and Receiver Perspective (RP): Investigated user behavioral intention, willingness to use the system for memory sharing, and its social impact through Yes/No questions and Likert-scale responses. These constructs, inspired by technology acceptance and behavioral intention models, provided additional insights into user engagement and social dynamics within augmented family photo album experiences.

- Physiological Data: Real-time motion data were collected to gain valuable insights into users' physical responses and interactions.

- Semi-Structured Interviews: Following system usage, participants were invited to participate in interviews to provide qualitative insights into their experience with cognitive Augmentation systems. These interviews focused on the perceived effectiveness of the systems in supporting cognitive tasks, usability challenges, and areas for improvement.

2.4.3 Data Analysis Methods and Tools

The data collected during the experimental phase were analyzed using a combination of quantitative and qualitative analysis techniques:

- Quantitative Analysis: Statistical methods were used to compare variables across different conditions, such as varying levels of task complexity or different system interfaces (e.g., embodied versus audio-based MR assistants). Descriptive statistics were used to summarize user feedback from the questionnaires, and correlations were calculated to assess relationships between key variables, offering insights into factors influencing user experience and system effectiveness. For the comparison of questionnaire results, statistical tests such as t-tests, ANOVA, and Mann-Whitney U tests were employed to identify significant differences between conditions.

- Qualitative Analysis: Interview data were subjected to thematic analysis, where recurring themes related to user experience, system usability, and cognitive engagement were identified. This qualitative analysis provided a deeper understanding of the user's subjective experiences and complemented the quantitative findings.

To conduct an analysis of the data collected in this research, R and Python were chosen as the primary programming languages for their complementary strengths in statistical analysis and data processing. All statistical analyses in R were conducted using R (v4.2.2). The following packages were utilized: ggplot2 for data visualization, dplyr for data manipulation, lme4 for mixed-effects modeling, car for ANOVA and regression diagnostics, and psych for descriptive statistics and psychometric analysis. Similarly, all statistical analyses in Python (v3.10.6 or v3.8) were performed using key libraries designed for data analysis and statistical computation. Matplotlib was used for data visualization, allowing the creation of a wide range of static and interactive plots. Pandas provided comprehensive tools for data manipulation and structuring, ensuring efficient handling of datasets. Pingouin was employed for statistical testing, offering a user-friendly interface for conducting t-tests, ANOVA, and correlation analyses. Seaborn enhanced visualization capabilities with advanced statistical plots, aiding in the interpretation of results. Lastly, Scipy was utilized for statistical functions, supporting hypothesis testing and probability distributions essential for rigorous data analysis.

2.4.4 Ethical Considerations

This research adhered to strict ethical guidelines to ensure the privacy, security, and well-being of participants:

- Informed Consent: All participants were provided with detailed information regarding the nature of the study, the use of their data, and their rights to withdraw from the study at any point. Informed consent was obtained before participation.
- Data Privacy: Collected data, including physiological and performance metrics, were anonymized to protect participant identities. Secure data storage systems were used to ensure that personal data were not accessible to unauthorized individuals.
- Impact on Participants: Participants were monitored for signs of fatigue or discomfort, and appropriate breaks were provided during extended sessions.

2.5 Discussion and Conclusion

This chapter addressed the research question: *How can Extended Reality (XR), Artificial Intelligence (AI), and sensor technologies be effectively integrated to develop and evaluate immersive and adaptive Cognitive Augmentation Systems (CAS) for diverse daily scenarios?*

Through an analysis of technological infrastructure, development frameworks, and evaluation methodologies, this chapter demonstrated how XR, AI, and sensor technologies can be systematically combined to create adaptive CAS that enhance both individual and collaborative experiences.

The technological foundation of CAS relies on XR devices such as HoloLens and Oculus Quest, which, when integrated with AI-driven frameworks and sensor-rich environments, enable immersive and context-aware experiences tailored to diverse user needs. Development platforms like Unity 3D and Android Studio ensure cross-platform compatibility.

To assess CAS effectiveness, the research employs a mixed-method evaluation framework, combining quantitative metrics—such as task performance, completion rates, and accuracy—with qualitative assessments that capture user immersion, usability, and perceived cognitive load. These rigorous evaluation methods ensure that each case study effectively measures the impact of CAS across various domains.

By integrating robust technological infrastructure, adaptive frameworks, and comprehensive evaluation strategies, this research demonstrates how XR, AI, and sensor technologies can bridge the gap between immersive simulation and personalized cognitive support. The findings highlight how CAS dynamically respond to cognitive and physical user contexts, reinforcing their applicability across diverse daily scenarios while identifying key areas for future refinement and optimization.

Chapter 3

Personal Augmentation

The rapid advancements in extended reality (XR), artificial intelligence (AI), and sensor technologies have opened up new possibilities for augmenting human cognition. As our daily lives become increasingly integrated with digital tools, the potential to augment personal cognitive abilities through these technologies has become a critical area of exploration. By focusing on ***personal augmentation***, this chapter highlights the potential of the convergence of these technologies in the context of everyday tasks.

3.1 Theoretical Background

Personal cognitive augmentation through XR, AI, and sensor technologies has been extensively studied across multiple domains, with a strong research focus on learning, problem-solving, memory, engagement, and interaction. Studies have demonstrated that these technologies significantly enhance cognitive processes by improving learning retention, problem-solving efficiency, memory recall, user engagement, and interactive experiences [587, 1052].

AI-driven immersive tutors dynamically adjust instructional content based on users' progress, leading to improved conceptual understanding and higher engagement across various educational contexts [1116, 697]. Similarly, XR-based procedural training has proven particularly effective in fields such as medicine, engineering, and the arts, where interactive, hands-on learning fosters greater knowledge retention and skill acquisition [185, 1399, 921, 414, 1387, 283]. Furthermore, sensor technologies play a crucial role in these advancements by capturing real-time user data, enabling adaptive feedback, and refining AI-driven personalization [757, 941]. These findings highlight the transformative role of AI, XR, and sensor-based systems in education, enabling more adaptive, interactive, and immersive learning experiences across diverse disciplines. A specific body of research has focused on language learning, which has emerged as one of the most successful areas benefiting from AI-powered XR environments. Immersive and interactive experiences have been shown to enhance engagement, comprehension, and retention. Studies indicate that AI-driven XR conversational agents provide real-time corrective feedback, accelerating fluency acquisition more effectively than traditional methods. Augmented reality (AR) learning platforms incorporating contextual speech recognition and multimodal feedback loops further improve pronunciation and grammar retention

[204, 599, 1421].

A growing body of research highlights how AI-powered XR environments enhance cognitive adaptability and structured reasoning in problem-solving. AI-enhanced XR simulations dynamically adjust task difficulty based on user performance, providing real-time feedback and fostering adaptive learning strategies [479, 240]. Cognitive augmentation extends beyond traditional learning applications to decision-support systems that help users process complex information in real time. For instance, the Wearable Reasoner, an AI-powered decision-support system, illustrates how AI and wearable technologies can enhance decision-making in ambiguous environments [286]. By classifying information as supported or unsupported and providing contextual explanations, the system improved users' ability to make informed, logical decisions. Similarly, AI-driven XR decision-making assistants have been shown to enhance critical thinking and situational awareness, particularly in fields requiring rapid and high-stakes decision-making, such as medical diagnostics and financial forecasting [1232, 1016, 1103]. These findings emphasize the role of AI-driven XR systems in augmenting problem-solving capabilities across various domains.

Memory retention has been another primary focus of XR-based cognitive augmentation, particularly through spatialized memory encoding techniques. Studies show that VR memory palaces significantly enhance recall performance by associating information with virtual spatial locations, an approach that has been shown to outperform traditional rote memorization strategies. One example is NeverMind, an AR application designed to enhance information recall by linking facts to familiar spatial environments, demonstrating significantly higher retention rates compared to traditional study techniques [1084]. These findings suggest that XR-based memory augmentation can provide effective cognitive scaffolding for learners across various domains.

XR and AI-driven sensor technologies have shown significant promise in improving interaction capabilities for individuals with movement impairments. Research on AI-assisted, sensor-based feedback systems indicates that real-time proprioceptive and haptic feedback can greatly enhance motor learning and interaction precision [513]. For instance, sensor-driven XR rehabilitation environments have been used to assist individuals with impaired mobility, integrating gait support strategies and real-time adaptive feedback to facilitate motor coordination [785, 403]. Similarly, AI-enhanced mixed reality frameworks have been deployed to improve upper limb rehabilitation in individuals with neuromuscular disorders, providing personalized motion assistance through XR-integrated motion capture [59]. These findings suggest that XR-driven cognitive augmentation can create highly adaptive, personalized rehabilitation and interaction systems, addressing specific motor and cognitive challenges faced by individuals with movement difficulties.

Despite substantial progress, key challenges remain in optimizing XR, AI, and sensor technologies for domain-specific applications. While research highlights their potential to enhance learning, problem-solving, memory, and motor skill development, effectively integrating these systems requires further exploration. Advancing this field necessitates a deeper investigation into how XR, AI, and sensor-based systems can be designed, adapted, and seamlessly implemented to support real-world cognitive augmentation across diverse contexts.

Specifically, this chapter addresses the key research question:

- RQ: How do cognitive augmentation systems impact individual learning, skill development, and cognitive processes?

3.2 Case Studies (N1–N8)

To address this research question, a series of case studies have been developed. These studies illustrate the potential of these emerging technologies to support cognitive augmentation at personal levels while also revealing the challenges and opportunities encountered in their implementation.

3.2.1 N1: Augmented Reality Language Learning for Dyslexia

Objective and Context

Learning a foreign language (FL) involves complex processes that span linguistic, cognitive, and cultural dimensions. For students with Specific Learning Disorders (SLDs), such as dyslexia, which is the most prevalent condition within this category, mastering a new language can be particularly challenging. Despite increased attention from various research fields and the implementation of legislative measures aimed at promoting educational equity, the obstacles faced by students with SLDs remain significant. Traditional educational settings often fail to effectively support these students, as elements like the class pace, teacher-student ratios, and assessment criteria can exacerbate their struggles, further complicating the learning experience [412]. This situation underscores the pressing need for teaching methods and materials that are more inclusive and accessible. The use of AI and Augmented Reality (AR) in language education introduces promising new approaches but also raises concerns about maintaining a balance between technological innovation and the human aspects of language learning.

In response to these challenges, the development of ARELE-bot—a mobile application combining AI (such as ChatGPT) and AR—seeks to revolutionize modern language education. This app aims to provide an accessible, personalized, and non-judgmental learning environment that complements traditional teaching methods, serving as a valuable tool for language teachers rather than a replacement. During the design and development of this app, particular focus is given to its effectiveness for students with dyslexia, by utilizing their unique cognitive skills, termed the 'holodysnomic brain.' This term, originating from 'Holo-' for global and '-dysnomia' for a deviation from usual cognitive processes, highlights the dyslexic strength in global and holistic information processing. These individuals demonstrate a remarkable ability to merge data from varied sources, and their robust holistic visual processing and visual memory offer significant advantages in specific tasks [108]. This leads to a distinctive approach to thought that positively deviates from the conventional norms, offering unique advantages in language learning contexts which ARELE-bot is designed to harness, providing specialized assistance for their specific areas of difficulty.

The central research question driving this case study is:

- RQ: How can AR technology, integrated with ChatGPT, be designed to support and enhance language learning for individuals with dyslexia?

Related work

This Section offers an overview of relevant research focusing on SLDs and dyslexia in Foreign Language Learning and on AI and AR's roles in language education. It also explores some of the critical challenges of the application of AI and AR technologies in language education.

Specific Learning Disorders, Dyslexia and Foreign Language Learning

SLDs pose a considerable challenge in the educational context. International estimates suggest that their global prevalence ranges from 3% to 15%, influenced by varying definitions and diagnostic criteria used across countries [42, 315, 600, 1429]. Based on neurobiological and evolutionary foundations, SLDs specifically affect the learning of essential academic skills such as reading, writing, and mathematics, while not altering general intellectual functions. They often co-occur with issues in self-regulation, social perception, and interaction but are not directly caused by external factors like cultural or educational influences [264]. SLDs are characterized by significant comorbidity and can coexist with other disorders, such as Attention Deficit Hyperactivity Disorder (ADHD) and emotional conditions like anxiety, low self-esteem, and depression [13, 823, 1343]. This added complexity leads to further challenges in students' educational journeys, often resulting in academic failures and impacting personal and social development [1065, 1101]. Among SLDs, dyslexia is the most widespread disorder, affecting about 80% of individuals with an SLD and significantly influencing the development of linguistic skills [1158, 1159]. Dyslexia is a neurobiological disorder, characterized by genetic, morphological, and neurofunctional anomalies [328, 463, 462, 410, 423, 1157, 1272], manifesting in difficulties in decoding and recognizing words.

Given these difficulties, students with SLDs, particularly those with dyslexia, face challenges in several areas of Foreign Language learning, as noted in Melero (2020). In reading and text comprehension, they struggle with text decoding and phonological processing, which requires extensive cognitive effort and affects their ability to understand texts deeply. Listening skills are hindered by problems in auditory processing and phonological memory, making it difficult to grasp spoken language, especially in foreign contexts. Writing is also a challenge due to lexical, morphosyntactic, and syntactic retrieval issues, impacting the quality of their written work and their ability to organize text effectively. Additionally, speaking and oral interactions are affected by difficulties in lexical retrieval and phonological processing, leading to reduced fluency and accuracy in their spoken language [843]. Additionally, memory retention, particularly for sequential or detailed information, can be a significant hurdle for them, as well as difficulties in organization [844, 845, 1199, 1200, 519]. These cognitive difficulties are further compounded by challenges in maintaining attention and motivation in conventional learning environments, making traditional language education methods less effective for them. These cognitive challenges are often accompanied by behavioral and emotional difficulties, including frustration, stress, and a decline in motivation, negatively impacting self-esteem and leading to avoidance behaviors. Anxiety related to linguistic performance can create mental blocks, hindering language performance [1001].

On the other hand, individuals with dyslexia exhibit a unique cognitive profile, often characterized by a holistic and global approach to information processing, as described in the 'holodysnomic brain' concept. Their strengths lie in their ability to integrate information from multiple sources, a skill that lends itself well to creative and artistic endeavors, as well as divergent thinking. This cognitive style also includes robust holistic visual processing and strong visual memory skills, providing them with distinct advantages in certain tasks [108]. However, these strengths are counterbalanced by challenges in traditional language learning areas.

Well-designed educational tools should therefore leverage these cognitive advantages while providing support in areas of weakness. By highlighting and utilizing their strengths in holistic and visual processing, and simultaneously addressing challenges in phonological and auditory processing, memory, and organizational skills, along with adaptive assessment, the design of these systems can offer a more effective and personalized learning experience for individuals with dyslexia.

Enhancing Language Learning: Integrating Artificial Intelligence and Augmented Reality Tools

AI-driven tools in language education, including AI-powered automatic speech recognition (ASR), AI-powered chatbots such as ChatGPT, and advancements in AI in Language Testing have transformed the methodology of language learning and education in language acquisition technologies [1259]. In the context of language learning, ASR emerges as a vital tool for pronunciation training and oral skill development. It enables the applications to accurately transcribe and assess spoken language inputs from learners, providing immediate feedback on their speech accuracy and fluency [1345]. Particularly noteworthy is the role of AI-powered chatbots like ChatGPT in this technological ensemble. ChatGPT, as an advanced chatbot, offers interactive and conversational practice by simulating real-life dialogues in the target language. This feature is crucial in not just enhancing language proficiency, but in providing a responsive and engaging learning environment. Users can practice and refine their language skills in a dynamic setting, closely mimicking real-world interactions. This hands-on approach facilitates a deeper understanding and retention of language, making ChatGPT an invaluable tool in language learning applications [1152]. Progress in language evaluation through AI, including ChatGPT, utilizing sophisticated algorithms, offers personalized and adaptive testing experiences, comprehensively measuring language proficiency [1410, 772].

Augmented Reality, on the other hand, adds an immersive dimension to language learning. By overlaying digital information onto the physical environment, AR applications can create context-rich, interactive scenarios that facilitate language comprehension and retention [128, 1221, 1218, 1224]. AR's potential is exemplified by its ability to simulate real-life situations where language skills are applied, thereby bridging the gap between theoretical knowledge and practical application. For instance, Ibrahim et al. [576] and Weerasinghe et al. [1334] introduce novel systems for immersive language learning through dynamic labeling of real-world objects. They compare this AR-based approach to traditional learning, finding that AR is more effective and enjoyable, with significant improvements in immediate and delayed recall tests. Additionally, an AR system designed for learning Japanese compound verbs, which utilizes image schema and animations, demonstrated notable improvements in post-test performance and retention [420]. In addition, AR can create virtual environments where learners can engage in simulated dialogues with native speakers or AI-driven characters, thereby improving their conversational fluency and comprehension. Such environments can mimic everyday situations like shopping, dining, or traveling, providing learners with practical language usage experiences [321]. Moreover, AR's interactive nature encourages active participation, which is essential for language retention and mastery [1084].

The Role of Artificial Intelligence and Augmented Reality in Enhancing Accessibility and Inclusivity

The integration of AI and AR in language learning applications also significantly contributes to making language learning more accessible and inclusive for a broader spectrum of learners. For instance, ASR applications are not only beneficial for pronunciation training but also serve as an essential tool for learners with writing or typing difficulties, enabling them to interact with the application through speech [426]. AI-driven chatbots can adjust their interaction style and content complexity based on the learner's profile, ensuring that the educational material is accessible and comprehensible to all users. Furthermore, advancements in AI in Language Testing incorporate adaptive algorithms that can modify the testing format to suit the needs of learners with disabilities, ensuring fair and equitable assessment conditions [476]. AR can provide visual and auditory cues in language learning scenarios, which are particularly beneficial for learners with SLDs or attention deficits [37]. By creating an engaging and multisensory learning environment, AR helps in maintaining focus and motivation among these learners [1335]. Additionally, AR's ability to create simulated real-world environments is invaluable for learners with mobility limitations, allowing them to experience diverse linguistic and cultural contexts without physical travel [38].

Critical Challenges of Application of Artificial Intelligence and Augmented Reality Technologies in Language Education

The integration of AI and AR technologies in language education, while offering numerous benefits, also brings critical challenges. The shift towards technology-mediated language instruction, such as AI-driven tools, can lead to a diminished presence of direct human interaction, which is vital for developing communication skills and cultural competencies in language learners. Kozar [682] emphasizes that the absence of face-to-face interaction can impact the development of pragmatic language skills, which are best nurtured through real-life conversational experiences. AI-driven chatbots, such as ChatGPT, offer interactive language practice but may lack the depth and flexibility of human tutors. They are often critiqued for their inability to fully understand and respond to the nuances of human emotion and cultural contexts, which are crucial in language learning, potentially leading to misunderstandings or limited conversational scope [401]. On the other hand, AR brings an immersive dimension to language learning, yet it is not without its drawbacks. Bower et al. [157] point out that while AR can create engaging, context-rich learning experiences, it may also lead to cognitive overload, as learners have to process both the real world and the overlaid digital information simultaneously. Additionally, Godwin-Jones [438] argues that the effectiveness of AR in language education is contingent on the quality and relevance of the augmented content, which can be challenging to align with specific learning objectives and cultural nuances. These criticisms underscore the need for careful integration of AI-driven tools and AR in language learning environments, ensuring that these technologies complement rather than replace the essential human elements of language acquisition.

Methodology

This section details key features of ARELE-bot, with particular emphasis on how its functionalities have been carefully designed to specifically meet the needs of students with dyslexia.

Design Strategies Tailored for the Requirements of Individuals with Dyslexia

Our literature review highlights the unique challenges that individuals with dyslexia face in language learning, such as difficulties in phonological processing, auditory processing, memory, organizational abilities, and maintaining attention and motivation. On the other hand, their strengths include the effective integration of diverse information sources and strong visual processing skills. Furthermore, it also underscores the advantages of integrating AI-driven tools and AR thoughtfully in language learning contexts, ensuring that these technologies enhance rather than supplant the crucial human aspects of language learning. Considering these elements, this section outlines the specific design strategies of ARELE-bot, tailored to meet the educational needs of students who present this learning disorder.

ARELE-bot has been meticulously developed with a user-centric focus, incorporating interfaces and modules specifically targeted to enhance the learning experience for learners facing such challenges. Capitalizing on their skills in visual processing and memory, the app highlights the significance of visual learning strategies, enabled through AR technology. AR components in ARELE-bot generate immersive, contextual-rich settings by superimposing digital data onto the real world, enhancing both motivation and attention. Further enhancing its approach, ARELE-bot offers a customizable learning experience, enabling users to tailor language proficiency levels [1]. This adaptable approach aligns with user preferences, easing cognitive load and stress, particularly benefiting dyslexic students by allowing them to learn at their own pace, enhancing confidence and motivation. Interactive and multisensory learning is a fundamental aspect of ARELE-bot's design, enhancing engagement through a combination of visual and auditory elements. The app creates an immersive learning experience by integrating interactive, conversation-based activities within an AR environment. Learners engage in dialogues with a teacher's avatar, practice vocabulary through voice interactions, and refine pronunciation in a dynamic, context-rich setting. This approach makes language practice more realistic, engaging, and relatable, fostering deeper learning and retention. ARELE-bot also includes features that aid in organization, planning, and sequencing with an emphasis on visual modes of interaction. Users can create and edit their visual dictionaries and visual semantic networks, helping them visually organize vocabulary and concepts for enhanced understanding and recall. The design of ARELE-bot also focuses on reducing cognitive load, presenting information in small segments with simple instructions and an intuitive, uncluttered user interface. This ensures a seamless and enjoyable learning experience without overwhelming the user with complex navigation or information.

[1] The language proficiency levels in ARELE-bot are based on the scale of the Common European Framework of Reference for Languages (CEFR).

Finally, ARELE-bot features an adaptive assessment system that personalizes language learning exams according to the proficiency level selected by the user, ensuring a customized educational experience. The app includes positive reinforcement, and continuous, constructive feedback as part of an extensive language learning assessment, designed to keep learners engaged and motivated. The app's assessments are designed to be stress-free and encouraging, focusing on understanding and progress, thus contributing positively to the overall learning experience.

Feature Description

The application starts with a registration and sign-in process. Upon entry, users are greeted by name and prompted to select their language proficiency level. This level of personalization is dynamic, allowing users to adjust their language level as they progress, thereby ensuring the learning experience evolves with them. Continuing this, the application offers four main features: conversation with the virtual teacher's avatar, discovering word meanings, exploring dictionaries, and examining language skills. These will be detailed in the following:

- Conversation with the virtual teacher's avatar: In the ARELE-bot language learning application, the user has the option to have a conversation with the virtual teacher's avatar, experienced through an AR interface that incorporates the use of OpenAI's chat feature. The user should scan the ground, to find a suitable place for the placement of the avatar. This action leads to the unveiling of the conversation interface which allows users to actively engage in simulated real-life conversations by speaking to the virtual teacher via a microphone button. This feature is instrumental in honing verbal communication skills, as it mirrors actual conversational scenarios. Moreover, the inclusion of a stop button empowers users to pause the teacher's responses, granting users agency, thus allowing learners to customize the interaction according to their unique learning requirements and preferences (See figure 3.1a).

- Discovering word meanings: Another functionality of ARELE-bot includes an interactive feature for learning the meanings of words and lexical chunks. Users can capture images or vocalize words and chunks to enhance their contextual understanding, multisensory learning, and memory retention (See figures 3.1b and 3.1c). In image capture mode, objects are labeled and bordered for easy identification (See figure 3.1b). Users then select a name from the detected objects list and access a detailed information page with various learning aids (See figure 3.1d). This page is also accessible for vocalized words, offering similar learning aids. It includes a suggested editable object name, a selection of images, and a sentence contextualizing the word's use. Users can listen to and adjust the pronunciation speed, practice speaking themselves, and receive feedback. The learning process concludes with saving the interaction in the cloud-based visual dictionary for future review, supporting long-term vocabulary retention.

- Exploring dictionaries: The ARELE-bot application enriches language learning with its advanced dictionary exploration and management features, crucial for building a strong vocabulary and semantic networks, thereby improving visual learning and organizational skills. Users can access and practice their stored vocabulary in the visual dictionary, enhancing retention and pronunciation accuracy. Additionally, the app enables the creation of visual semantic networks by selecting category names and adding visual nodes from saved objects, aiding in understanding language structure (See figure 3.1e). Users also have the option to edit these networks at a later stage by adding new categories or images and forming connections between them, allowing for a flexible and dynamic learning experience (See figure 3.1f).

- Examining the language skills: In the design of ARELE-bot, a significant component is the examination module (See Figures 3.2), which utilizes the Open AI API and is customized according to the user's chosen language proficiency level. This module offers a suite of exams meticulously crafted to align with the user's language proficiency as defined by CEFR [2]. Utilizing AI models from OpenAI, the exams are dynamically generated, ensuring a tailored personalized experience. Each exam segment - reading, vocabulary, listening, and grammar - is strategically designed to assess specific linguistic competencies. For instance, the reading exam presents a concise text of 100-150 words, followed by five multiple-choice questions, aimed at evaluating comprehension skills. Similarly, the vocabulary section challenges lexical knowledge through ten targeted questions. The listening and grammatical components, comprising five and ten questions respectively, are structured to test auditory processing and the understanding of various grammatical aspects. A notable element of these exams is the immediate, static feedback mechanism, which motivates users to persist in finding the correct answer. Moreover, the integration of time-tracking functionalities aids learners in developing effective time management skills, a crucial aspect often overlooked in language learning.

Technical Implementation

The development of the ARELE-bot language learning application was carried out using Android Studio [451], an integrated development environment (IDE) tailored specifically for Android application development. The app was designed to run on Android smartphones, ensuring compatibility with devices supporting ARCore functionality. Development and testing were performed on Android devices such as the Samsung Galaxy S20, chosen for their high computational performance and robust AR capabilities, which ensured smooth rendering and interaction with AR features. The primary programming language used in the development was Kotlin, selected for its modern features, concise syntax, and seamless integration with Android development frameworks [451]. Kotlin's interoperability with Java also allowed for leveraging existing libraries and ensured efficient performance in a resource-constrained environment like mobile devices. JavaScript was also used for specific tasks, particularly in integrating the front-end interface with dynamic back-end functionality, due to its versatility in managing APIs and handling interactive elements.

The application incorporated a variety of advanced technologies to achieve its core functionality. OpenAI API (GPT-3.5-turbo) [944] powered the conversational AI component of the app, enabling the virtual teacher avatar to engage users in

[2] The Common European Framework of Reference for Languages (CEFR) is an international standard for describing language ability.

dynamic and personalized interactions. The API generated language exercises tailored to the learner's proficiency level and provided real-time feedback, making the learning experience more responsive and individualized. For example, during conversational practice, the API dynamically adjusted sentence complexity and offered contextual examples of word usage to enhance understanding.

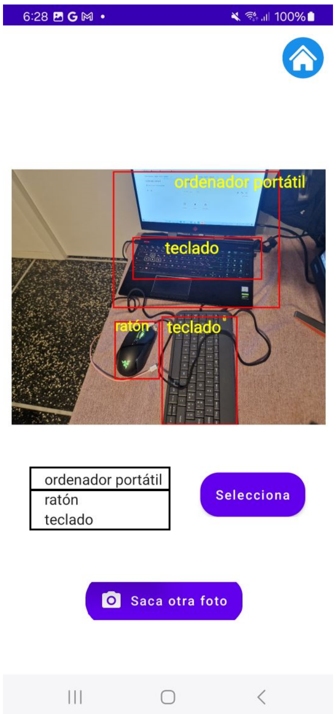
The app's AR capabilities were implemented using the Sceneform Library [449], which enabled the placement and interaction of virtual objects, such as the virtual teacher avatar, within real-world environments. To further enhance the learning experience, TensorFlow Lite Vision API [447] was used for real-time object detection. This feature allowed the application to identify objects captured by the device's camera and associate them with vocabulary words in the target language. For instance, pointing the camera at a book prompted the app to display the word "book" in the selected language, facilitating contextual learning.

On the back end, the Parse Platform SDK [973] and Back4App [71] ensured secure and scalable management of user data, such as learning progress, personalized assessments, and interaction logs. These platforms supported the dynamic generation of content, ensuring a consistent and user-friendly experience. To support speech-based interaction, the app used the Android Speech Package [448] for speech-to-text and text-to-speech functionality. This enabled users to engage in pronunciation exercises and conversational practice with real-time feedback on spoken accuracy. Speech inputs were processed and compared to predefined pronunciation standards.

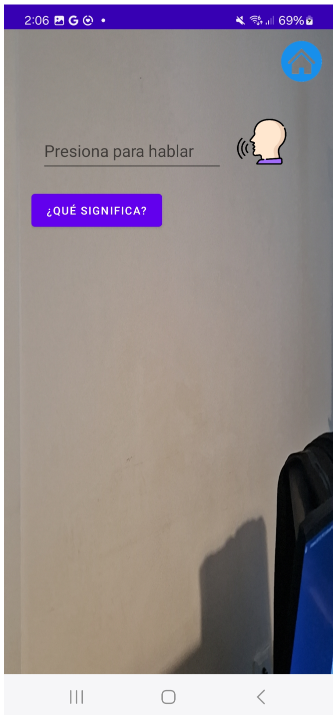
The virtual teacher avatar, central to the app's interactive experience, was developed using Ready Player Me [1045], which allowed for the creation of a highly customizable 3D character. Animations were crafted using Blender [142], adding realistic and engaging movements to the avatar, further enhancing the immersive learning experience. The avatar acted as a guide, delivering personalized feedback, and simulating real-world conversational scenarios to build fluency and confidence.

The system architecture integrated all these components to create a cohesive and efficient learning environment. Real-time interaction between the front-end application, AI-driven back end, and AR functionality ensured that the app was adaptive to user input and responsive in delivering personalized content. Each technological choice was made to align with the app's objectives of enhancing engagement, improving retention, and providing an inclusive and supportive learning experience for students with dyslexia.

(a) Conversation with the avatar



(b) Image overlay



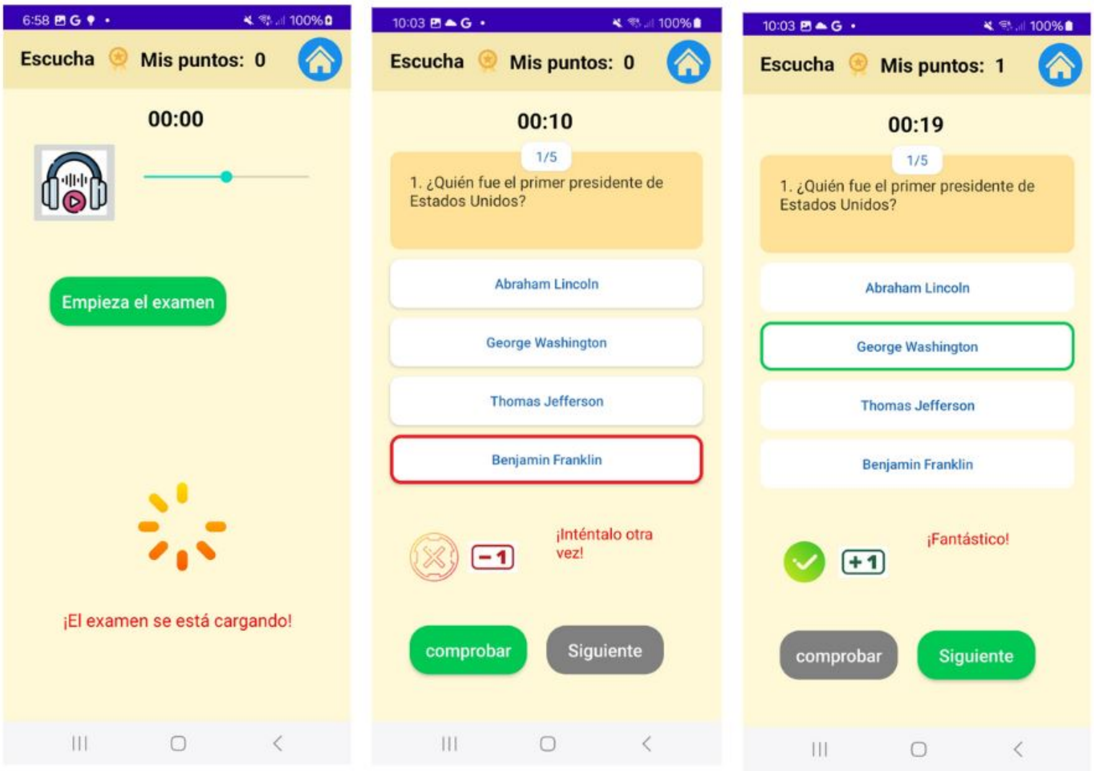
(c) Speech recognition

(d) Information page, and building visual dictionary

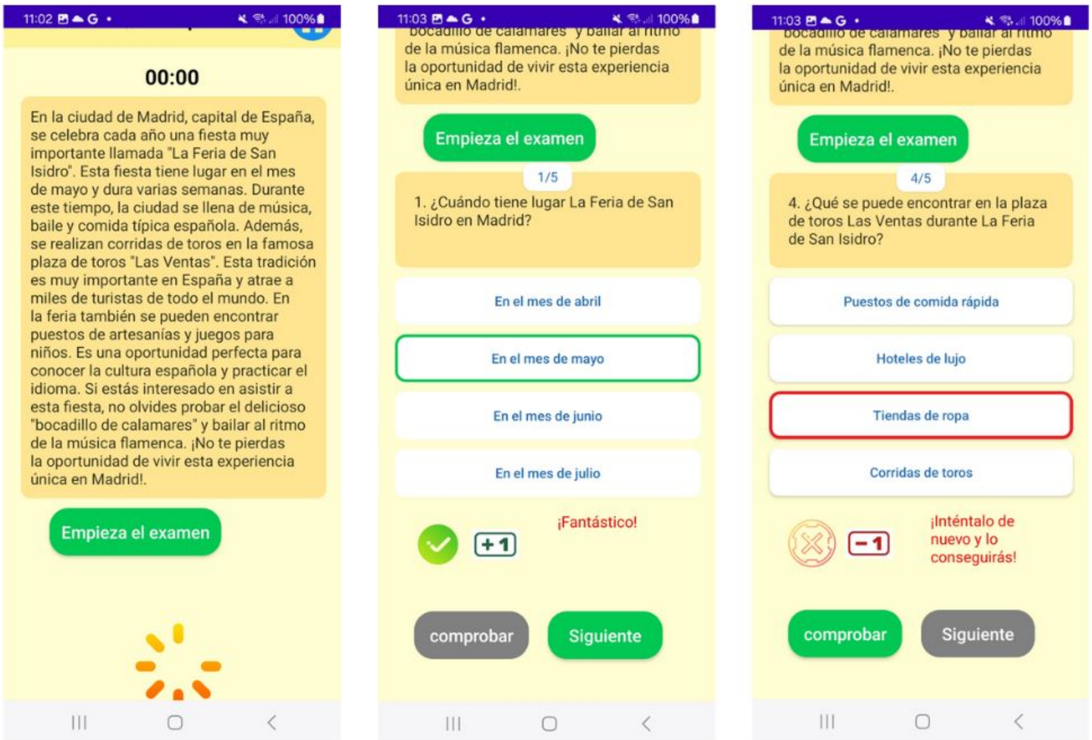
(e) Creating semantic networks

(f) Editing semantic networks

Figure 3.1: A collection of the App's interfaces



(a) Listening Exam



(b) Reading Exam

Figure 3.2: Language Exam Interfaces—Examples include (a) a listening exam and (b) a reading Exam interface.

Proposed Evaluation Plan

While this study focuses on the design and technical implementation of ARELE-bot, a comprehensive evaluation is planned as a future step to assess both its short-term and long-term impact on language learning for students with dyslexia. The evaluation will examine its effectiveness in enhancing language acquisition, addressing cognitive strengths and challenges, and influencing emotional factors such as motivation, confidence, and anxiety reduction. The proposed study will involve participants aged 10–16 with a formal diagnosis of dyslexia who are learning Spanish as a second language. Individuals with severe cognitive impairments beyond dyslexia-related challenges will be excluded to maintain the study's focus. Additionally, participants should have basic familiarity with digital devices to ensure effective interaction with the application. Parental or guardian consent will be required for participation, ensuring ethical compliance and participant well-being.

To assess short-term outcomes, participants will complete pre- and post-study language assessments, user satisfaction surveys, and emotional feedback surveys. Metrics such as task accuracy and task completion time will be collected through the app's backend infrastructure, providing insights into immediate learning gains, engagement levels, and usability. For long-term evaluation, follow-up assessments will be conducted at intervals (e.g., three and six months post-study) to measure the retention of language skills, continued engagement, and the sustained impact on confidence and motivation. These assessments will help determine whether the benefits of AI-driven language learning persist over time.

The evaluation will employ Python-based tools for data analysis. Statistical methods such as paired t-tests will compare pre- and post-assessment results to gauge immediate improvements, while repeated-measures ANOVA will assess changes over time across participant subgroups (e.g., age, baseline proficiency levels). Descriptive statistics will summarize emotional response ratings, while thematic analysis of qualitative feedback will identify patterns in users' emotional and cognitive experiences.

By integrating both short- and long-term assessments, this evaluation will provide a more comprehensive understanding of ARELE-bot's effectiveness in supporting dyslexic learners, ensuring its impact extends beyond initial engagement and contributes to sustained language development.

Conclusion and Discussion

ARELE-bot is designed to meet the cognitive, emotional, and behavioral needs of students with SLDs, with a particular focus on dyslexia. By transforming their challenges into strengths, the app fosters an inclusive language learning environment. Built on a neurodiversity framework, it highlights visual, multisensory, organizational, and communication skills, while offering adaptable, real-time assessments in a supportive, low-stress space that minimizes anxiety. Rather than replacing traditional teaching methods, ARELE-bot is meant to complement and support educators. The app holds the potential to open new avenues for both students and teachers, enhancing language education through its immersive, engaging, and personalized approach.

However, several limitations must be acknowledged. One significant challenge was ensuring diversity and relevance in AI-generated language exercises. The GPT-

3.5 model occasionally struggled with generating non-repetitive questions for language exams, leading to redundant content that could affect engagement. Additionally, some AI-generated answers lacked nuance, which may have confused learners rather than provided meaningful guidance. Addressing these limitations in future iterations of ARELE-bot will be essential. Upgrading to models like GPT-4 or exploring open-source AI solutions could enhance the diversity, accuracy, and contextual relevance of generated content at a feasible cost. Additionally, incorporating advanced personalization mechanisms, such as reinforcement learning-based adaptation, could improve the system's ability to dynamically adjust exercises to individual learning patterns.

In summary, future research should prioritize refining AI-generated content, enhancing adaptability, and conducting user studies to evaluate both the short-term and long-term effectiveness of AI-driven language learning tools in inclusive education. Additionally, usability studies should investigate how ARELE-bot can be seamlessly integrated into traditional classroom settings, ensuring that both students and educators fully benefit from its capabilities in real-world learning environments.

3.2.2 Insights

The findings of this study have been published in [482].

Objective

The primary goal of this case study is to develop an AR-based language learning application, ARELE-bot, that enhances language acquisition for students with dyslexia. The application aims to leverage the visual and holistic learning strengths of dyslexic learners through immersive, adaptive, and supportive XR environments.

Technical Infrastructure

ARELE-bot was built using Android Studio with Kotlin as the primary programming language due to its compatibility with Android and its modern features. The backend is managed through Parse Platform SDK and Back4App, ensuring secure storage of user data and seamless access to learning materials. The development leverages OpenAI's GPT-3.5-turbo-instruct model to enable interactive conversations with a virtual teacher, vocabulary searches with voice-based word meaning retrieval, supporting personalized language exercises, and real-time feedback. To enhance user engagement with the physical world, TensorFlow Lite Vision API is used for object detection, allowing users to associate vocabulary words with real-world objects.

Interaction Modalities and Sensor Integration

The application supports multimodal interaction, tailored to the cognitive needs of dyslexic learners:

- **Speech Recognition**: Utilizing the Android Speech Package for speech-to-text and text-to-speech functions, users can engage in spoken interactions with the virtual teacher, perform voice-based word searches, and receive feedback on pronunciation.

- **Object Detection**: Through TensorFlow Lite, the app enhances vocabulary learning by allowing users to identify and label real-world objects, deepening word association.

- **Visual Interaction**: The application integrates dynamic visual aids, including visual dictionaries and semantic networks, to support vocabulary acquisition and conceptual understanding. Learners can explore interactive word maps, where words are connected based on meaning, context, and usage. Additionally, image-assisted word associations reinforce reading fluency and comprehension.

Potential Findings

ARELE-bot demonstrates the potential for significantly enhancing engagement and retention in language learning for students with dyslexia. By offering an immersive, adaptive environment that aligns with dyslexic strengths, the application addresses cognitive challenges and fosters a supportive learning experience, promoting both language comprehension and user motivation.

Technical, Usability Challenges and Future Directions

One significant challenge was ensuring diversity and relevance in AI-generated language exercises. The GPT-3.5 model occasionally struggled with generating non-repetitive questions for language exams, resulting in redundant content that could affect engagement. Additionally, some AI-generated answers lacked nuance, potentially confusing learners. Upgrading to models like GPT-4 or exploring open-source AI solutions could mitigate these issues by providing more robust language generation capabilities at a feasible cost.

3.2.3 N2: Mixed Reality Virtual Assistant in Puzzle-Solving

Objective and Context

Mixed Reality (MR) is a groundbreaking technology that seamlessly blends the physical and digital worlds, offering a transformative approach to tasks requiring advanced spatial skills [1078]. This technology offers unique opportunities to manipulate and observe how humans interact with spatial information in dynamic and immersive environments. Advances in computer science have enabled the creation of highly interactive and contextually aware MR systems, pushing the boundaries of user engagement and cognitive processing across various fields. For example, MR helps designers visualize and evaluate design elements, thus facilitating on-site design modifications and decision-making processes [283]. Moreover, MR applications in architectural and engineering education allow students to interact with virtual 3D models of buildings and mechanical systems. This leads to improved spatial visualization and understanding of complex structures [685]. In the medical field, MR has been utilized to train surgeons, offering virtual simulations of anatomical structures and surgical procedures that improve spatial awareness and precision [1109]. Additionally, MR has shown promise in enhancing spatial navigation skills, allowing individuals to practice and improve their ability to navigate in a controlled and supportive environment [752]. However, MR's benefits are particularly striking in assembly tasks, where precise spatial coordination and sequencing are crucial. In these scenarios, MR provides real-time guidance and enables users to visualize and interact with virtual components, thereby reducing errors, improving accuracy, and boosting efficiency during the assembly process [68, 1329, 307].

Integrating Conversational Virtual Agents (CVAs) as an interactive layer can provide real-time guidance in MR environments [179, 802]. A CVA is a sophisticated software system engineered to simulate human-like conversations [699]. CVAs have evolved from simple rule-based chatbots to sophisticated systems capable of natural language understanding and interaction. Initially developed for customer service, CVAs now find applications across diverse domains such as healthcare, education, and entertainment [1018, 482, 594]. The concept of agents and humans coexisting in a shared MR environment has introduced greater intelligence into MR experiences. Prior studies have highlighted the general benefits of MR supported by CVAs [46, 540] enhancing both task performance and the social aspects of user interaction [540, 859]. This enhancement boosts engagement, motivation, and performance in virtual settings [859, 368].

Puzzle-solving exemplifies an assembly-like challenge that benefits from MR-based guidance [810]. Solving a 2D puzzle, traditionally done on a physical table, requires advanced spatial cognitive skills such as visual perception, mental rotation, pattern recognition, piece matching, spatial organization, spatial reasoning, and spatial memory to decompose a problem into manageable parts and synthesize them into a coherent whole [746, 543]. The literature highlights the adoption of MR technologies, supported by state-aware guidance, as an effective way to enhance these cognitive skills [1075, 1402], particularly in puzzle-solving scenarios [744, 243, 1270]. These technologies can provide real-time feedback directly integrated into the puzzle-solving process. This interaction fosters a deeper understanding of how individual components contribute to the overall puzzle image [744, 1270]. The multi-sensory nature of MR experiences can enhance the user's capacity to process and integrate spatial information, thus leading to improved performance [294].

Prior research on puzzle-solving in extended reality (XR) environments highlights the critical role of collaboration, whether through interaction with another individual or by leveraging guidance provided by CVAs in immersive settings [169, 479, 95, 514]. Some studies highlight the critical role of avatar intelligence and task complexity in co-solving immersive puzzles [240, 238]. Moreover, investigations into avatar presentation and social presence reveal how visual and interactive elements significantly shape collaboration dynamics and enhance task performance [582, 961, 479]. Since puzzle-solving tasks have great potential to stimulate the need for interaction and collaboration with agents, their integration with a CVA could greatly benefit from enhancements in both task performance and social interactions. This social interaction can transform the solitary puzzle-solving activity into a collaborative effort. However, the dynamics of these interactions might differ significantly depending on whether the CVA offers continuous guidance or assists the user only on demand [1059]. Continuous guidance suits tasks requiring close monitoring, like beginner training or time-sensitive activities. Still, it may lead to over-reliance and limit autonomy, thus reducing the user's ability to work independently [124, 1407]. Conversely, on-demand assistance fits tasks needing autonomy, problem-solving, or exploration. This solution fosters engagement, critical thinking, and accomplishment while allowing users to learn through the support available when required [704].

Prior studies on CVAs in XR puzzle-solving environments have explored the benefits of visual cues for guidance [243, 744, 487]. We expand the field by examining the impact of CVA representation modalities—voice-only and embodied—on task efficiency, cognitive workload, and social presence in puzzle-solving tasks. Focusing on auditory guidance and CVA-user dialogues, this work highlights the performance boundaries and challenges associated with each modality, emphasizing the need to align agent modalities with task and user needs and offering valuable insights for CVA design.

We employed the CVA classification design architecture [313] and the MiRAS (Mixed Reality Agents) Cube Taxonomy [540] to integrate a CVA named "Katie" into the MR application for on-demand user guidance. We explored two different modalities for Katie: a Voice-only version and an Embodied form, which incorporated the voice with basic lip-syncing and idle movements (see Figure **??**). In the follow-up study, we selected 34 participants to evaluate the designed modalities and focused on the following key Research Questions (RQs):

- RQ1: How does the representation mode of the CVA (Voice-only vs. Embodied Avatar) influence puzzle-solving performance and user interactions during complex spatial puzzle-solving in an MR environment?
- RQ2: What is the impact of the representation mode of the CVA (Voice-only vs. Embodied avatar) on participants' cognitive workload and social presence during complex spatial puzzle-solving in an MR environment?
- RQ3: What are the participants' perceptions of usability and technology acceptance in this MR experience?

By addressing these questions, this study contributes to the understanding of how different forms of assistance can be optimized for enhanced user performance and satisfaction in MR environments. The findings may inform the design of future intelligent assistants, leading to more intuitive and effective human-computer interactions.

Related Work

MR systems are widely utilized across various tasks requiring spatial reasoning, precision, and coordination [283, 685, 1109, 752], with particular prominence in industrial and assembly processes [68, 1329, 921, 1402, 307]. A key feature of MR in assembly tasks is its ability to offer state-aware guidance by integrating visual and auditory cues in the context [1329]. This technology significantly reduces errors and increases efficiency [1075, 1402], offering a more interactive and reliable alternative to traditional instruction manuals [921].

Puzzle solving can be seen as a form of assembly task [810], where components must be carefully aligned and fitted together to create a functional structure. These tasks require strong spatial reasoning and memory, attention to detail, and a methodical approach to problem-solving [746, 543]. MR-enhanced puzzle simulations have demonstrated significant value in education and training by fostering active learning, critical thinking, collaboration, and enhancing spatial problem-solving skills [243, 744, 1270]. The guidance in these exampled MR systems is typically provided through visual cues that confirm correct or detect wrong placements or suggest potential piece placements during the assembly or puzzle-solving process. For example, Lima et al. [744, 487] used an RGB-D camera to accurately detect and highlight correctly assembled pieces. Another notable example is JigsAR [1270], a system developed to assist users in assembling jigsaw puzzles. JigsAR uses color quantization and image histograms to compare puzzle pieces with a database, suggesting the three most probable correct placements for each piece.

However, there is very limited literature exploring voice-driven feedback in MR systems for puzzle-solving, despite its potential to enhance user interaction and engagement in MR environments [943], as well as systems that offer on-demand guidance. On-demand guidance allows users to request help as needed, promoting autonomy, focus, and a personalized, less intrusive experience, especially suitable for tasks requiring focus, such as puzzle-solving [1407, 704]. By managing information flow, this approach boosts confidence and engagement, making it ideal for educational and training settings [1059]. This underscores the importance of balancing assistance with minimizing distractions [124].

Shared virtual worlds emphasize the potential for real-time collaboration in immersive environments. For example, research in this domain demonstrates how remote expert support and multi-user coordination can streamline tasks. Adapting these mechanisms could bridge the gap between individual efforts and synchronized teamwork, providing valuable insights for designing MR systems optimized for collaboration and teleoperation [432, 1414, 168]. Previous studies in puzzle-solving in XR underscore the role of collaboration [169, 95, 514]. Although human companions play a valuable role in fostering engagement and teamwork, CVAs also offer the potential to provide immersive, scalable, and context-aware guidance to enhance task efficiency in MR environments [1323]. Many works in the literature explore the usage of different types of CVAs to improve human communication and interpersonal skills in various training contexts like healthcare, customer service, and sales [1018, 594].

CVAs can be classified by purpose, communication channels, and response generation architecture [313]. Task-oriented CVAs are designed for specific works, ensuring precise assistance [1063]. Communication channels like text and voice CVAs support various interaction needs, from detailed instructions [681] to hands-free tasks [1140] allowing users to focus on physical components and spatial awareness. Embodied CVAs enhance interaction by combining verbal and visual cues, which can be particularly beneficial in tasks that require social aspects, and collaboration [1063, 654]. CVA architectures range from rule-based, for consistent responses [584], to retrieval-based, which adapts to dynamic inputs, and AI systems for more natural interactions [804]. The MiRA Cube Taxonomy [540] classifies virtual agents in MR environments along three dimensions: corporeal presence, interactive capacity, and agency level. Agents are categorized by their presence as stronger in the virtual or physical domain or balanced in both. Interactive capacity refers to their ability to sense and act in these environments, while agency is classified from basic (weak) to complex (strong). Current research on CVAs in MR has largely focused on agents characterized by high virtual presence and interactivity, yet possessing relatively limited agency [540]. Prominent examples include MARA, a mobile city guide designed to enhance tourist experiences [1127], and Welbo, a virtual assistant for interior design [46]. More advanced systems like ALIVE [792] and the Invisible Person [1019] incorporate greater agency through sophisticated architectures capable of modeling internal states and complex behaviors, which aim to enhance the overall level of realism in interactions. These frameworks guide the integration of CVAs into immersive experiences.

Many studies have examined the degree of realism in CVAs across various tasks and contexts. Realistic agents have been found to be more appealing and engaging for communication, as they provide visual cues such as eye contact, facial expressions, body representation, and synchronized body and lip movements. Conversely, invisible agents are often preferred for visually intensive tasks, where their lack of visual distractions allows users to focus more effectively [1054]. Beun et al. [119] demonstrated that a realistic virtual head improved memory test scores compared to text-only representations, though not significantly more than a cartoon character. Similarly, visible CVAs have been shown to enhance social presence and improve performance in tasks such as anagram solving and Question-and-Answer games in AR [881, 258].

Research on integrating CVAs in MR puzzle-solving has explored the effects of avatar intelligence, self-similar appearance and voice, avatar realism, and task complexity [240, 479, 582, 961, 238], all of which play a vital role in shaping trust, user engagement, and group dynamics. However, despite these advancements, the specific effects of CVA representations on spatially demanding tasks in MR, such as puzzle-solving, require further investigation, particularly in the context of CVA-user dialogue, voice-driven interactions, and on-demand assistance.

Material and methods

This section provides an overview of the system design and architecture, the development process, the data analysis methodology, and the refinement of our system through a pilot study.

System design and architecture

The system architecture comprises four primary modules: User Interface, Puzzle Manager, CVA (Voice-only or Embodied avatar), and Data Logger (see Figure 3.4).

The User Interface processes user inputs and provides necessary feedback. During the puzzle-solving experience, the User Interface leverages the capabilities of the MRTK to accurately interpret pinch gestures. This allows the user to initiate the experience by interacting with a virtual button. The individual puzzle pieces were printed as 10 cm x 10 cm squares, resulting in a complete puzzle dimension of 40 cm x 40 cm (16 pieces). This size was selected to ensure that the puzzle was large enough to be manageable within the experimental setup. The module employs the Vuforia engine to identify and track individual puzzle pieces by treating each piece as a 2D image target. When the user physically moves a piece (see Figure 3.5b), Vuforia tracks the movement and communicates the status to the Puzzle Manager. Additionally, when a user selects a piece with a pinch gesture (see Figure 3.5c), the app highlights the selected piece by generating a blue border around them, thereby aiding users in focusing on specific puzzle elements and indicating the user's intended interactions. The module, built on MRTK, captures spoken input, interprets it as commands, and communicates them to the CVA Katie, enabling users to ask vocal questions about a piece's position or orientation. In our study, 'orientation' refers strictly to the direction the puzzle piece faces. There are four possible orientations (0°, 90°, 180°, 270°).

Depending on the agent's communication channel, categorized based on CVA classification architecture—either Voice-only or Embodied (see Figure 3.3), the User Interface configures the type of feedback to communicate with the user. In the Embodied avatar condition, the virtual agent will be represented by a lifelike avatar seated near the table where the user is situated, gazing attentively at the puzzle board (see Figure 3.3). During assistance, the avatar features lip-sync animations synchronized with audio instructions and natural sitting animations, such as subtle breathing. These features align with the corporeal presence dimension of the MiRA Cube Taxonomy, enhancing the user's perception of the avatar as a lifelike entity. When not assisting, it continues to display subtle sitting animations, maintaining a consistent yet unobtrusive sense of corporeal presence [377]. In the Voice-only version, the interaction is limited to audio feedback, where the assistant's voice guides the user without any visual or embodied representations.

The Puzzle Manager manages the state and dynamics of the puzzle-solving process. First, it prepares the puzzle board and ensures all settings are ready for user interaction. It continuously receives input from the user interface regarding the movement and orientation of pieces, updating the positions and orientation arrays accordingly. It checks whether each piece is correctly positioned and oriented by comparing its current state to the expected configuration and, upon request, reports the validity of each piece's placement and orientation to the CVA. Furthermore, it logs data related to user interactions with puzzle piece positioning to the data logger.

The CVA adheres to a task-based, rule-based design, as outlined in CVA classification architecture. It processes user queries and offers corrective guidance, such as positional and directional adjustments ("Move up" or "Rotate clockwise") or confirming correct placement and orientation. Table 3.1 provides a detailed list of the available user commands and the agent's responses, including a table on the right-hand side of the architecture diagram linked to the "Response Setter" module, outlining the logic used to evaluate position and orientation queries. The linear and non-exact nature of the CVA's guidance was intentionally designed to challenge users, encouraging exploration, problem-solving, and more frequent interaction with the assistant. This setup guarantees high interactive capacity with highly responsive interactions while maintaining low agency through consistent and predictable responses, as categorized in the MiRA Cube Taxonomy. The minimal user-CVA interaction was intentional in both modalities, as the system balances autonomy and assistance, promoting user-driven problem-solving [704, 1407]. Additionally, the CVA logs data related to user queries to the data logger.

Finally, the Data Logger records logs of user interactions throughout the experiment sessions.

The User Interface processes user inputs and provides necessary feedback. It gives the user the possibility to initiate the experience by interacting with a virtual button within the MR environment that sends a command to the Puzzle Manager.

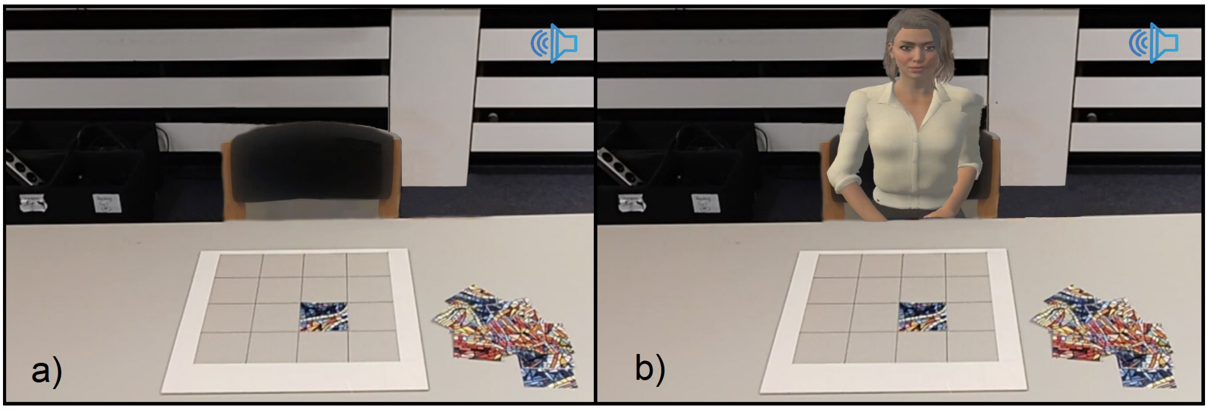


Figure 3.3: Two CVA modalities used in the puzzle-solving task

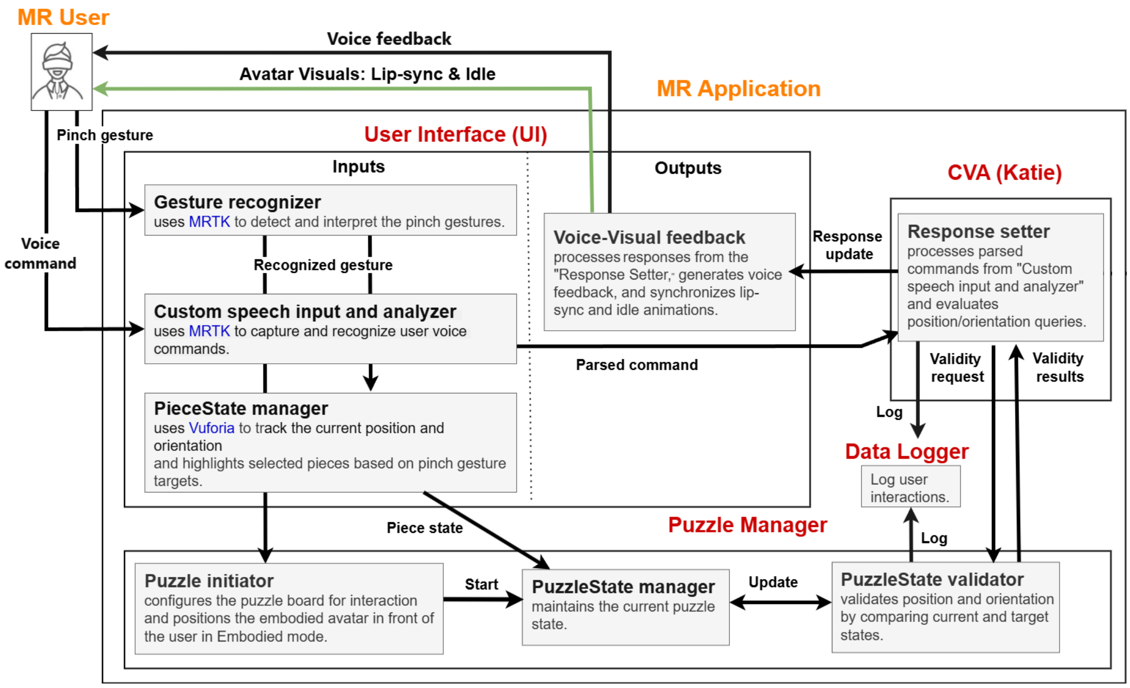


Figure 3.4: The system architecture. Black arrows indicate common elements across all conditions, while the green arrow applies only to the Embodied condition. Descriptions of components using MRTK or Vuforia highlight these technologies in blue.

During the puzzle-solving experience, the User Interface leverages the capabilities of the MRTK to accurately interpret pinch gestures. Additionally, the module employs the Vuforia engine to identify and track individual puzzle pieces by treating each piece as a 2D image target. It continuously communicates the status of the pieces to the Puzzle Manager. In addition, the module, built on the MRTK, captures spoken input and interprets it as commands for the system. Then, these commands will be communicated to the CVA Katie. When the user physically moves a piece (see Figure 3.5b), Vuforia tracks the movement and communicates the status to the Puzzle Manager. Additionally, when a user selects a piece with a pinch gesture (see Figure 3.5c) the app highlights the selected piece by generating a blue border around

Position Queries	
User Command	**Assistant Response**
Position	This piece is correctly positioned.
If Not Correct	
	The piece needs to move further up.
	The piece needs to move further down.
	The piece needs to move further to the left.
	The piece needs to move further to the right.
	Place the piece on the board.
orientation Queries	
User Command	**Assistant Response**
Orientation	This piece is correctly oriented.
If Not Correct	
	The piece needs to be rotated counterclockwise.
	The piece needs to be rotated clockwise.

Table 3.1: User commands and CVA responses.

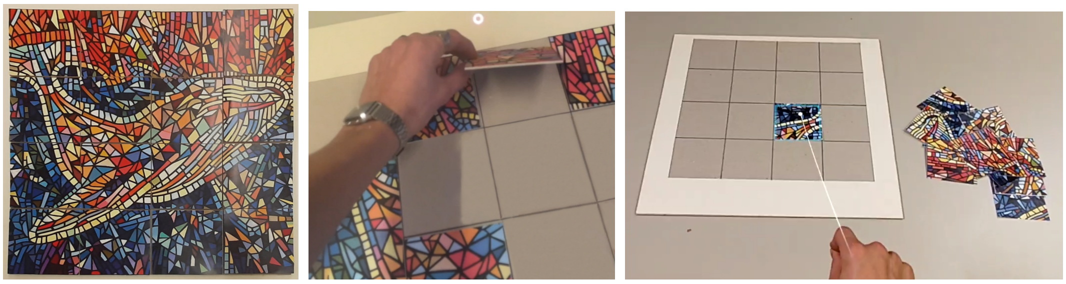
them, thereby aiding users in focusing on specific puzzle elements and indicating the user's intended interactions. Then, the user can vocally ask questions about the piece position or orientation. Depending on the agent's presentation mode—either Voice-only or Embodied (see Figure 3.3) the User Interface will configure the type of feedback provided, whether Audio or Visual, to communicate effectively with the user. In the Embodied avatar condition, the virtual agent will be represented by a lifelike avatar seated idly near the table where the user is situated, gazing attentively at the puzzle board Figure 3.3. The avatar will feature lip-sync animations to synchronize visual cues with audio instructions, enhancing the sense of corporeal presence [377]. This creates a virtual, vivid, and tangible interaction experience, making the avatar appear both engaging and immersive. In the Voice-only version, the interaction is limited to audio feedback, where the assistant's voice guides the user without any visual or embodied representations. This mode focuses purely on auditory communication.

The Puzzle Manager manages the state and dynamics of the puzzle-solving process. First, it prepares the puzzle board and ensures all settings are ready for user interaction. It continuously receives input regarding the movement and orientation of pieces from the User Interface, updating the positions and orientation arrays accordingly. It checks whether each piece is correctly positioned and oriented by comparing the current state to the expected configuration and reports the validity of each piece's placement and orientation to the CVA upon request.

The CVA in the application is designed to interact with the user by providing real-time feedback on the position and orientation of puzzle pieces. This module, following a task-based architecture, focuses on the puzzle-solving task while adhering to a rule-based architecture that ensures contextually relevant assistance. In

Table 3.1 we provide a detailed list of the available user commands and the agent's responses. The linear and non-exact nature of the CVA's guidance was intentionally designed to challenge users, encouraging exploration, problem-solving, and more frequent interaction with the assistant. This setup guarantees high interactive capacity with highly responsive interactions while maintaining low agency through consistent and predictable responses.

Finally, the Data Logger records logs of user interactions and system events throughout the experiment sessions. Upon starting the application, the Data Logger initializes the log file.



(a) (b) (c)

Figure 3.5: Puzzle interactions. (a) Solved puzzle, (b) Placing a piece, (c) Pinch gesture for CVA guidance.

System Development

The application was developed using Unity3D (v2021.3.21f1). The development process incorporated the Mixed Reality Toolkit (MRTK) (v2.8.3), and the Vuforia Software Development Kit (SDK) (v10.18.4). The MRTK was instrumental in implementing hand gestures, voice commands, and spatial mapping. The Vuforia SDK further enriched the experience by facilitating precise recognition and tracking of physical puzzle pieces. The application was deployed on the Microsoft HoloLens 2.

Tools for Statistical Analysis

All statistical analyses were conducted using Python (v3.10.6). The following packages were utilized: Matplotlib (v3.7.1) for data visualization, Pandas (v2.1.4) for data manipulation, Pingouin (v0.5.4) for statistical testing, Seaborn (v0.13.2) for advanced plotting, and Scipy (v1.13.1) for statistical functions.

A Pilot Study for System Refinement

Prior to the main experiment, a pilot study with 16 participants was conducted to evaluate the initial version of our system and identify potential issues in the experimental setup. None of these participants participated in the main experiment to avoid familiarity or learning biases. Participants were selected to represent a diverse range of ages: seven were aged 21-24, four were under 20, three were between 24 and 29, and two were aged 30 to 34. Regarding gender, five were female, nine were male, and two did not specify. The participants also varied in their experience with MR technologies: ten had never used them, four used them rarely, one used them often, and one used them regularly. Their puzzle skill levels ranged from low (6 participants) to moderate (7) and high (3).

Some technical issues emerged during the pilot study, particularly in the Embodied condition. After approximately 14 minutes, frequent application crashes occurred due to a memory leak caused by rendering the avatar's 3D model. These crashes resulted in data loss and disrupted the user experience. This required improving memory management and optimizing avatar rendering.

Participants encountered difficulties using the pinch gesture to interact with puzzle pieces and requesting assistance from the CVA. To address this, we introduced a familiarization phase. This phase ensured that participants understood the appropriate distance and hand orientation required for effective gesture control, accounting for variations in user height. We proceeded with the main experiment only after participants successfully made at least two requests to the assistant using the gesture.

Some participants faced challenges engaging with the CVA due to the length of spoken commands. Simplifying prompts to single words (see Figure 3.4) improved speech recognition speed and enhanced usability, aligning with studies on simplified command design improving user experience and reducing errors [525, 927].

Initially placed directly in front of users, the CVA avatar was often out of view due to the limited field of view of the HoloLens 2 and users' focus on the puzzle. Repositioning the avatar closer while maintaining its position in front of the user improved visibility. This adjustment aligns with findings indicating that the proximity and spatial placement of virtual agents within a user's field of view can enhance social presence and engagement [554].

Experimental settings

The experimental settings aimed to evaluate two CVA presentation modes, i.e. Voice-only and Embodied avatar, during a physical puzzle-solving task.

Study Design

The experiment utilized a between-subjects design to evaluate the effectiveness of the MR application and the two different CVA presentation modes. Participants were randomly assigned to one of two groups: one group interacted with an embodied CVA (a 3D avatar with sitting idle animations and lip-sync), while the other group interacted with a Voice-only CVA.

Task Design

Participants were tasked with solving a physical 2D square-piece puzzle (see Figure 3.5a), featuring a colorful and moderately complex planar mosaic pattern [1397]. The selection of a 2D puzzle task is grounded in its capacity to engage key spatial cognitive skills, including visual perception, mental rotation, and spatial reasoning [746, 1385]. Furthermore, puzzle-solving's inherently interactive and collaborative nature aligns seamlessly with the study's focus on exploring human-agent interaction dynamics within MR environments. The task was intentionally designed to balance complexity—stemming from the intricate visual pattern, the absence of a reference image, and the lack of precise positioning or orientation guidance—and familiarity, achieved through an edge-matching puzzle format, to ensure it was appropriately challenging. This design not only made the puzzle less feasible to solve independently but also encouraged participants to engage with the CVA for guidance, enhancing their problem-solving efficiency without fostering excessive reliance on external assistance. Tasks that are excessively complex or unfamiliar, as noted in prior research, may compel participants to rely heavily on external assistance, complicating the comparison of different assisting strategies [957]. Moreover, such complexity can distort data on participant effort, making it less reliable for analysis [506]. To ensure a fair comparison, we intentionally avoided incorporating embodied features that provide more explicit guidance, such as pointing, as these could have oversimplified the task and raised concerns about the fairness of comparing the modalities. This carefully considered design ensures the task remains suitable for evaluating user interaction and the effectiveness of the assisting modalities. The task had no time limit and was considered finished only when the puzzle was solved, with confirmation from the participants and the experimental assistant.

Procedure

Initially, the puzzle pieces were randomized and arranged on the right side of the board. The experimental software was launched, and the specific experimental condition was set. After a brief welcome, participants completed a short pre-questionnaire and signed a consent form before proceeding to the puzzle-solving station. At the puzzle station, participants were equipped with MR glass (HoloLens 2). Detailed instructions about the task were provided, emphasizing the support available from the digital assistant. They were briefed on the steps to complete the puzzle and how to conclude the task. Participants then engaged in a brief familiarization task designed to acquaint them with the system. During this task, participants were taught how to manipulate the puzzle pieces using their real hands and how to communicate with the assistant for guidance using pinch gestures. After completing the puzzle, they were asked to complete a questionnaire.

Participants

A total of 34 individuals participated in the study.

Participants were required to meet the following selection criteria: they had to be university affiliates or professionals with backgrounds in scientific disciplines, be within the age range of 22 to 40 years, and have no prior cognitive or motor impairments that could interfere with the puzzle-solving task. Additionally, individuals with extensive prior experience in MR applications were excluded to ensure a balanced evaluation of usability and interaction effects. The participants were randomly divided into two groups, with 17 assigned to each condition. Before the experiment, participants completed a pre-questionnaire to record demographic information, including age and gender. Additionally, they were asked to rate their puzzle-solving skills and frequency of using MR applications on a Likert scale ranging from 1 to 5. The selected population consisted of 12 females and 22 males, with a mean age of 29.68 years (SD = 9.22). When asked about their puzzle-solving skills on a Likert scale (1 to 5), the participants averaged a moderate level (M = 3.15, SD = 0.94). They reported varying levels of experience in terms of their frequency of using MR applications, with an overall average score of 1.97 (SD = 1.12) on the same Likert scale.

Measurements

This section details both the subjective and objective metrics utilized to evaluate the Embodied and Voice-only conditions. Our selection of measures is informed by methodologies previously applied in research involving comparable virtual entities [859].

Objective measures include (i) Puzzle-solving performance, quantified by recording *the total time taken by participants to complete the puzzle in seconds*, as well as *the precise timing of each correct piece placement and orientation.* (ii) User interactions with the assistant track *the number of verbal commands given to the CVA*, enabling analysis of interaction frequency and patterns across various modalities. Additionally, *the types of questions asked by participants* are categorized into those concerning the position and those regarding the orientation, with each *question's timing* logged to provide a temporal profile of user inquiries throughout the task.

Subjective measures encompass several key aspects of participant experience. (i) Social presence is evaluated using a validated questionnaire adapted from the Networked Minds Social Presence Inventory [502], which assesses *co-presence* (the feeling of sharing a virtual space with the assistant), *attention allocation* (the extent to which both the participant and the assistant are focused on the same task, ensuring a coordinated and collaborative interaction), and *perceived message understanding* (the perceived clarity of communication), and *perceived affective understanding* (the recognition of emotional intent). The usability of the MR system was assessed using the System Usability Scale (SUS) [171], a widely recognized tool that provides an overall usability score based on participants' ratings of *perceived ease of use*, *learnability*, *system efficiency*, and *complexity.* Cognitive workload during the puzzle-solving task is measured via the NASA Task Load Index (NASA-TLX) [506], where participants rate their experience across dimensions such as *mental, physical,* and *temporal demands, performance, effort,* and *frustration*, culminating in a weighted workload score that reflects the overall perceived task load. Finally, the Technology Acceptance Model (TAM) [293] is employed to gauge participants' *perceived usefulness.*

This combination of objective and subjective measures provides a comprehensive assessment of participant interaction performance and experiential aspects of the MR system.

Results

This section presents the results of the statistical analyses, which reveal potential differences or equivalences among the two CVA modalities.

Objective Measures

The results presented in this section encompass two aspects: puzzle-solving performance, including completion time and success rates for piece placement and orientation across conditions, as well as interaction patterns with the CVA.

Puzzle-solving performance

Puzzle Completion Time

Normality was assessed using the Shapiro-Wilk test, which indicated that the scores for the Embodied group were normally distributed while the Voice-only group deviated significantly from normality ($W = 0.880$, $p = 0.031$). A two-tailed Mann-Whitney U test revealed a significant difference in completion times between the two groups ($U = 229.0$, $p = 0.0038$). For detailed statistics please refer to Table 3.3 and Figure 3.6a. These results indicate that participants in the Voice-only CVA condition completed the puzzle significantly faster than those in the Embodied condition.

Success Rates for Piece Placement and Orientation

The success rate in this study measures the proportion of puzzle pieces correctly positioned or oriented by participants on their first attempt without requiring further adjustments. This metric provides valuable insight into the assistant's effectiveness in facilitating initial puzzle-solving accuracy and the participants' problem-solving skills. In the Voice-only condition, success rates were 42.86% for positioning and 36.61% for orientation (see Table 3.2). By contrast, the Embodied condition, where participants received verbal cues along with visual lip-syncing and a virtual body, demonstrated lower success rates, with 20.54% for positioning and 16.07% for orientation (see Table 3.2). Two-proportion Z-tests showed significant success rate differences between the Voice-only and Embodied conditions for positioning ($Z = 3.39, p = 0.00069$) and orientation ($Z = 3.30, p = 0.00098$). In both cases, participants in the Voice-only condition had significantly higher success rates, indicating that auditory guidance alone was more effective than the Embodied condition for accurately placing and orienting puzzle pieces on the first attempt.

Table 3.2: Success Rates of Voice-only and Embodied conditions.

Variable	Construct	Voice-only CVA (%)	Embodied CVA (%)	p-value
Success Rate (%)	*Position*	42.86	20.54	**0.00069**
	Orientation	36.61	16.07	**0.00098**

User Interactions with the Conversational Virtual Agent

Number of Verbal Commands

Normality was assessed using the Shapiro-Wilk test, which indicated that the scores for both groups were normally distributed. An independent samples t-test, comparing the means, resulted in $t(32) = -0.244$, $p = 0.8$, indicating no significant difference between the groups in the total number of verbal commands (see Figure 3.6b). For questions related to puzzle piece positioning, the Shapiro-Wilk test confirmed normality for both groups. An independent samples t-test showed no significant difference between the groups ($t(32) = -0.209$, $p = 0.84$; see Figure 3.6c). For orientation-related questions, the Shapiro-Wilk test indicated that the Embodied group's scores approached the threshold for normality ($W = 0.896$, $p = 0.058$), while the Voice-only group's scores were normally distributed. A Mann-Whitney U test was conducted, yielding $U = 133.0$, $p = 0.70$, confirming no significant difference in the number of orientation-related questions between the groups (see Figure 3.6d). Detailed descriptive statistics for all measures are reported in Table 3.3.

Furthermore, we performed the TOST (Two One-Sided Tests) tests on position- and orientation-related questions within predefined bounds ([-2, 2]), which highlighted the equivalence between the Embodied and Voice-Only modalities. Position-related questions reached t-statistics of 1.88 ($p = 0.034$) and -2.25 ($p = 0.016$). Rotation-related questions reached t-statistics of 2.83 ($p = 0.004$) and -3.37 ($p = 0.001$), thus confirming equivalence.

Comparison between overall Position and Orientation Questions

A Shapiro-Wilk test indicated that the distribution of overall position-related questions followed a normal distribution, whereas the distribution of overall orientation-related questions did not ($W = 0.930$, $p = 0.031$). A two-tailed Mann-Whitney U test was conducted, yielding a U statistic of 970.0 and a p-value of 0.0001, indicating a significant difference between the overall number of questions asked about position and orientation across all data. For detailed statistics refer to Table 3.4 and Figure 3.6e. These results suggest that participants focused more frequently on spatial positioning than adjusting orientations. This difference highlights a potential cognitive emphasis on placement strategies during puzzle-solving activities.

Comparison of Users Interaction Patterns with Conversational Virtual Agent

Figure 3.7 shows the distribution of position- and orientation-related questions asked during the puzzle-solving task, categorized by condition (Voice-only vs. Embodied) and normalized over time. The heatmap provides a temporal visualization of the frequency of these questions across the task's progression. Darker shades indicate a higher frequency of questions. Participants in the Voice-only condition consistently asked more position-related questions during the early stages of the task, particularly within the 0–40% task completion range. The number of questions peaked at 28 during the 0–10% interval and remained consistent at 28 in the 10–20% interval. Similarly, in the Embodied condition, participants exhibited a high frequency of position-related questions during the first half of the task, peaking at 31 in the 0–10% interval. As the task progressed (50–100% completion), the number of position-related questions gradually decreased in both conditions, with an overall reduction of approximately 40%. Participants in both conditions asked fewer questions for orientation-related questions than position-related ones. However, these questions were slightly more concentrated in the early stages of the task for both conditions. In the Embodied condition, orientation-related questions were distributed more evenly across the remainder of the task after an initial peak. These patterns suggest that participants sought clarification on both position and orientation primarily in the early stages of the task, with orientation-related inquiries being less frequent overall.

To further validate these trends, we performed analyses using ANCOVA (Analysis of Covariance). Results confirmed that 'Position' requests were significantly more frequent than 'Orientation' requests ($F = 76.89$, $p = 4.6e - 07$), and the frequency of requests decreased significantly over time ($F = 22.54$, $p = 0.00031$). These trends were consistent across request types ($F = 1.30$, $p = 0.27$). Additionally, defining 'Embodied' and 'Voice-only' categories, time was shown to significantly reduce the number of questions ($F = 24.50$, $p = 0.00021$) at the same rate across modalities ($F = 1.27$, $p = 0.278$), with no significant differences among categories ($F = 2.12$, $p = 0.17$). These results align with the findings from the heatmap analysis and further support the robustness of the observed interaction patterns.

Subjective Measures

Following the analysis of objective measures, subjective measures are explored, focusing on usability, cognitive workload, social presence, and perceptions of the system's usefulness.

System Usability Scale

Usability was measured using the System Usability Scale (SUS). A Shapiro-Wilk test confirmed that both groups followed a normal distribution. An independent samples t-test revealed no statistically significant difference between the groups ($p = 0.42$). Detailed SUS scores are reported in Table 3.5. Both groups scored above the threshold for marginal usability (60–70 range). This demonstrates that the system achieved acceptable usability across both interaction modalities [81]. Additional analyses were conducted on specific usability constructs, such as perceived ease of use, learnability, system efficiency, and complexity. While Table 3.5 indicates slight variations in scores across constructs, no statistically significant differences were found between the two conditions (all p > 0.05).

The TOST test results, conducted with equivalence bounds of [-1,1], indicate that all variables are equivalent between the two modalities. Perceived ease of use has t-statistics of 3.51 ($p = 0.0007$) and -4.67 ($p = 0.00003$). Similarly, learnability reaches t-statistics of 4.72 ($p = 0.00002$) and -2.92 ($p = 0.00314$). System efficiency has t-statistics of 5.05 ($p = 0.000009$) and -5.68 ($p = 0.000001$). Lastly, complexity shows t-statistics of 4.07 ($p = 0.00014$) and -2.85 ($p = 0.00379$). These findings highlight equivalence across all variables within the specified bounds.

NASA-TLX

The subjective workload was assessed using the NASA-TLX scale across both the voice-only and Embodied conditions. Results indicated that some dimensions followed a normal distribution while others did not. For dimensions with a normal distribution (mental demand, performance, effort), independent samples t-tests were performed. For dimensions that did not follow a normal distribution (physical demand, temporal demand, frustration), Mann-Whitney U tests were utilized. Detailed scores, including means and standard deviations for all dimensions, are reported in Table 3.5. A significant difference was observed for effort ($p = 0.001$), indicating higher perceived effort in the Embodied condition. No statistically significant differences were found for mental demand ($p = 0.32$), physical demand ($p = 0.58$), temporal demand ($p = 0.39$), performance ($p = 0.76$), or frustration ($p = 0.61$).

The TOST test results, conducted with equivalence bounds of [-1.5,1.5], indicate equivalence for performance and frustration between the two modalities. For performance, the mean difference is -0.17, with t-statistics of 2.31 ($p = 0.0137$) and -2.92 ($p = 0.0031$). Similarly, the mean difference for frustration is 0.11, with t-statistics of 2.002 ($p = 0.0269$) and -1.71 ($p = 0.0483$). For the remaining variables, equivalence was not established.

Co-Presence

The co-presence aspect of social presence was measured using the Networked Minds Social Presence Inventory. A Shapiro-Wilk test confirmed that both groups followed a normal distribution. An independent samples t-test was applied to compare the groups. No statistically significant differences were found between the groups for overall social presence ($p = 0.96$), co-presence ($p = 0.3$), attention allocation ($p = 0.1$), perceived message understanding ($p = 0.97$), or perceived affective understanding ($p = 0.98$). Detailed scores, including means and standard deviations for all dimensions, are reported in Table 3.5. A Pearson correlation was conducted to explore the relationship between the number of questions asked and the overall co-presence score, as both variables followed a normal distribution. The results showed a weak positive correlation ($r = 0.12$), but this was not statistically significant ($p = 0.5$).

The TOST test results, conducted with equivalence bounds of [-1,1], indicate equivalence for perceived message understanding and perceived affective understanding between the two modalities. For perceived message understanding, t-statistics are 2.21 ($p = 0.0168$) and -2.26 ($p = 0.0153$). Similarly, for perceived affective understanding t-statistics are 1.99 ($p = 0.0275$) and -2.07 ($p = 0.0232$), also confirming equivalence. In contrast, equivalence was not established for co-presence and attention allocation.

TAM

The system's acceptance was measured using the Technology Acceptance Model (TAM), specifically focusing on perceived usefulness. A Shapiro-Wilk test indicated that the Embodied group deviated from normality ($W = 0.859$, $p = 0.015$), while the voice-only group followed a normal distribution. A two-tailed Mann-Whitney U test revealed no significant difference between the groups ($U = 159.500$, $p = 0.62$). Detailed scores are reported in Table 3.5. The TOST test results, conducted with equivalence bounds of [-1,1], indicate equivalence for perceived usefulness between the two modalities. The t-statistics equal 3.24 ($p = 0.0014$) and -2.98649 ($p = 0.0027$), confirming equivalence.

Table 3.3: Summary of Objective Measures Between Voice-only and Embodied Conditions

Variable	Construct	Voice-only CVA		Embodied CVA		p-value
		Mean (M)	SD	Mean (M)	SD	
Puzzle-solving time (seconds)		1118.12	528.16	1652.71	475.62	**0.0038**
Number of Verbal Commands	*Total*	15.82	8.78	15.12	8.10	0.8
	Position	11.06	5.92	10.71	5.34	0.85
	Orientation	4.41	3.65	5.76	1.99	0.7

Table 3.4: Overall Comparison of Verbal Commands for Position and Orientation Questions Across All Data (Aggregated Across Conditions).

Variable	Construct	Position (M, SD)	Orientation (M, SD)	p-value
Number of Verbal Commands	Position vs. Orientation Commands (Overall)	10.88, 5.55	5.76, 1.99	**0.0001**

Table 3.5: Summary of Subjective Measures Between Voice-only and Embodied Conditions

Variable	Construct	M (Voice)	SD (Voice)	M (Emb)	SD (Emb)	p-value
Social Presence	*Co-presence*	4.81	1.45	4.18	1.22	0.30
	Attention Allocation	4.27	0.93	4.81	1.04	0.10
	Message Understanding	4.94	1.20	4.95	1.39	0.97
	Affective Understanding	2.35	1.27	2.37	1.58	0.98
SUS	*Ease of Use*	3.7	0.66	3.55	0.75	0.56
	Learnability	3.31	0.66	3.32	0.75	0.96
	Efficiency	3.03	0.43	2.94	0.68	0.88
	Complexity	1.97	0.94	2.12	0.88	0.62
NASA-TLX	*Mental Demand*	5.35	2.29	6.06	1.75	0.32
	Physical Demand	3.35	2.60	3.00	2.45	0.58
	Temporal Demand	3.06	1.85	3.59	1.73	0.39
	Performance	7.76	1.95	7.59	1.33	0.76
	Effort	3.06	1.85	3.59	1.73	**0.001**
TAM	*Usefulness*	3.66	0.86	3.70	1.00	0.62

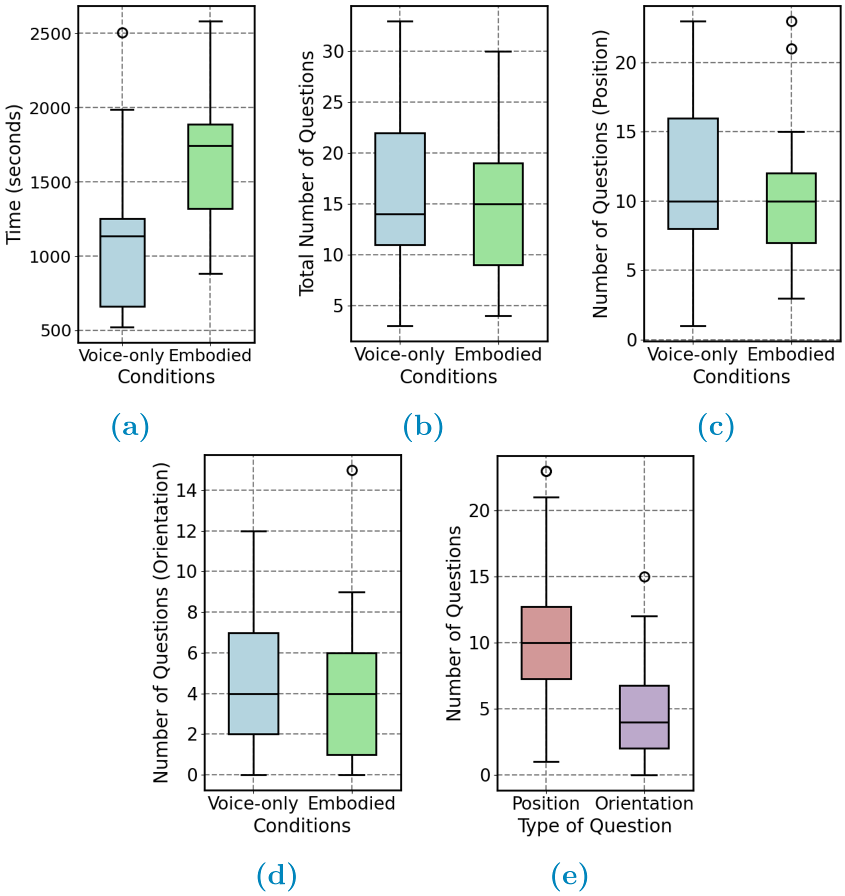


Figure 3.6: Figure 4: (a)–(d) compares task time, the total number of questions, and position/orientation questions by condition; (e) compares the overall number of position and rotation questions.

Discussion, Limitations, and Future Works

In this section, we seek answers to the RQs. *RQ1: How does the representation mode of the CVA (Voice-only vs. Embodied Avatar) influence puzzle-solving performance and user interactions during a 2D spatial puzzle-solving task in an MR environment?* Participants in the Voice-only condition completed the puzzle faster (see Table 3.3 and Figure 3.6a) and more accurately in terms of success rate (see Table 3.2) than those with an Embodied avatar. This supports prior research that auditory guidance alone is effective for tasks requiring concentration on visual tasks (as for our puzzle case study), likely because the Embodied assistant adds cognitive load through simultaneous visual and auditory inputs [1054]. Indeed, in our study, the effort construct of the NASA-TLX (see Table 3.5) was higher for the Embodied modality and statistically different from the Voice-only one. We assume the added visual dimensions from the avatar might have been distracting the user, offering no functional value for puzzle-solving [654, 993]. Furthermore, in the Embodied modality, the observed success rate for orientation is 16%, below the chance level. This suggests participants may employ strategies that lead to frequent errors, potentially due to the puzzle's complex and ambiguous pattern. For instance, we observed that participants often prioritize positioning pieces correctly and tend to test orientations sequentially. When a piece appears to fit physically, they may leave it in an

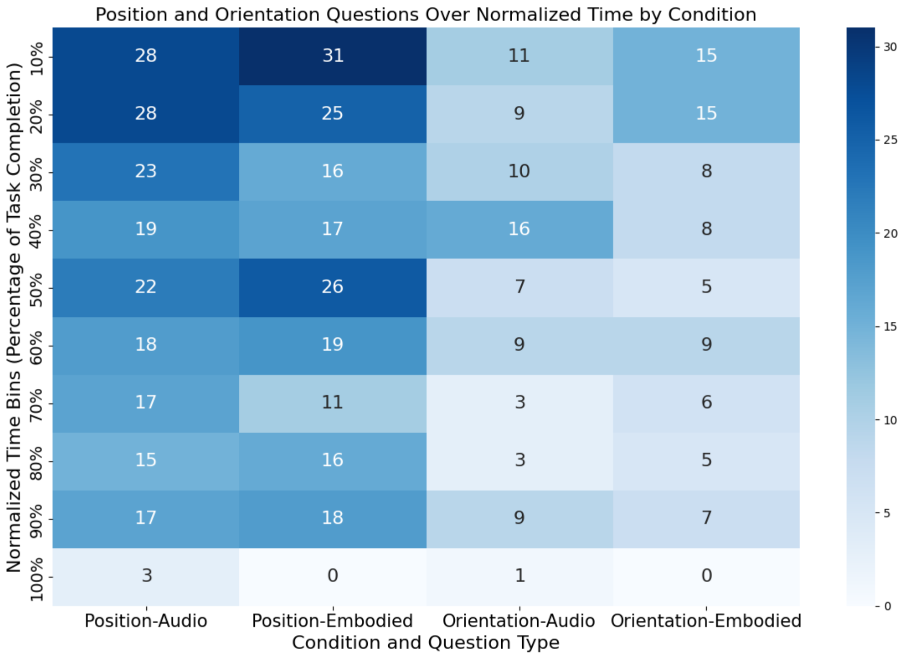


Figure 3.7: Distribution of the number of position and orientation-related questions by condition (Voice-only vs. Embodied).

incorrect orientation, likely under the assumption that it is already correct. This behavior needs further investigation to better understand its impact on performance. The confirmed equivalence, as demonstrated by the TOST tests, in the number of position-related and orientation-related questions posed to both CVA modalities suggests that, in the puzzle-solving task, the requests are primarily driven by the task's demands rather than the mode of interaction with the CVA. In our analysis, we also highlighted the pattern concerning the number of position and orientation-related questions across the puzzle-solving task (Figures 3.6e, 3.7 and Table 3.4). The overall number of position-related questions is significantly higher than the number of orientation-related questions (Table 3). In addition, participants in both conditions asked significantly more position-related questions early in the task, with a peak during the first 0-20% of task completion (Figure 3.7). This indicates that users generally struggled more with positioning puzzle pieces at the beginning, regardless of the CVA's representation mode, as supported by the ANCOVA analysis. This initial difficulty aligns with prior findings that positioning challenges are common in spatial tasks [307, 1329], particularly during the early stages, when users are still familiarizing themselves with the puzzle structure and task requirements [957]. As the task progressed, the frequency of position-related questions decreased by nearly 40%, suggesting that participants grew more confident and independent in handling piece placements. This decline highlights the importance of early guidance in helping users build competence, reducing the need for assistance as they advance through the task. In contrast, orientation-related questions were fewer overall but still concentrated in the early stages of the task. While participants primarily faced difficulties with positioning, they also needed clarification on spatial orientation during the initial phase. This early focus on orientation-related questions underscores the challenge posed by spatial rotation, even though it was less frequent than positioning issues. The ANCOVA results provide further statistical validation for these trends, confirming that 'position' requests were significantly more frequent than 'orientation' requests and that the frequency of requests decreased significantly over time. Importantly, these patterns held consistent across request types and CVA modalities, with no significant differences in interaction trends between the Embodied and Voice-only conditions. The statistical analysis corroborates these trends in question frequency, offering insights for improving task design. If more questions are consistently asked early in the task, this suggests the need for clearer initial guidance or a more intuitive onboarding process to help participants overcome early obstacles more effectively.

RQ2: What is the impact of representation mode of the virtual assistant (Voice-only vs. Embodied avatar) on participants' cognitive workload and social presence during a 2D spatial puzzle-solving task in an MR environment? As mentioned for the RQ1, the higher cognitive workload in the Embodied condition, particularly in terms of effort, is a noteworthy finding. The visual elements of the Embodied CVA, such as lip-syncing and body animations, likely added to the cognitive load. This aligns with cognitive load theory, which indicates that additional sensory inputs can increase task difficulty, especially when those inputs do not directly contribute to task success [955]. Furthermore, as supported by [1054], it is important to note that while the Embodied CVA tends to be more engaging and appealing, it is not as effective when it comes to tasks, such as puzzle solving (the success rate was higher in the case of Voice-only as stated in Table 3.2). The frustration across the CVA modalities is equivalent and low, and the performance is equivalent and high, which may be attributed to the clarity of the task and the assistance provided by the CVA. Additionally, the perceived message understanding is equivalent and high, indicating that users felt there was clear message understanding between themselves and the CVA, contributing to reduced frustration. Interestingly, the lack of significant differences in social presence between the two conditions suggests that the visual embodiment of the CVA was not necessary to foster a sense of co-presence during puzzle-solving. Previous research has indicated that Embodied agents tend to enhance social presence in interactive environments [881, 258], yet in this study, the functional utility of the CVA appears to play a more critical role than its visual presence. It is possible that the cognitively demanding nature of the task overshadowed the potential benefits of visual embodiment, as participants may have prioritized task completion over interpersonal engagement. This is a crucial distinction, as it suggests that the effectiveness of embodiment features may depend on the nature of the task—socially engaging tasks may benefit from visual embodiment, while cognitively demanding tasks may not.

RQ3: What are the participants' perceptions of usability and technology acceptance in this MR experience? In both the Voice-only and Embodied conditions, participants generally found the system intuitive and effective regardless of the representation mode (Table 3.5). The TOST results confirm equivalence in usability and perceived usefulness. These findings suggest that both modalities are perceived as equally effective and user-friendly for supporting task completion. The results suggest that while visual embodiment may enhance user engagement in some contexts, it does not appear to offer substantial benefits in terms of usability or acceptance for tasks like puzzle-solving. This highlights the importance of aligning system design with task-specific requirements. In this case, it appears that reducing unnecessary visual inputs enhances both performance and user experience.

Limitations and Future Works

This section discusses the study's limitations and outlines opportunities for future research. The initial pilot study (Section 3.2.3) played a crucial role in identifying and addressing several of the technical and interaction-related challenges of the system. Regarding hardware limitations, the battery constraints of the HoloLens 2 device caused challenges during longer sessions, requiring frequent recharging and significantly limiting the number of participants per day. Our study focused on the impact of CVA modality (Voice-only vs. Embodied) on performance and user experience, but some influencing factors were beyond its scope. For instance, the gender of the CVA, known to affect trust and engagement [683, 554], was not addressed. Future research could examine the role of agent gender in influencing interaction dynamics, providing a more holistic understanding of user-agent experiences. The limited non-verbal behaviors of the CVA in our study, such as the absence of gestures or dynamic gaze shifts, may have influenced participants' sense of co-presence and engagement, as described in [1400], thus suggesting a promising direction of analysis in exploring highly realistic avatars (acting as human instructors), combining social, conversational, and visual elements. Although NASA-TLX is widely used to measure workload, it does not differentiate between the intrinsic, extraneous, and germane components of cognitive load, which are critical for understanding task-specific demands. Further investigations could adopt a suitable tool to measure these components like the one described in [47]. Furthermore, social inhibition effects, where an Embodied CVA may increase arousal and reduce accuracy, have been observed [1398, 23, 859]. Future studies should understand their impact on task performance. Additional works should explore the impact of continuous versus on-demand guidance of CVAs in MR environments, as this could affect task autonomy and learning outcomes. Furthermore, alternative interaction modes and their impact on usability should also be assessed. While the pinch gesture is intuitive in theory, it can be difficult for some users to execute it consistently. Another area for enhancement lies in the integration of more advanced feedback mechanisms. While the current guidance system provides linear, rule-based feedback, future systems could implement more detailed, real-time adaptive feedback that dynamically adjusts to the user's progress, delivering personalized and responsive guidance tailored to the user's performance at each stage. Finally, expanding the task complexity to include different types of puzzles or spatial challenges would allow researchers to assess the generalizability of these improvements. By testing the system on a greater variety of scenarios, follow-up research could gain deeper insights into how Embodied and Voice-only CVAs perform under different conditions and how improvements in guidance and interaction methods may be obtained across tasks.

Conclusion

This study examined the effects of Voice-only versus Embodied CVAs in an MR puzzle-solving task, providing insights into their influence on performance, cognitive workload, social presence, and user experience. Through an evaluation of 34 participants, we found that Voice-only CVA significantly improved puzzle-solving efficiency. Participants completed the task faster and had higher success rates in placing and orienting puzzle pieces. The Embodied CVA, while potentially more visually engaging, resulted in a higher cognitive workload, particularly in terms of effort, and did not provide a performance advantage in task completion. Both modalities showed equivalent outcomes in interaction patterns, including position- and orientation-related queries, perceived usability, perceived performance, frustration, and usefulness, suggesting these were influenced by task demands rather than the mode of interaction, with an equivalent message and affective understanding highlighting the role of clear communication over the need for embodiment. In conclusion, while both Voice-only and Embodied CVAs have their merits, the choice of modality should be tailored to the specific task. The findings indicate that for tasks like puzzle solving, requiring spatial cognition and problem-solving, Voice-only CVAs may be more effective as they provide necessary guidance without overwhelming users with additional visual stimuli.

3.2.4 Insights

Some of the findings from this study have been published in [486].

Objective

The primary goal of this case study is to develop an MR-based virtual assistant application designed to aid users in puzzle-solving tasks. The application leverages the immersive and interactive capabilities of MR to enhance cognitive engagement, improve problem-solving efficiency, and assess the impact of different virtual assistant modalities (embodied vs. audio-only) on user experience.

Technical Infrastructure

The MR virtual assistant application was developed using Unity3D and the MRTK SDK to create an immersive MR environment where users can interact with both the virtual assistant and the puzzle elements. The assistant operates on a rule-based system powered by a pre-programmed algorithm that provides real-time hints and adaptive feedback.

Interaction Modalities and Sensor Integration

The application supports multiple interaction modalities to enhance usability:

- **Gesture and Hand Tracking**: Using the HoloLens 2's integrated hand-tracking capabilities, users interact with puzzle components by selecting, rotating, and moving them, providing a hands-on approach that aligns with natural interaction.
- **Voice Commands**: Voice recognition allows users to interact with the virtual assistant through spoken commands, triggering hints or explanations without needing manual input, which helps streamline the puzzle-solving process.

Evaluation and Data Collection Framework

The effectiveness of the CVA was evaluated through both quantitative and qualitative metrics:

- **Objective Metrics:** Metrics such as total task completion time, number of hints requested, and error rates provided insights into user efficiency and problem-solving accuracy.
- **Interaction Patterns:** Types of user inquiries—categorized as positional or rotational guidance—alongside the timing of each question were recorded to analyze interaction dynamics across CVA modalities.
- **Subjective Feedback:** cognitive workload, social presence, and User satisfaction, were evaluated through validated instruments, including the NASA-TLX for assessing cognitive workload, the Social Presence Questionnaire (SPQ) for measuring the perceived social presence, the System Usability Scale (SUS) for usability assessment, and the Technology Acceptance Model (TAM) for understanding perceived usefulness of the virtual assistant.

Main Findings
The study yielded several key insights into the effectiveness and user experience of the MR Virtual Assistant in puzzle-solving tasks:

- **Task Efficiency and Accuracy:** The Voice-only CVA modality significantly improved task completion time and accuracy compared to the Embodied modality. Participants in the Voice-only group completed puzzles more efficiently, suggesting that the reduced visual load allowed them to focus more on the task.
- **Cognitive Workload (NASA-TLX):** NASA-TLX results indicated a higher cognitive workload associated with the Embodied CVA, especially in terms of effort. Suggesting that this additional visual interaction with the Embodied assistant increased the effort required, which sometimes distracted users from puzzle elements.
- **Usability (SUS):** Both modalities scored well on the System Usability Scale (SUS), indicating that users found the interface easy to navigate and interact with.

Technical, Usability Challenges and Future Directions
The development and implementation of the MR Virtual Assistant for puzzle-solving presented several key challenges:

- **Field of View Limitations:** The limited field of view of the HoloLens 2 device required precise positioning of the virtual assistant to ensure it remained visible while users focused on puzzle pieces. This constraint demanded the assistant be relocated closer to the puzzle area to facilitate a natural line of sight between the puzzle and the assistant.
- **Battery Life Constraints:** Extended sessions placed significant demands on the HoloLens 2 battery, necessitating frequent recharges that limited participant throughput per day. Managing battery efficiency became essential to ensure consistent performance across trials.

- **Gesture Recognition Consistency:** Certain gestures, such as pinch gestures used for selecting or manipulating puzzle pieces, were difficult for some users to execute consistently.

Future research should explore hardware solutions with a wider field of view or adaptive rendering techniques that reposition the virtual assistant based on user gaze tracking to improve visibility. Battery efficiency could be enhanced through power-optimized rendering, and hardware refinements to extend device usage time. Additionally, advancing gesture recognition with multimodal interactions, such as voice commands and eye tracking, alongside machine learning-driven improvements, could enhance usability and accessibility for a broader range of users.

3.2.5 N3: Learning Rubik's Cube Notations

Objective and Context

The introduction of eXtended Reality (XR) has revolutionized educational practices by enhancing engagement, personalizing learning experiences, and fostering skill development [577]. XR enables real-time interaction with virtual objects via mobile and wearable devices, creating a limitless learning environment [1226, 1333, 577, 40]. In both academia and industry, XR supports Experiential Learning (EL), an approach emphasizing hands-on experience and active experimentation [135, 672, 1333]. XR provides key EL features such as 3D visualizations, object manipulation, and augmented physical environments, enabling "learning by doing" [577, 1212, 1415]. Digital Twins (DTs) can play a critical role in this process by allowing users to manipulate objects in both virtual and physical spaces, supporting dynamic, state-aware learning [609, 89, 1149]. DTs in XR offer benefits such as improved knowledge retention, flexible learning, and personalized experiences [290, 1149, 1220]. While XR and DTs have been widely studied in domains like manufacturing and healthcare [1133, 1423], their application in sequential educational tasks, especially those involving virtual guidance, remains underexplored [722, 1229].

This study addresses this gap by exploring how DT-driven XR can enhance the learning of Rubik's Cube notations, a key element in algorithmic thinking and problem-solving [276, 864]. Solving the cube requires understanding a system of notations representing face rotations [17], which can be challenging to memorize and apply. This study proposes an MR-based framework integrating state-aware, dynamic guidance to teach Rubik's Cube notations, using a Smart Rubik's Cube (SMR)[1364] that continuously synchronizes with its virtual counterpart. The study tests three learning modalities: textual-annotation guidance (T-ANG), visual-annotation guidance (V-ANG), and interactive-annotation guidance (I-ANG). The first two build on prior research on virtual annotations[722], while I-ANG introduces hand interaction with the SMR's digital twin before applying the moves to the physical cube, enhancing learning retention through EL [1332, 1243]. A user study was conducted to compare the modalities and determine which method yields the best learning retention. The results provide insights into designing effective XR experiences for procedural learning, particularly in real-world applications.

In particular, in this paper, we seek answers to the following research questions (RQs):

- RQ1: Which DT-driven guidance method leads to the highest performance in short-term skill retention?
- RQ2: Is there a relation between performance time and accuracy generated by different guidance methodologies?
- RQ3: What is the relation between guidance usability, cognitive load, and technology acceptance while performing sequential instructions?

Related Work

Characterized by active participation and reflection as outlined in Kolb's framework [672], EL involves learners encountering new experiences, reflecting, adapting concepts, and applying them in real-world scenarios to improve understanding and practical skills. Both XR and DTs have been shown to enhance the effects of EL, particularly for sequential instruction learning [672, 609, 722, 1149, 324, 1023, 856].

The study presented in [722] introduced a framework assessing immersive visual cues across various modalities and motor tasks, analyzing the differences between two types of guidance: (i) Annotation, which uses 3D texts and objects, and (ii) Tutor, featuring 3D character demonstrations across tasks like maze escape, stretching exercise, and crane manipulation. The annotation approach was more effective for tasks requiring spatial knowledge and quick action recall, while the Tutor approach performed well for more complex tasks with multiple steps. This work highlighted the efficacy of immersive guidance in knowledge transfer, yet acknowledged the limitations of learning transfer due to the reliance on a fully Virtual Reality (VR) environment. To overcome this, some recent works resorted to MR paradigms taking as use case automotive and toy assembly, where users receive step-by-step guidance providing visual instructions that enhance comprehension and reduce errors [516, 548, 1374, 1229]. Authors of [1374] explored video-annotated MR for step-by-step guidance, whereas [1229] expanded MR tutorials of complex assemblies using object detection for state-awareness, both demonstrating their effectiveness in real-world contexts. Elements such as arrows and text were designed to assist users and to improve self-directed learning and knowledge application skills in instructional task learning [1360, 953, 1393, 320]. In both VR and MR, the implemented guidance approaches have been designed and assessed to determine their impact on user performance and experience during complex sequential tasks [722, 1374, 593].

So far, the role of DTs in educational settings has been explored and contextualized in [1133, 1149, 856]. However, not many works provide DT state-aware MR systems to effectively guide users through DTs and their physical counterparts for learning complex procedural tasks. To the best of our knowledge, only a few studies test the potential synergy between DTs and MR paradigms in educational pipelines, such as [609, 1149]. In particular, [609] introduced an MR framework for remote collaboration in education and training to empower users through DTs to refine their skills in a realistic environment [609]. Moreover, the authors of [1149] outlined how DTs enhanced the learning experience by letting users interact with an accurate digital model that mirrors its real-world counterpart. However, these works lacked real-time feedback between the physical and virtual realms, critical for effective EL [701, 152].

To the best of our knowledge, no general framework for MR guidances driven by state-aware DTs in the context of sequential task learning [1360, 320] is available. This work proposes a novel state-aware DT framework, which includes two visual MR guidances, inspired by [722], and a novel mixed virtual and physical DT-driven modality. This framework supports and accelerates Kolb's experiential learning cycle [672] by allowing learners to interact with a DT for practical experience, review outcomes with MR guidance, and apply abstract concepts to real-world tasks [1333]. In the following, we present the design, implementation, and assessment of such an approach.

Materials and Methods

We introduce an MR system that allows one to learn Rubik's Cube notation (i.e., an instructional sequential learning task) while interacting with both the physical and virtual realm through a state-aware DT [1333, 1325]. In this Section, we detail the system architecture and its logging system, and the three implemented MR interfaces.

System Architecture

The system architecture follows the Model–View–Controller (MVC) pattern, comprising two primary components: an MR application and communication middleware that connects the physical Smart Rubik's Cube with its digital twin (DT). The architecture is depicted in Figure 3.8.

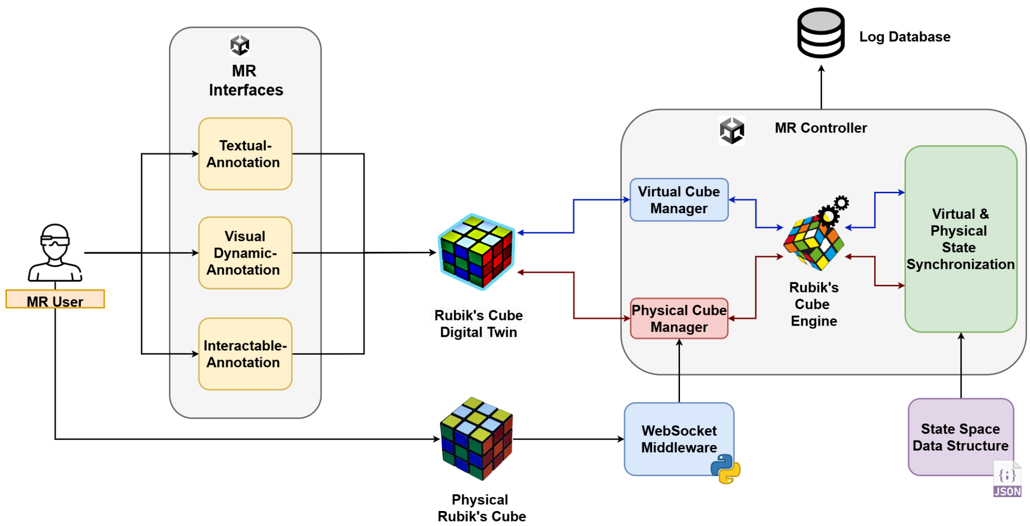
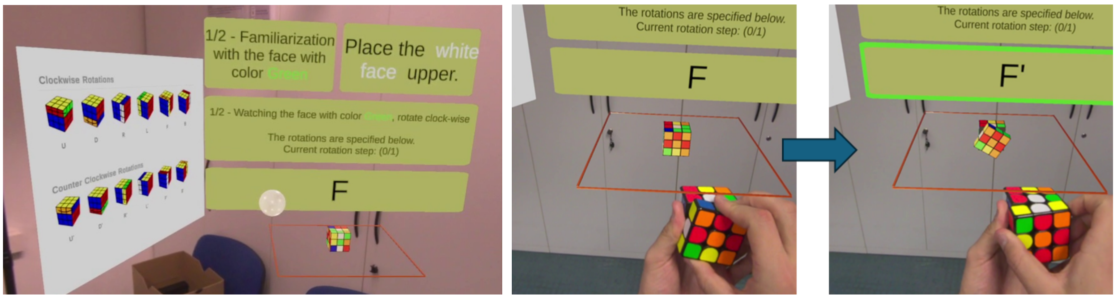


Figure 3.8: System architecture diagram.

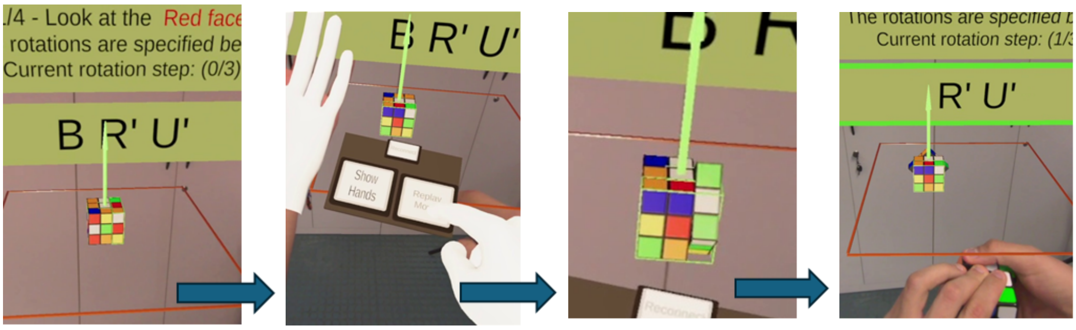
The system provides three distinct MR-driven interface modalities designed to deliver different forms of user guidance: Textual Annotation Guidance (T-ANG), Visual-Dynamic Annotation Guidance (V-ANG), and Interactable Annotation Guidance (I-ANG). Each modality caters to unique interaction preferences while maintaining the same fundamental goal of teaching Rubik's Cube notations through hands-on, state-aware guidance. The Textual Annotation Guidance (T-ANG) modality serves as the baseline interface, resembling a traditional "paper-based" tutorial. In this modality, static textual annotations are displayed alongside the virtual representation of the Rubik's Cube to provide users with detailed instructions on how to perform each move (Figure 3.9). A white panel presents the Rubik's Cube notation and the meaning of each move, including clockwise and counterclockwise rotations, making this modality ideal for users who prefer to reference static information while manipulating the physical cube. In this mode, the system continuously synchronizes



(a) (b)

Figure 3.9: T-ANG modality interface. (a) Static visual guidance with a white panel mimicking an "instruction paper"; (b) The user follows the rotation instruction on the physical cube, mirrored by the virtual one.

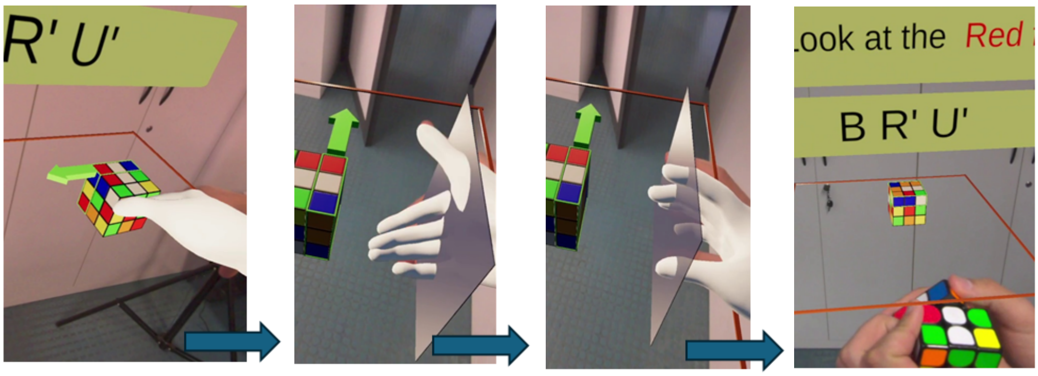
the physical cube with its virtual twin, updating the state of the digital cube in real time. Users can directly manipulate the physical cube, and the virtual cube reflects their actions, providing dynamic feedback on their progress. The Visual-Dynamic Annotation Guidance (V-ANG) modality introduces a more immersive, animated approach to instruction delivery (Figure 3.10). Instead of static text, this interface uses dynamic visual cues and animations to guide users through the Rubik's Cube-solving process. Green arrows and bounding boxes are rendered around the virtual cube to indicate the correct face orientation and the specific rotations required. This modality supports users by providing a step-by-step animation of the



(a) (b) (c) (d)

Figure 3.10: V-ANG modality interface. (a) The green arrow indicates the correct position of the white face; (b) The user clicks the "Show moves" button; (c) The virtual cube shows an animation of the current rotation sequence; (d) The user mimics the seen rotations.

moves required to solve the Rubik's Cube. By pressing the "Show moves" button, users can visualize an animated sequence of the required rotations, which they can mimic on the physical cube. The real-time synchronization between the physical and virtual cubes helps reinforce the learning of Rubik's Cube notations through immediate visual feedback. The V-ANG modality supports implicit learning by allowing users to learn through observation and replication, which encourages a more intuitive understanding of the moves. The Interactable Annotation Guidance (I-ANG) modality is the most interactive of the three. It not only displays visual cues but also allows users to directly manipulate the virtual cube using hand-tracking technology (Figure 3.11). In this mode, users can interact with the digital twin of the Rubik's Cube before replicating the moves on the physical cube. In I-ANG,



(a) (b) (c) (d)

Figure 3.11: I-ANG modality interface. (a) The green arrow indicates the face rotation direction while a bounding box indicates the face to be rotated; (b-c) The user rotates the correct face of the virtual cube; (d) The user replicates the same actions on the physical cube.

users are guided by visual elements such as green arrows and bounding boxes that highlight the face of the cube to be rotated and the direction of rotation. The system prompts users to perform the rotations first on the virtual cube using hand gestures, and then on the physical cube. This modality provides a deeper level of engagement by incorporating direct interaction with the virtual cube, thereby improving the transfer of knowledge from the virtual to the physical world. The I-ANG modality aims to reinforce learning through active participation, where users manipulate both the virtual and physical cubes, encouraging a hands-on, learn-by-doing approach.

Independently of the chosen modality, the system synchronizes users' actions on the Rubik's cube with its DT counterpart in a state-aware approach. These dynamical adaptations are implemented by the virtual and physical cube manager (within the MR controller) (see Figure 3.8). Such components continuously communicate with a custom Rubik's cube engine, which is defined to interpret the signals coming from the physical and virtual cubes. The State Synchronization Component (SSC) maintains a coded version of such information. The SSC internally stores the state of the virtual and the physical cube, providing dynamic feedback to both managers to adapt the visualized information to guide the users in the sequential instruction execution and learning. When an experiment begins, such a state follows a JSON-like key-value data structure, which codifies the instructions hierarchically: a sequence of phases composed by a sub-sequence of steps. Once the user performs a phase/step, the system fetches the next until the last, representing the end of the task. This data-driven approach provides a natural compatibility of our system with any sequential instruction process. Concerning communication with the physical cube, we implemented an additional middleware that continuously receives signals from the smart Rubik's Cube (via Bluetooth), interprets them, and streams them to the Physical Cube Manager through a web socket interface (See Figure 3.8).

To collect data involving the user's activity we integrated a logging system with a local database exploited by the different experimental stages, logging each relevant action made by the user.

AR Interface Design

Our system provides three kinds of user interfaces: T-ANG, V-ANG, and I-ANG. Despite providing different guidances, all the interfaces will always display the same kind of instruction in four yellow virtual panels placed on top of a virtual table where Rubik's Cube DT lies. Moving a simple white sphere a user can drag the table around the surrounding space. A Menu is provided to exploit the modality-dependent functionalities. Any modality will always include a Menu button to show/hide the virtual hands rendered by hand-tracking (used to interact with the digital cube). The provided sequential instructions are always composed by a triplet of $<$ *position of white face* (PWF), *the color face to place in front of the user* (CFF), and *the sequence of rotations to perform* (SQR) $>$. This format follows the one provided by classical Rubik's Cube solving algorithm learning instructions [1237, 820, 214, 840] and is implemented adopting dynamical visual annotations. The PWF is always placed in the top-right panel, the CFF in the central one with the info regarding the current step, and the SQR is instead positioned in the bar below (Figure 3.9a). The SQR is updated at each move: a correct one will remove the leftmost instruction. Otherwise, a novel sequence will appear to let the user backtrack from one or more errors. Finally, the information on the top-left panel informs the user about the current status. The instructions are presented identically in the three modalities to isolate the role of the guidance types.

The AR interface for the Rubik's Cube teaching system was designed to enhance usability and spatial reasoning through three interactive modalities tailored to diverse learning needs. The system ensures real-time synchronization between the physical cube and its digital twin, maintaining instructional accuracy. Visual guidance plays a key role in reducing cognitive load. Green visual elements, such as arrows and bounding boxes, reinforce progression and clarity, helping users focus on relevant cube sections without distraction. Animated demonstrations (V-ANG modality) simplify rotation sequences, making procedural learning more intuitive, while dynamic error feedback immediately highlights mistakes and provides corrective guidance. The I-ANG modality holds the potential to deepen cognitive engagement by allowing direct virtual cube manipulation via hand-tracking, requiring users to perform actions in the digital space before applying them physically. This enhances spatial transformation skills and reinforces procedural learning. To balance usability and clarity, the system selectively displays only the most relevant cues at each step, minimizing visual overload. Step-by-step guidance accommodate both beginners and experienced users, ensuring accessibility. The design aligns with AR research, demonstrating how animated guidance and real-time feedback improve spatial understanding and procedural learning [1106, 1333, 879].

Experimental Setting

In this Section, we detail the experimental phase performed to investigate whether the three different proposed modalities affect participant semantics understanding in a short-term performance setting.

Apparatus

The Rubik's cube MR application was implemented with the Unity Engine (v 2021.3.15f1) targetting the Varjo XR-3, integrated with the hand-interaction system implemented through the UltraLeap SDK. Such a device was picked because of its high level of immersiveness and photorealism, which are core factors in MR learning contexts [76, 626]. For the physical smart Rubik's Cube middleware, we implemented a Python (v 3.8) web socket server that communicates via Bluetooth 4.0 with a Giiker Super Cube I3Se through the bleak library. The pre and post-experience questionnaires were furnished within the Google Form platform. All the experimental sessions were carried out on an MR-capable Alienware Aurora R15 (Intel Core i7 Computer Gaming, 16 GB di RAM, SSD 512 GB+1 TB, NVIDIA GeForce RTX 4080).

Procedure and task

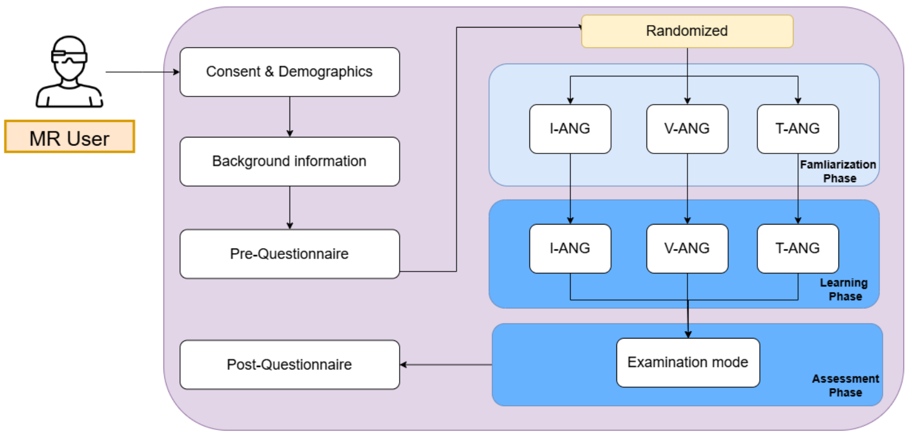


Figure 3.12: Experimental session procedure.

Figure 3.12 outlines the experimental procedure. Each participant agreed to participate in the experimental trial and to provide answers to a basic demographics questionnaire, including age, gender, and education level. The users also answered a background information questionnaire related to Rubik's Cube notation. Finally, they indicated their expertise with different immersive technologies.

The experimental phase started by randomly assigning participants to one of the modalities, adhering to the established protocols [722, 840]. This random allocation ensured their uniform distribution across all modalities, thereby minimizing potential selection bias. Throughout the experiment, participants remained unaware of their group assignments. This selection mechanism matches a "between-group" framework that enabled us to evaluate the effectiveness of the guidance modalities within the same procedural context.

For all considered modalities, users underwent a modality-dependent familiarization phase. In this phase, a user got acquainted with the MR device and the visual guidance of the specific modality by executing the same sequence of four rotations of the cube. The main learning phase then started: a user exploited the modality-dependent guidance to perform random but deterministic sequential instructions. In such a sequence, each rotation (clockwise and counter-clockwise) appeared at least twice, to guarantee a balanced stimulus. A user could make mistakes and fix them using the dynamic visual guidance provided by the DT-driven engine.

An Assessment Phase (AP), the same for all users for all modalities, follows the learning phase. The AP comprised two phases of increasing difficulty: the first included 5 instructions (AP1) and the second one 10 (AP2) instead (this was motivated by theories in cognitive load theory, working memory capacity, and explicit sequence learning) [1255, 1021, 173, 1338]. The 15 moves were uniformly and deterministically sampled from all the possible Rubik's Cube rotations. During each phase, a user was requested to implement the sequence of instructions shown on yellow panels without the assistance of the virtual cube and the visual guidance as these were removed from the user's view. The AP lets us verify how each modality influenced the user's semantic understanding and the working memory capacity. In particular, we measured those constructs by analyzing both the number of correctly performed moves and the temporal patterns exhibited during the AP. After the AP, users evaluated their experience through a post-questionnaire which consisted of several scales aimed at capturing usability, cognitive load, technology acceptance, and perceived difficulty (further detailed in Section 3.2.5). The adopted sequences are detailed in the Supplementary Material.

Participants

We enrolled 45 participants for our study. Selection criteria required participants to be university affiliates, including students from bachelor's, master's, or doctoral programs, or professionals in scientific disciplines. Eligible participants were aged 20 to 37 years and were required to have no severe motor impairments that could affect their ability to manipulate a Rubik's Cube. Additionally, expert-level Rubik's Cube solvers were excluded to prevent performance bias, while individuals with significant prior experience in advanced MR/VR environments were also excluded to ensure that pre-existing familiarity did not influence the study results.

Considering our randomized trial procedure, our participants equally went into one of three experimental conditions: T-ANG ($n = 15$), V-ANG ($n = 15$), and I-ANG ($n = 15$). This number of users amounts to a number that has repeatedly proven to be sufficient to discover over 80% of existing interface design problems [1106, 879]. Each participant completed a pre-experience questionnaire to provide their demographic details, prior experience within MR and VR, and familiarity with Rubik's cube notation (PRE-X and ITRC-X respectively in Table 3.6).

The selected population amounted to 15 females and 30 males, with a mean age of 27.2 years ($SD = 4.5$). Such participants were all university members, picked among students, from bachelor (15/45), master (21/45), or doctoral programs (7/45) from different scientific disciplines, and professional workers (2/25). We also outline that 85% of our population was right-handed, a relevant factor for manual task performance analysis, like Rubik's Cube execution [820]. By analyzing the answers to PRE-X items, 29 participants indicated prior experience with MR or VR, while 16 reported no prior exposure (PRE-1). Further examination of their experiences with MR/VR (PRE-2) indicated that, on average, respondents had modest familiarity

Code	Question	Answer Type
PRE-1	Have you ever experienced Mixed Reality (MR) or Virtual Reality (VR) before?	Binary (0,1)
PRE-2	Have you ever used a smartphone to experience Mixed or Virtual reality (VR) before?	5-point Likert scale
PRE-3	Have you ever used a head-mounted display (HMD) for mixed reality or virtual reality (VR) before?	5-point Likert scale
PRE-4	Have you ever used the Varjo XR3?	5-point Likert scale
ITRC-1	Do you have any previous experience with solving a Rubik's Cube?	5-point Likert scale
ITRC-2	Do you know what an F rotation is?	Binary (0,1)
ITRC-3	Do you know what the Red face is?	Binary (0,1)
ITRC-4	Are you interested in learning the notation and resolution methods of the Rubik's Cube?	5-point Likert scale

Table 3.6: Items of the Pre-questionnaire, including a mix of yes/no, and 5-point Likert scales.

with smartphone-based MR/VR (M = 2.29, SD = 1.3) and (PRE-3) slightly higher exposure to Head-Mounted Displays (HMDs) (M = 2.44, SD = 1.43). Considering the MR device employed, the Varjo XR3, the majority of respondents (36 out of 45) reported no prior experience using it (PRE-4). Furthermore, (ITRC-1) the participants showed low experience with the Rubik's Cube (M=2.59 and SD=1.17). This is confirmed by the general unfamiliarity with fundamental Rubik's Cube concepts such as the "F rotation" (ITRC-3) and the "Red face" (ITRC-4) (91% and 62% respectively). Despite this, (ITRC-2) the respondents exhibited an interest in acquiring Rubik's Cube notation knowledge (M=3.62, SD = 1.02).

Measurements

The measured variables consist of both implicit performance metrics and explicit scale evaluations. In particular, we measured two main performance variables (continuous and discrete), collected and aggregated by the logging system: (i) Time Taken to perform each move (TS), i.e., how long a participant takes to complete an AP step (related to RQ2). From the sum of each time step, we also derived the Total time (TT); and (ii) Accuracy of each move (M-ACC), evaluating participants' ability to follow the provided instructions correctly. From this, we also derived global accuracy (ACC) and the Success Rate (SR), which equals one only if all moves are implemented correctly (related to RQ1). We then evaluated the users' attitudes towards the implemented modalities (related to RQ3) with questionnaires concerning: usability, adopting the System Usability Scale (SUS) [171] which comprises 10 items rated on a scale from 1 (Strongly disagree) to 5 (Strongly agree); task cognitive load, exploiting the NASA Task Load Index (NASA-TLX) [506] to assess participants' mental effort and resource allocation during the learning process; technology acceptance model using a use-case customized version of the Technology Acceptance Model (TAM) questionnaire [292]. Finally, we developed a custom Assessment Phase Perceived Complexity (APPC) scale to check whether the perceived complexity of the final AP was aligned with the obtained performances. This was composed of two 5-point Likert Scale questions related to the two APs: "*How do you rate the difficulty of accomplishing sequence (x) (the sequence with y rotations) in the assessment phase?*", where the couple (x, y) is instantiated as (1,5) and (2,10), in the two sequences that have been carried out by each participant. Finally, following a "think-out-loud" approach, we asked for opinions on the used modality (reported in the Supplementary material) [1220, 879].

Results

All the statistical analyses were performed using Python (v3.10.6) with the packages Matplotlib (v3.8.4), Pandas (v2.2.2), Pingouin (v0.5.4), Seaborn (v0.13.2), Scipy (v1.13.0), and Numpy (v1.26.4). The results obtained from the assessment phase (composed of AP1 and AP2) are here presented per modality, considering as study variables the performance metrics (accuracy score and time) and the usability, technology acceptance, and cognitive load highlighted by the adopted SUS, TAM, NASA and APPC scales.

Performance analysis

To analyze performance-related variables, we report in Table 3.7, Figure 3.13 and Figure 3.14, the overall time/accuracy/success rate performance statistics, the accuracy boxplots and the time taken to perform each move respectively, for both of the APs and all the three surveyed modalities. In the following, we detail the analysis to check statistically relevant differences, applying strict criteria ($p \leq 0.05$). We performed a normality check with the Shapiro-Wilk test [1044]. Non-normality emerged for the considered variables, under different modalities $p < 0.05$. Therefore, we performed the non-parametric Kruskal-Wallis H-test [831], followed by a pair-wise Mann-Whitney U Test, to assess the origin of the significative difference.

	AP1 (5 instructions)			**AP2 (10 instructions)**		
	TT	**ACC**	**SR**	**TT**	**ACC**	**SR**
T-ANG	59.40 (27.40)	1.87 (1.55)	13%	75.07 (46.27)	3.67 (3.70)	7%
V-ANG	71.67 (48.30)	**3.33** (1.50)	33%	61.40 (23.22)	**7.60** (2.47)	40%
I-ANG	58.60 (25.29)	**3.40** (1.35)	20%	50.80 (20.75)	**7.27** (2.81)	33%

Table 3.7: Summary of performance metrics—time in seconds, accuracy, and success rate—across two assessment phases (AP1 with 5 instructions, AP2 with 10 instructions). Metrics are presented as mean (SD), with significant values in bold.

Accuracy Analysis

Figure 3.13 reports the comparison of the correct performed moves (ACC) over the three modalities and the two assessment phases. Both the V-ANG and the I-

ANG modalities exhibit higher scores compared with the T-ANG in both assessment phases. Moreover, considering AP2, both V-ANG and I-ANG have highly centered (both have a median equal to 8.0) and negatively skewed distributions. In particular, T-ANG exhibits a generally low score with high variability, centered at a median value equal to 1.0 and 3.0, respectively, for AP1 and AP2. However, those two modalities also have very similar scores. This distribution should also be paired with the SR reported in Table 3.7: V-ANG and I-ANG exhibit the highest success rate. In the T-ANG modality, the SR decreased during the AP2 (10 actions) compared to the value obtained during the AP1, whereas in the V-ANG and I-ANG modalities, it increased.

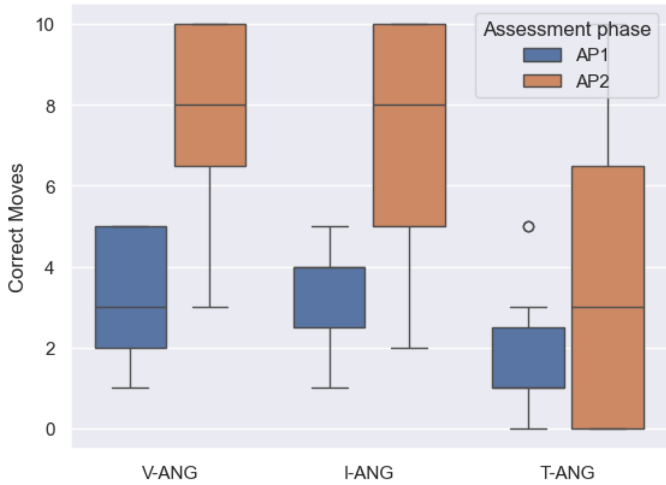
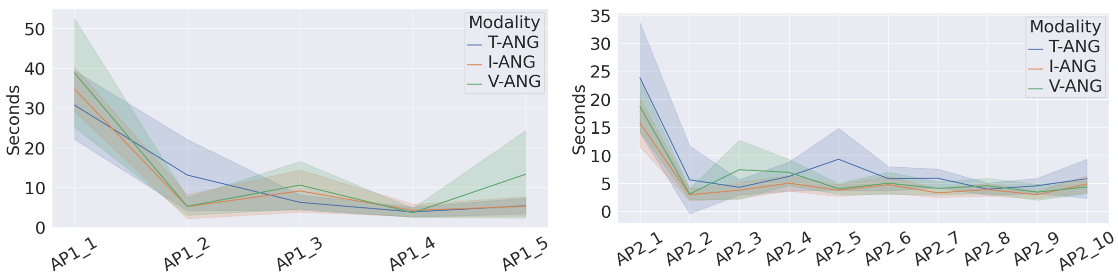


Figure 3.13: Boxplots illustrate correct move distribution across two assessment phases (AP1: 5 moves, AP2: 10 moves) and modalities.

Initially, the distribution of the score variable across the three distinct modalities during the two assessment phases was evaluated for normality using the Shapiro-Wilk test [1044]. All the considered variables exhibited non-normality ($p < 0.05$). We so performed the non-parametric Kruskal-Wallis H-test, which tests the null hypothesis that the population median of all of the groups is equal (used for 3 or more groups) [831]. It corresponds to a non-parametric version of the ANOVA. The Kruskal-Wallis H-test highlighted a statistically significant difference between the three considered distribution modalities for both the AP1 (H = 8.45, p = 0.015) and AP2 (H = 10.43, p = 0.005). However, rejecting the null hypothesis does not indicate which of the groups differs. For this reason, we performed the non-parametric Mann-Whitney U Test to assess whether the obtained scores were sampled or not from the same distribution [832]. We applied this test as a post-hoc and pairwise comparison between all three groups [954]. The Mann-Whitney U Test highlighted a statistically significant difference between the V-ANG and the T-ANG group (U = 170.5, p = 0.015) and I-ANG and the T-ANG group (U = 173, p = 0.011) for AP1. No significant difference was instead detected between the underlying distributions of V-ANG and the I-ANG. The same phenomenon was exhibited in the AP2, where a significant difference was highlighted between the V-ANG and the T-ANG group (U = 181, p = 0.004) and I-ANG and the T-ANG group (U = 176, p = 0.008) with a stronger effect.

Time Series Analysis

Performance time is a crucial variable in instruction execution, and we so analyze it starting from the overall TT. We statistically analyzed the taken metrics with a between-group perspective (i.e., comparing times in the APs for the three modalities). As before, we checked normality with the Shapiro-Wilk test [1044], and at least one variable in the considered groups was statistically labeled as not-normal ($p < 0.05$). For this reason, we again adopted the Kruskal-Wallis H-test [832] that did not highlight any significant differences for both AP1 (H = 0.33, p = 0.849) and AP2 (H = 3.73, p = 0.155). However, from Table 3.7 the T-ANG and I-ANG modalities generally exhibited lower time concerning V-ANG. We so hypothesize that some significative differences could be found in the execution times of the single instructions. For this reason, we calculated the difference between the execution of each instruction, visually reporting their overall means and standard deviations in Figure 3.14.



(a) (b)

Figure 3.14: Time performance (mean and standard deviation) comparison: over AP1 (a) and AP2 (b). Delta differences between a move and the previous one are reported.

Except for an initial delay (given by the interpretation of the appeared instructions), all the modalities converged on an average value of < 10 s per move execution time. Some of the steps, however, exhibited more variability than others. For this reason, we performed the same statistical analysis for each of them, and since those variables did not meet the normality assumption ($p < 0.05$) we proceeded with the same setting. The Kruskal-Wallis H-test exhibited a statistically significant difference between the modalities on step AP2_7 instruction time (H = 6.2, p = 0.045). We then investigated which modalities led to such a difference. The Mann-Whitney U Test highlighted a statistically significant difference between the I-ANG and the T-ANG groups ($U = 170.5$, $p < 0.05$).

Finally, following known approaches, we investigated whether time (TT) is correlated with the accuracy (ACC) [722]. To this date, we performed a 2×2 Pearson Correlation Analysis between the TT and TS variables, and the ACC, and M-ACC variables [938]. In this correlation analysis, we considered the three implemented modalities to evaluate whether a common pattern emerged. The Pearson test outlined a significant negative correlation between the TS and ACC variables, on the AP2_5 ($r = -0.45$, $p < 0.05$) and AP2_9 ($r = -0.38$, $p < 0.05$), indicating that the time taken to perform such moves is inversely proportional to the final accuracy. A similar statistically significant negative correlation was highlighted between TS and M-ACC, on AP1_2 ($r = -0.32$, $p < 0.05$) and AP2_5 ($r = -0.46$, $p < 0.05$). It is worth noticing that these two steps emerged as the most uncertain ones (Figure 3.14). For the other correlation tests, no statistically significant values were highlighted.

Questionnaire analysis

			T-ANG	V-ANG	I-ANG
Scale	Construct	Range	M(SD)	M(SD)	M(SD)
SUS	Positive quality	[1 - 5]	**3.55 (0.61)**	3.44 (0.56)	3.41 (0.66)
	Negative quality	[1 - 5]	**2.21 (0.55)**	2.43 (0.84)	2.25 (0.55)
	Total (SUS Score)	[1 - 100]	**66.67 (12.2)**	62.67 (15.96)	64.5 (11.27)
NASA	Mental demand	[1 – 10]	5.8 (1.57)	**4.6 (2.13)**	5.73 (1.71)
	Physical demand	[1 – 10]	3.8 (2.4)	3.87 (2.53)	**3.2 (2.21)**
	Temporal demand	[1 – 10]	3.87 (2.45)	**2.8 (1.57)**	3.73 (2.19)
	Performance	[1 – 10]	4.47 (1.77)	3.93 (1.75)	**3.87 (1.6)**
	Effort	[1 – 10]	5.4 (1.76)	**5.07 (1.87)**	5.8 (1.74)
	Frustration level	[1 – 10]	4.27 (3.08)	**3.53 (2.33)**	4.13 (3.02)
	Total	[1 – 10]	4.6 (1.53)	**3.97 (1.29)**	4.41 (1.47)
TAM	PU	[1 - 5]	3.59 (0.9)	**3.69 (0.62)**	3.67 (0.78)
	PEOU	[1 – 5]	3.6 (0.7)	**3.75 (0.61)**	3.4 (0.83)
	Total	[1 – 5]	3.59 (0.78)	**3.72 (0.53)**	3.55 (0.73)
APPC	APPC-1	[1 – 5]	2.73 (1.16)	**2.0 (1.07)**	2.67 (0.72)
	APPC-2	[1 – 5]	3.4 (1.3)	**2.27 (0.88)**	2.93 (0.96)

Table 3.8: Questionnaire results reported for the different modalities in the form of Mean (Standard Deviation). The best results per each considered scale and construct are in bold.

The results of the surveyed scales (SUS, NASA, TAM, and APPC) are reported in Table 3.8. We analyzed them through a one-way statistical analysis, to check whether one of the modalities effectively influenced usability, cognitive load, technology acceptance, or perceived level of task difficulty [359, 722, 139]. Again, we performed a normality check with the Shapiro-Wilk test [1044] to highlight non-normality ($p > 0.05$). We performed the non-parametric Kruskal-Wallis H-test [831], followed by a pair-wise Mann-Whitney U Test, to identify the origin of significant differences indicated by the H-test.

SUS

Results of the SUS scale (1 to 5 Likert scales) were computed into a total score, and two subscales: positive and negative usability scores [171]. For the total score, no significant main effect for the modality (T-ANG vs V-ANG vs I-ANG) (H = 0.47, p = 0.79) was found. For the positive usability score, the Kruskal-Wallis H-test did not find any significant difference (H = 0.55, p = 0.75). The same happened for the negative usability construct (H = 0.31, p = 0.85). These results overall suggest that the usability of the systems, on an acceptable level on average (> 60), does not differ too much across modalities. However, participants generally found the T-ANG modality more usable ($M = 66.67$, $SD = 12.20$).

NASA

The results of the NAS scale (1 to 10 Likert scales) were computed into a total score, and its 6 dimensions [171]. Concerning NASA's total score, no significant difference for the modality (T-ANG vs V-ANG vs I-ANG) (H = 1.48, p = 0.48) was found. Specifically, analysis of the mental demand (NASA1) yielded a non-significant result (H = 3.29, p = 0.19), suggesting that the level of mental demand required by the task did not significantly differ across the modalities. Similarly, the physical demand (NASA2) analysis produced a non-significant finding (H = 0.77, p = 0.68). The analysis of task pace (NASA3) also revealed non-significant results (H = 1.83, p = 0.40), suggesting no significant variation in the pace of task performance. Additionally, the assessment of task success (NASA4) showed non-significant findings (H = 0.83, p = 0.66). The same was measured for the effort (NASA5) (H = 1.50, p = 0.47), and frustration (NASA6) constructs (H = 0.30, p = 0.86). In summary, these findings suggest that the modality used did not significantly influence participants' experiences in terms of mental and physical demands, task pace, task success, effort, and negative affect. However, for all the considered constructs, the V-ANG and I-ANG modalities exhibited better scores compared to the T-ANG modality (Table 3.8).

TAM

Results of the TAM scale (1 to 5 Likert scales) were computed into a total score, and two sub-constructs, the Perceived Usability (PU) and the Perceived Ease of Use (PEOU) [171]. For the total score, no significant main effect for the modality (H = 0.13, p = 0.94) was found. For the PU construct, the statistical examination did not uncover any significant difference (H = 0.02, p = 0.99). Concerning the PEOU, again no significant differences were highlighted (H = 1.37, p = 0.5). These results indicate that both the perceived usability and the perceived ease of use did not differ too much across modalities. Overall scores were acceptable (> 3.50) and the V-ANG conditions were generally preferred over the others, indicating users found the visualization by visual tutoring more comfortable.

APPC

The APPC custom questionnaire (1 to 5 Likert scales) was examined for both assessment phases. For APPC-1 the Kruskal-Wallis test found a marginal difference among the different modalities (H = 4.83, p = 0.09). To discriminate which modality led to such a result, we subjected this variable also to the pair-wise Mann-Whitney U Test, which highlighted a significant difference between the I-ANG and V-ANG modalities (U = 159.0, p = 0.04) and a marginally significant one for V-ANG and T-ANG (U = 72.0, p = 0.08). Also for APPC-2, a significant difference was identified (H = 6.94, p = 0.03) and the pairwise analysis showed that this result was caused by the difference among V-ANG and T-ANG (U = 56.0, p = 0.02) and marginally by the one within among I-ANG and V-ANG (U = 155.5, p = 0.06). Pairing this with the descriptive results reported in Table 3.8, it can be appreciated how the V-ANG modality was the one that provided the lowest perceived complexity. We performed a Pearson correlation analysis on the APPC-1 and APPC-2 variables against the global accuracy score, examining both without modality distinctions. While for the APPC-1 no significative correlation was found (p = 0.17), a substantial negative correlation was identified for APPC-2 (r=-0.40, p = 0.01) indicating an inversely proportional relationship within the perceived complexity in the second assessment phase and the obtained global score.

Discussion, limitations and future works

The present discussion is driven by the RQs. Concerning RQ1 ("*Which DT-driven guidance method leads to the highest performance in short-term skill retention?*"), we found that both the I-ANG and V-ANG groups showed better performances than the T-ANG in terms of accuracy and success rate (Table 3.7). However, we did not find any statistical difference between the I-ANG and V-ANG modalities. This effect also emerges from the correlation obtained between the perceived task difficulties (measured with the APPC-x items) and the accuracy variables (ACC and M-ACC): the higher the perceived difficulty, the lower the accuracy score. In essence, the T-ANG assessment phases were always perceived as more difficult than the other modalities. This point deserves further investigation as [1033, 404, 722] identified interfaces such as T-ANG as low complexity ones and thus justified in this way the better results they observed in their use in learning procedural tasks in virtual reality. Based on the cited works, this assumption was initially made during the design phase of our system. However, in this paper, we are observing an opposite type of behavior in MR. Hence, the complexity of an MR interface may require a more accurate definition, in cognitive terms, thus leading to future research works. Furthermore, we did not find any statistical significance difference while comparing cognitive load components measured by the NASA scale in different modalities. The high perceived difficulty of T-ANG could be due to the difficulty experienced translating instructions from a virtual paper into physical actions without additional spatial cues [73]. In addition, while assisting participants during the T-ANG experiments, we noticed they constantly focused on the virtual paper, performing the steps as quickly as possible. This may suggest that the T-ANG participants aimed at imitating actions depicted in the virtual paper rather than grasping the underlying manipulation concepts. The emphasis on speed seen in T-ANG participants could be further investigated by adopting the lens of cognitive load theory. In fact, according to [1254], learning experiences that do not adequately manage cognitive loads can overwhelm a learner's cognitive capacity. These excessive cognitive demands may lead to a reliance on surface-level processing strategies like the imitation observed in the T-ANG modality [1254]. Finally, we outline that a higher learning effect was observed for the I-ANG and V-ANG modalities [220, 722]. We hypothesize that such outcomes may be due to the spatially assisted learn-by-doing approach that I-ANG and V-ANG implement.

Considering RQ2 ("*Is there a relation between performance time and accuracy generated by different guidance methodologies?*") the general performance time did not exhibit statistically significant differences among modalities. However, we found out that there is a negative correlation between the accuracy and execution time at a single move level. This happens at the middle steps of the two sequences (AP1_2 and AP2_5) which also amount to those where a greater variability in execution time is recorded: the higher the time the lower the accuracy. We then paired this result with the differences highlighted in the user's perceived difficulty: the I-ANG users' perceived difficulty was similar to the ones of T-ANG but with opposite accuracy and time performance (APPC-x in Table 3.8). We interpret this phenomenon on two levels. On one hand, the T-ANG modality did not produce the expected learning effect as also proven by the user's lower accuracy (Table 3.7), which can be directly linked to the poor spatial integration of the provided instructional elements [1254]. Indeed, assisting users while performing the assessment phase, we noticed how T-ANG subjects showed uncertain behaviors, as many vocally reiterated their inability to recall the necessary steps and their expectation of making errors. On the other hand, we can assume that the I-ANG users perceived the difficulty of the AP more acutely, likely influenced by difficulties encountered in prior learning phases. This might be because the I-ANG modality involves performing the same actions, first in a virtual setting and then in a physical one, a feature not found in other modalities, which could affect users' final evaluations. When extending the analysis to the V-ANG modality, we can observe that the correlation that stands is the one between the perceived complexity and accuracy, thus contradicting the initial conjecture negatively correlating accuracy to completion time. The analysis exhibits the influence of the specific experimental setting on the results, leading to guidelines for future works that should include as many modalities as possible.

Considering RQ3 ("*What is the relation between guidance usability, cognitive load, and technology acceptance while performing sequential instructions?*"), the statistical analysis carried out on the considered scales, did not exhibit any relevant differences in the three modalities. This is a noticeable result, considering that more complex visualizations and manipulations (I-ANG, V-ANG) resulted in being equally usable and simple in comparison to interfaces including a lower level of complexity (T-ANG) [722]. These findings also support what was already previously discussed about the performance metrics. To corroborate such results, we additionally examined the learning efficiency metric reported in [1335] which evaluates the trade-off between the learning gain and perceived mental effort. In particular, we calculated it from the AP and APPC constructs. The analysis revealed that the values were skewed towards zero, indicating minimal learning gain corresponding to a fatigue increase. Specifically, the T-ANG was slightly negative, the V-ANG tended toward neutrality, and the I-ANG showed a slight positive learning efficiency. This indicates lower perceived difficulty and positive performance for I-ANG, despite the complexity of the interface during the preparatory phase, thus supporting our findings.

Finally, we discuss the limitations of our study. While the study demonstrated the benefits of different MR guidance modalities, several technical and usability challenges were encountered, particularly related to the stability of the Smart Rubik's Cube hardware and its integration within the DT system. One significant issue was Bluetooth stability and synchronization, as maintaining a reliable connection between the cube and the system proved challenging. Intermittent disconnections disrupted real-time synchronization, affecting interaction continuity and potentially impacting task performance. Ensuring a low-latency, robust communication protocol in future iterations could mitigate these issues. Another challenge stemmed from gesture recognition accuracy in the I-ANG modality, where some users struggled to execute precise hand movements, leading to unintended moves or recognition errors. Improving gesture tracking algorithms and incorporating real-time corrective feedback could enhance user control and system reliability. Moreover, ensuring usability across modalities required balancing cognitive demand and engagement to prevent information overload while maintaining user involvement. Refining interface design and integrating adaptive feedback mechanisms will be crucial in optimizing learning outcomes and interaction fluidity. We did not conduct a long-term retention test, which could have provided valuable insights into the long-term effects of the different learning modalities. In addition, we did not comprehensively test the combined influence of all modalities, which could have elucidated potential synergistic or antagonistic effects. Moreover, our population was composed of a variety of 45 people with different education levels (bachelor, master, Ph.D.) who came from different fields of study (humanities and engineering faculties), exhibiting different habits towards the usage of XR devices (low overall). We chose such a group as a representative sample for XR-based educational interventions [980]. Our results therefore apply to this specific context and population [564, 1106, 1006].

Given such limitations, future works will expand this study by incorporating additional forms of visual guidance [320]. This will enhance our understanding of the impact of visual aids on user interactions and their effectiveness. Future studies will also explore the long-term effects of AR-based instruction on spatial reasoning abilities, examining how sustained exposure to AR environments influences users' cognitive skills over time. We will also conduct experiments with a more diverse population, including different socioeconomic backgrounds, educational levels, and age ranges. Additionally, we plan to test the framework using various HMDs to evaluate its robustness and adaptability across different technological platforms and immersive settings, thereby further verifying its practical utility.

Conclusions

We introduced a novel DT-driven MR system tailored for learning procedural tasks. Resorting to a specific use case, learning Rubik's Cube notations, we provided a contextual understanding of the developed MR guidance applicability in procedural task learning. The experimental campaign enabled us to evaluate and compare the effectiveness of these modalities, considering short-term skill retention, performance accuracy, usability, cognitive load, and technology acceptance. The extensive analysis highlighted how state-aware DTs provide guidance and positive learning outcomes when paired with dynamic visual and virtually interactable objects. These results pose the basis for novel EL experiences, empowered by real-time XR interactions. Our approach can be adapted to any sequential task involving interaction with a physical object whose states can be tracked by sensors. Minor modifications to our platform can make it applicable to a variety of scenarios.

3.2.6 Insights

The findings of this study have been published in [487].

Objective

This case study explores how users can effectively learn Rubik's Cube notations through the integration of XR and Digital Twin (DT) technologies. The focus is on leveraging interactive and visual XR interfaces to enhance cognitive and spatial learning, providing step-by-step instructions and real-time visual cues to facilitate understanding and application of Rubik's Cube notations.

Key Technologies

- **Mixed Reality Interface**: Provides real-time visualization of Rubik's Cube rotations and notations to aid in skill acquisition.
- **Digital Twin (DT) Framework**: Allows continuous synchronization between the physical Rubik's Cube and its virtual representation, enabling dynamic, state-aware guidance for learners.
- **Varjo VR3 Headset**: Selected for its high-resolution display, enabling clear, immersive visual overlays that support accurate learning of rotational notations.

Evaluation and Data Collection Framework

The study employed both quantitative and qualitative methods to evaluate user performance and engagement:

- **Objective Metrics:** Metrics such as task completion time, accuracy, and interaction frequency with each learning modality were recorded to assess performance and retention of Rubik's Cube notations.
- **Subjective Feedback:** User experience, usability, and cognitive load were measured using validated instruments, including the System Usability Scale (SUS) for usability, NASA-TLX for cognitive load, and Technology Acceptance Model (TAM) to assess perceived usefulness and ease of use.
- **Interaction Patterns:** Different guidance modalities—Textual Annotation Guidance (T-ANG), Visual-Dynamic Annotation Guidance (V-ANG), and Interactable Annotation Guidance (I-ANG)—were evaluated for their impact on learning effectiveness and user preference.

Main Findings

- **Performance and Success Rate:** V-ANG and I-ANG outperformed T-ANG in accuracy and success rate, especially in the more challenging second assessment phase (AP2).
- **Questionnaire Results:** No significant differences in usability, cognitive load, or technology acceptance across modalities, though V-ANG and I-ANG were slightly preferred for ease of use and perceived as less complex. T-ANG scored slightly higher in overall usability.

Technical, Usability Challenges, and Future Directions

The study encountered several Technical and Usability Challenges:

- **Bluetooth Stability and Synchronization:** Maintaining a stable Bluetooth connection between the Smart Rubik's Cube and the DT system proved challenging, with occasional disconnections affecting synchronization and user experience.
- **Gesture Recognition Accuracy:** Some users reported difficulty executing hand gestures accurately, which impacted interaction with the I-ANG modality and occasionally led to unintended moves.
- **Usability Across Modalities:** Balancing usability with cognitive demand was essential, as each modality presented unique challenges in maintaining user engagement without overwhelming them with visual or interactive information.

Future improvements should focus on enhancing connection reliability, refining gesture detection algorithms, and optimizing interface designs to support a more seamless and intuitive user experience.

3.2.7 N4: Outdoor Augmented Reality Application for Workout Assistance

Objective and Context

Extended reality (XR) has gained significant popularity across various fields, including entertainment, education, and healthcare [919, 1043]. Augmented Reality (AR) enhances users' perception of their surroundings by overlaying and interacting with virtual objects, allowing the detection, recognition, and processing of objects and actions [127, 1202, 1118]. In physical activities, AR has been adopted to enrich real-world training, such as in professional and amateur training [150, 651], enhancing engagement [1261, 1213, 489], and measuring performance [978, 680, 907]. However, AR systems have yet to be fully leveraged for high-dynamic sports (e.g., running, body-weight exercises) and outdoor activities, mainly due to hardware and software constraints [79, 1202, 1118]. Designing AR systems for dynamic sports presents challenges, particularly in ensuring ergonomic Head Mounted Display (HMD) use during athletic movements and providing relevant, unobtrusive information [1202]. Outdoor AR systems also need to account for changing lighting conditions and hologram visibility [1147, 522]. Furthermore, customizing activities based on real-time biometric data and user characteristics is essential to keep workouts personalized and engaging [1267, 815]. Sensory feedback is another critical factor for maintaining motivation during workouts [1360, 1202, 1118]. Given the lack of comprehensive AR applications addressing these needs, this study presents Magic Augmented Workout (M-AGEW), an AR system designed to assist users in outdoor sports like jogging and calisthenics. It dynamically overlays relevant workout information, adapts plans based on historical sensor data, and provides real-time feedback and visual elements to enhance user engagement. M-AGEW is developed in collaboration with a leading sports equipment company, and early evaluations with professional athletes support its acceptance for outdoor training.

In this study we aim to answer this research question:

- RQ: How does the integration of real-time, data-driven feedback in an AR environment impact users' performance and engagement during outdoor workouts?

Related works

Although XR systems for sports activities assistance, guidance, and training exist even commercially, just a few focus on highly dynamic sports [978, 680, 907]. Among these, some concentrated on jogging [1261, 1213, 489] while others on sports like tennis, football, and skiing [755, 651, 150, 162].

In the context of jogging, some of the relevant studies focused on increasing the enjoyment of exercising outdoors [1261, 1213, 489]. To this aim, authors of [1261, 1213] presented an AR app showing virtual elements to increase user engagement while running. In [489], an AR system has been developed focusing on the competitive social aspects by displaying digital avatars while jogging, demonstrating that virtual partners increase the enjoyment of running. However, none of these works provided a data-driven AR interface, displaying any form of real-time feedback on user performance or activity completion.

Another aspect to consider corresponds to the adaptiveness of the training experience [815, 809, 556]. Adaptive training amounts to a training pipeline tailored to the user's needs exploiting technological training systems and techniques. In this context, [815] introduced ExerCube, an adaptive fitness game setup for indoor training. The game difficulty is adjusted to players' individual game and fitness skills in two ways: speed of race and heart rate (with a pre-set range of heart rates), while also taking into account the number of mistakes made (i.e., cognitive and mental focus). The authors showed that the flow, enjoyment, and motivation of a user in the ExerCube game are on par with personal training. In the commercial sector, applications like "ZRX: Zombies Run"[3] offer dynamic, audio-driven activity experiences, where users listen to immersive soundtracks that simulate escaping from zombies, enhancing motivation and engagement. However, such systems are primarily designed for joggers and lack real-time biometric tracking and modular visualizations of workout data.

In conclusion, to the best of our knowledge, none of the cited works provided a data-driven AR interface specifically designed to support the outdoor workouts, for both jogging and body-weight activities.

Materials and Methods

M-AGEW (Magic Augmented Workout) is an augmented reality system designed to provide real-time guidance and feedback during outdoor workouts. It dynamically adjusts workout scenarios based on user performance and manages activities such as *Jogging*, *Sprint*, *Body-Weight*, and *Rest*. The system displays dynamic user interfaces on the AR headset, progressively adapting the workout difficulty according to the user's actions, ensuring a personalized and evolving training experience.

Device Choice

For this high-dynamic sports application, we evaluated two AR devices. Two devices were shortlisted: Magic Leap 1 (ML1), and Hololens 2 (HL2)[853]. Table 3.9

[3] https://zrx.app/

compares these devices by Field of View (FOV), weight (W), maximum brightness (MBR), and AR library support [1107, 715, 1386].

In summary, HL2 provides robust tracking features and a relatively wide FOV but is heavier; EMBT is lighter yet offers a smaller FOV and lower brightness for outdoor use. After weighing these factors, we selected ML1 because it achieves the most balanced combination of ergonomics, moderate weight, sufficient FOV, and reliable outdoor visibility.

Headset	FOV	BL [h]	W [g]	MBR [nit]	AR Libraries
HL2	52°	3	556	500	Windows Mixed Reality, MRTK
ML1	50°	3	316	≈210	Magic Leap Unity SDK

Table 3.9: Comparison between the considered AR devices' features, including AR library support.

System Architecture

M-AGEW implements a client-server paradigm in a data-driven setting. The client, implemented as an AR experience with the ML1, acts as a dynamic visualization tool, while data is stored and processed on a remote server. GPS locations are collected from a companion smartphone app, as the location service provided by the ML1 is network-driven and, therefore, not sufficiently accurate to meet the application's needs. The server component holds the main logic and is responsible for the primary computational workload. Specifically, the server collects data from the ML1 and smartphone client devices to compute workout states. The workout is modeled as a Finite State Machine (FSM). The server sends updates to the AR client application to trigger interface rendering for the current activity. Figure 3.15 provides a visual summary of the M-AGEW system architecture.

This architecture offers multiple benefits:

1. It allows users to flexibly create workout plans.
2. It prevents overloading the limited computational capabilities of AR devices (e.g., RAM and battery life).
3. It provides a low-cost approach for deploying M-AGEW on other AR devices, allowing developers to adapt the interaction system for different hardware while maintaining the same logic and UI elements.

The M-AGEW client app was developed using the Unity Game Engine, targeting the Magic Leap 1 (ML1) AR device. To enhance outdoor visibility, specific display filters were applied to improve contrast and readability under varying lighting conditions. M-AGEW also includes a mobile Android app for GPS data collection, running on a Samsung Galaxy S22. The server component was implemented as a REST API in Python, utilizing the Flask web framework along with open-source libraries for data analysis and system functions.

M-AGEW implementation

1. Workout data structure: Workout plans have been modeled using a custom key-value data structure, which contains the list of phases of the workout, and the list of the exercises to carry out in each phase along with their difficulties. The main activity corresponds to Jogging, Sprint, and Body-Weight alternated with Rest activity provides the resting time. Completing one activity lets a user advance until reaching the end state which corresponds to the end of the workout. Between each activity, if a user's performance is considered good by a thresholding mechanism, the system asks the user whether s/he would like to proceed with a more intense set of exercises.

2. Virtual trainer assistant: M-AGEW integrates a digital avatar that vocally interacts with the user during the different steps of the workout [120]. The avatar is used to (a) inform when one activity ends and a new one starts, (b) ask whether one would like to increase the intensity of the workout, and (c) provide dynamic motivational messages during high-fatigue activities.

3. Jogging: During a jogging session, a given user can track his/her current position and destination, along with the suggested path, on a minimap generated with Open-StreetMaps [948]. In addition, the user can visualize biometric information to monitor his/her health throughout the workout and its progress. A colored bar indicates the actual user's fatigue level, calculated taking into account the speed and distance traveled so far. Figure 3.16a reports a graphical visualization of the elements so far described. In the jogging session, progress is determined by reaching a specific Point Of Interest (POI), defined by a $\langle \text{latitude}, \text{longitude} \rangle$ pair. The user is considered to have reached the POI if they are within a radius r of the POI's center. To verify this, we calculate the geodesic distance between the user's current location and the POI's center. If the distance is less than or equal to r, the user is considered to have reached the POI, and the activity advances to the next state.

4. Sprint: The Sprint activity is a special case of jogging, where users run at their maximum speed in a straight-line path. Their location is monitored to check if they reach the final POI. The interface displays the distance through a dynamic circular element and a progress bar visually represents progress, scaling based on the distance covered (see Figure 3.16b). This aimed at encouraging users to reach the end of the activity.

5. Body-Weight and Rest: In the body-weight activity, the user is asked to execute one or more exercises. In case the execution of the exercises requires a real-world facility, the user is guided towards the POI which is located with an interface similar to the Jogging one; but in this case, the biometric stats would not be visible, and an image representing the real-world location is placed on the top-right section of the view. In case the execution of the exercises does not require any facility, the user will just visualize the exercise. The exercises can be quantified in terms of time or number of repetitions. In the timed case, the interface shows a timer indicating how much time is left until the exercise is completed; otherwise, when defined as a set of repetitions, the system

shows a descending counter corresponding to the missing repetitions. In this particulate implementation, repetition times have been estimated beforehand thanks to the collaboration of fitness experts. During the execution, a completion status circle is provided along with the same fatigue level bar provided in the Jogging activity (Figure 3.16a). In the Rest activity, a simple timer representing the rest time is displayed.

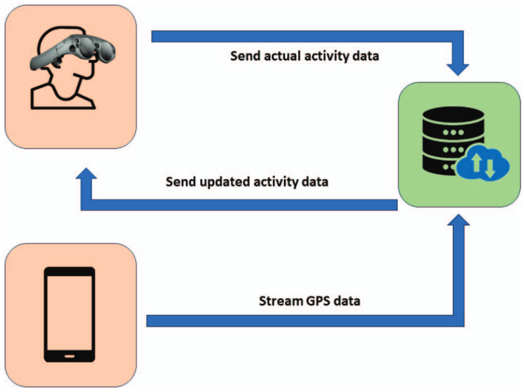


Figure 3.15: System architecture.

(a) Jogging Activity. (b) Sprint Activity.

Figure 3.16: AR interfaces for jogging (a) and Sprint activities (b).

Experimental Setting

To assess user satisfaction with M-AGEW, we designed a custom workout that incorporated all the activities described in Section 3.2.7. This workout took place at the headquarters of a leading sports equipment company and included warm-up exercises, jogging, sprinting, and body-weight activities.

Participants To assess the efficacy of our system, we enlisted eight professional company workers and athletes (2 females and 6 males). Participants were required to have an active background in structured workouts, ensuring they had relevant experience with physical training. Additionally, individuals with severe physical impairments that could hinder workout performance were excluded to maintain an unbiased evaluation of the system's effectiveness. The population had an average

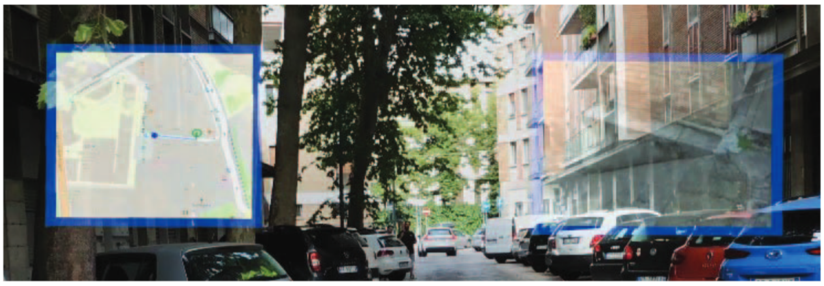


Figure 3.17: Body-weight activity: user performing the exercise.

age of M: 37.12 (SD: ±3.64). They tested the applications and answered a survey where they reported their opinions about their perceived comfort and usability. Most participants identified themselves as non-tech-savvy and reported having only basic expertise with AR, enabling the study to assess usability across different levels of technological familiarity.

Measurements To gather insights into the user experience and system performance, participants completed three key assessments:

- Short User Experience Questionnaire (UEQ-S): Captured subjective user experience and emotional responses [1132].
- Technology Acceptance Model (TAM): Evaluated perceived usefulness and ease of use [1389].
- NASA Task Load Index (NASA-TLX): Measured perceived workload, including mental, physical, and temporal demands [506].

These assessments provided comprehensive insights into the user experience, system acceptance, and potential areas for improvement in the M-AGEW system design.

Results

The bar chart in Figure 3.18 summarizes the UEQ-S results, showing positive ratings for usability (PQ) and emotional engagement (HQ). The PQ dimension scores are skewed towards positive ones indicating a positive assessment of usability and effectiveness in relation to the user experience. The users particularly perceived the system as very easy to use but at the same time, they were neutral or relatively negative about the system's ability to be supportive. The HQ dimension got slightly higher average scores, suggesting an even stronger response in terms of emotional appeal and enjoyment, in particular for the perceived level of innovativeness. However, they were neutral or slightly unfavorable concerning its level of excitement. Figure 3.19 presents TAM scores. The overall PU items report an average high score (≥ 4) exhibiting a slightly negative skewness. However, the scores regarding the "Ease of achieving desired outcomes" report a trend toward values ≤ 4 (items Q5). This could be due to the fact that the users were not used to such kinds of AR devices. The overall PEU scores exhibit, instead, lower scores with respect to

PU items except for "The flexibility of interaction" (item Q9). The lower score items measure factors related to ease of usability and learning. The lower score can be so explained by the low level of comfort of our participants with respect to AR paradigms. In fact, as indicated by the spread reported in the different PEU boxplots in Figure 3.19, some of the users found M-AGEW generally easy to use and useful.

The NASA-TLX questionnaire (Please see figure 3.20) implies a moderate workload level experienced by the majority of participants. In particular, our participants found using the system not too mentally or temporally demanding (items Q1 and Q3), even if they found achieving the task physically burdensome (item Q2). Moreover, the overall performance score was high, indicating that participants found the task challenging to complete efficiently. This suggests that while the cognitive load was manageable, the physical effort required and task complexity contributed to an increased perceived workload.

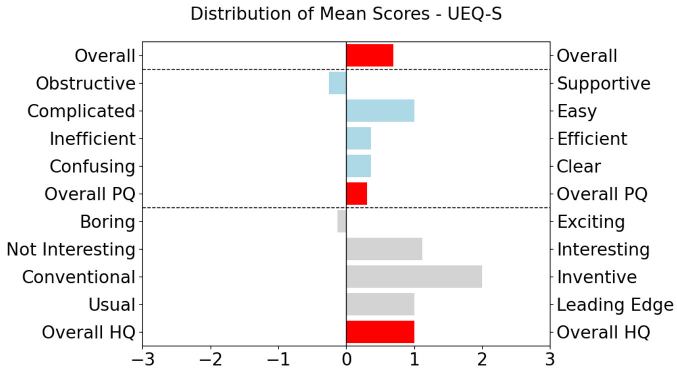


Figure 3.18: Comparison of mean scores from UEQ-S questionnaire. The questions measure the PQ and HQ dimensions.

Conclusions & Future works

In this work, we introduced M-AGEW, an AR system that supports users in outdoor workouts with a data-driven approach. M-AGEW guides a user through three different outdoor activities, namely *Jogging*, *Sprinting*, and *Body-Weight*. Our work is currently limited by the number of activities it supports, tested population, and measured factors. The system does not integrate external devices capable of measuring real-time velocity, acceleration, and GPS in parallel, such as commercial smartwatches, that could improve novel and already implemented workout activities [1126]. In future works, we plan to include external devices along with Human Digital Twin paradigms [1266, 90, 1220] to exploit user-generated and prior data to detect the completion of physical activities, create a dynamic training schedule and also prevent injures [90]. We will also explore ergonomic, engaging, and motivational factors that could lead to a holistic AR system to improve a user's experience. This will require an adaptation of the AR interface for early AR headsets (e.g., MagicLeap 2) that possess higher specs for luminance and outdoor visibility (e.g., dynamic dimming [715]) which will require a small amount of work, considering the M-AGEW flexible software architecture. With such a perspective, we will

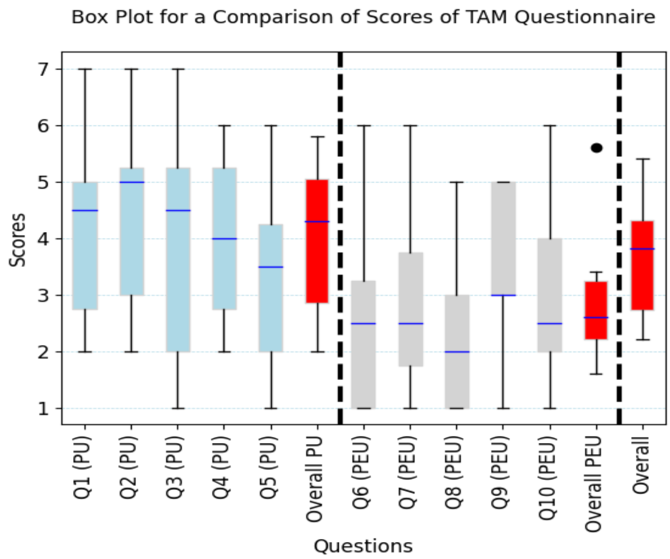


Figure 3.19: Comparison of scores from the TAM questionnaire. The questions measure the Perception of the application's Usefulness (PU) and the Perception of the Ease of Use (PEU).

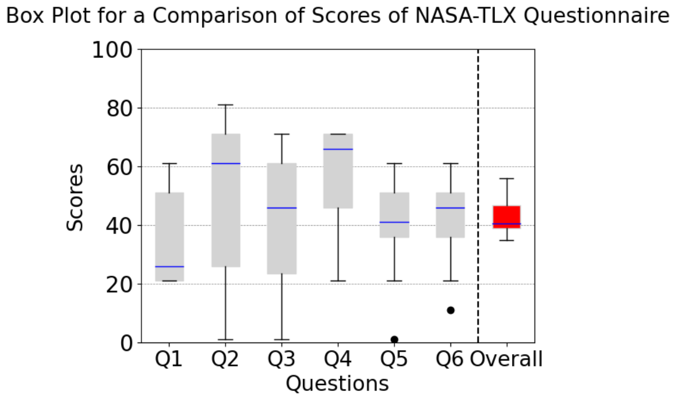


Figure 3.20: Comparison of scores from the NASA-TLX questionnaire measuring various dimensions.

carry out a user-testing campaign with a more varied users-base to further validate and improve the effectiveness of M-AGEW.

Conclusions & Future Works

In this work, we introduced M-AGEW, an AR system that supports users in outdoor workouts with a data-driven approach. M-AGEW guides a user through three different outdoor activities, namely *Jogging*, *Sprinting*, and *Body-Weight*. While the system demonstrated its potential to enhance outdoor workouts, several technical and usability challenges emerged during its implementation and user testing. One key challenge was outdoor visibility, as maintaining clear AR element visibility across varying lighting conditions required adjustments, such as the use of external sunglasses and display brightness optimization. Future improvements should explore adaptive display technologies that dynamically adjust brightness and contrast based on real-time environmental lighting conditions to enhance AR usability in outdoor settings. Another challenge pertained to device ergonomics. Although the Magic Leap 1 headset was effective for data visualization, it was not originally designed for high-movement activities, leading to comfort and stability issues during vigorous exercises. Addressing this limitation may involve developing lightweight, motion-friendly AR headsets or integrating AR-enabled smart glasses that better support dynamic physical activity. Additionally, user familiarity with AR varied across participants, with less tech-savvy users encountering initial difficulties in navigating the interface. This highlights the need for a streamlined user interface and interactive onboarding modules to reduce the learning curve and improve accessibility for the broader adoption of AR-based workout systems.

In addition, our work is currently limited by the number of supported activities, tested population, and measured factors. The system does not integrate external devices capable of measuring real-time velocity, acceleration, and GPS in parallel, such as commercial smartwatches, which could enhance both existing and novel workout activities [1126]. In future work, we plan to include external devices along with Human Digital Twin paradigms [1266, 90, 1220] to leverage user-generated data for activity detection, dynamic training scheduling, and injury prevention [90]. We will also explore ergonomic, engaging, and motivational factors to create a holistic AR workout system that optimizes the user experience. This will require adaptations of the AR interface for newer headsets (e.g., Magic Leap 2), which offer higher luminance and outdoor visibility improvements, such as dynamic dimming [715]. Given M-AGEW's flexible software architecture, these adaptations will require minimal development effort. To further validate and enhance the system's effectiveness, we will conduct a user-testing campaign with a more diverse participant base, ensuring broader applicability across different user demographics. Additionally, expanding the AR fitness assistance system to support a wider range of exercise types, such as running and swimming, will enhance its versatility. Future work will focus on integrating user feedback from real-world fitness scenarios to refine system adaptability and responsiveness, ensuring a more personalized and effective workout experience.

3.2.8 Insights

The findings of this study have been published in [1222].

Objective

The primary objective of the M-AGEW (Magic AuGmentEd Workout) system is to enhance outdoor high-intensity workouts, such as jogging and calisthenics, through a data-driven augmented reality (AR) interface.

Key Technologies

- **Magic Leap 1 Headset**: An AR device providing real-time workout guidance and visual data.
- **Client-Server Architecture**: The client device functions as a display interface, while a remote server handles data processing to reduce the load on the headset and allow real-time adaptability.

- **Data Collection and Analysis**: GPS tracking through a mobile app, REST APIs, and threshold-based adjustments to dynamically customize workout intensity based on user performance.

Evaluation and Data Collection Framework

The M-AGEW system was evaluated using subjective assessments:

- **Subjective Feedback**: User satisfaction, cognitive workload, and usability were evaluated through multiple assessments:
  - **UEQ-S (User Experience Questionnaire - Short Version)**: Captured participants' emotional responses and overall user experience.
  - **Technology Acceptance Model (TAM)**: Assessed perceived usefulness and ease of use of the AR system.
  - **NASA-TLX**: Used to gauge cognitive workload, specifically mental, physical, and temporal demands experienced during workouts.

Main Findings

- **Workload and Usability (NASA-TLX and UEQ-S Results)**: A relatively high workload was reported, with significant physical demands attributed to device weight and task complexity. While cognitive load remained manageable, participants found the task physically strenuous. Despite these challenges, the system achieved high usability ratings, indicating that users still found it intuitive and effective in supporting task completion.

- **Technology Acceptance (TAM Results)**: Users perceived the AR system as highly useful for guiding workout intensity.

Technical, Usability Challenges, and Future Directions

The study revealed several challenges in the implementation and user experience of the M-AGEW system:

- **Outdoor Visibility**: Maintaining clear visibility of AR elements in varied outdoor lighting required adjustments, including using external sunglasses and optimizing display brightness.

- **Device Ergonomics**: The Magic Leap 1 headset, while effective for data visualization, was not originally designed for high-movement activities, presenting a challenge in comfort and stability during vigorous exercises.

- **User Familiarity with AR**: Less tech-savvy participants faced initial challenges in operating the AR interface, highlighting the potential need for a streamlined user interface or introductory training module.

- **Usability Across Modalities**: Balancing usability with cognitive demand was essential, as each modality presented unique challenges in maintaining user engagement without overwhelming them with visual or interactive information.

Future research should explore adaptive display technologies that dynamically adjust brightness and contrast based on real-time environmental lighting conditions to improve AR visibility in outdoor settings. To address device ergonomics, the development of lightweight, motion-friendly AR headsets or integration with AR-enabled smart glasses could enhance comfort and stability during high-intensity workouts. Additionally, improving user accessibility through a streamlined interface and interactive onboarding modules could reduce the learning curve for non-tech-savvy users, ensuring broader adoption of AR-based workout systems. Further investigations should focus on refining multi-modal interaction strategies to optimize user engagement across different interfaces, ensuring intuitive and responsive experiences. Expanding experiments to include diverse user demographics—varying in age, physical ability, and technological familiarity—will provide deeper insights into personalization and accessibility needs. Moreover, testing the system across various head-mounted displays (HMDs) and mobile AR platforms will help assess cross-device compatibility and adaptability in different immersive environments. In addition, future work should enhance the AR fitness assistance system by expanding support for a broader range of exercise types, such as running and swimming, to improve versatility and applicability. Incorporating user feedback from real-world fitness scenarios will be essential in refining system adaptability, ensuring personalized and effective workout experiences tailored to individual needs.

3.2.9 N5: Bi-Manual Interaction Techniques for Upper Limb Differences

Objective and Context

Virtual reality (VR) has become prominent in various fields, including entertainment, education, and healthcare. However, its design often demands physical abilities that may challenge or exclude individuals with motor, cognitive, or perceptual limitations [1294]. A major barrier for people with mobility impairments, such as those with cerebral palsy or multiple sclerosis, is the need for hand-held controllers to navigate and interact within virtual environments (VEs). This poses particular difficulties for individuals with upper limb differences, a user group largely overlooked in VR research [520]. Upper limb differences affect the function, structure, or mobility of the arms and hands, and may be either congenital or acquired through injury or illness. Although some VR applications now support alternative input methods like eye-tracking or brain-computer interfaces, most still rely on two controllers—one for each hand—or require bi-manual hand tracking [882]. This design mirrors real-world tasks that involve both hands, such as writing (where one hand stabilizes the paper) or opening a bottle (where one hand holds the bottle and the other twists the cap). While this bi-manual interaction creates a more natural and immersive experience in VR, it can significantly limit accessibility for individuals unable to use both hands or controllers effectively [39].

In this study, we investigate how VR applications can be made more accessible to people with upper limb differences. In particular, we aim to answer the following research questions:

1. RQ1: What do people with upper limb differences think of having different

levels of responsibility on their affected hand in VR?

2. RQ2: How do different bimanual interaction techniques, designed specifically for individuals with upper limb differences, compare in terms of user satisfaction and efficiency?

To address these research questions, we exploited a three-step user-centered design approach. We developed three prototypes for bi-manual interaction VR, using EMG and motion tracking data. Drawing on feedback from a participant with upper limb differences these techniques are designed with varying degrees of reliance on the affected hand, thereby accommodating different levels of upper limb functionality. To evaluate the user preference of these interaction techniques, we run a user study involving four participants with upper limb differences. In a second study, we invited 26 participants without upper limb differences to evaluate the prototypes in terms of efficacy and usability.

Related Work

Bi-manual tasks

Bi-manual tasks are activities that require the coordinated use of both hands, often involving complex movements where each hand performs a different role [1100]. These tasks are integral to many daily activities and occupational functions, ranging from simple actions like tying shoelaces to more intricate operations such as playing a musical instrument or performing surgical procedures. The coordination in bi-manual tasks involves intricate neural mechanisms, where the brain's motor areas synchronize the movements of both limbs, taking into account the different roles and motions of each hand [1256]. Bi-manual tasks can be broadly classified into two categories: symmetrical and asymmetrical movements [1372]. In symmetrical bi-manual tasks, both hands perform identical or very similar movements at the same time, as seen in activities like pulling a rope or lifting a heavy object with both hands. These tasks often rely on synchronized, in-phase coordination between the hands. On the other hand, asymmetrical bi-manual tasks involve each hand performing different roles, such as holding a nail with one hand while hammering it with the other, or typing on a keyboard while holding a phone. In these cases, the coordination is more complex, with one hand typically playing a stabilizing or supportive role while the other hand performs the primary action. Asymmetrical tasks often require more advanced motor control and are more demanding in terms of skill development. This coordination is not merely the sum of two independent actions but a complex integration of motor control strategies that often require practice and skill development [318]. Challenges in performing bi-manual tasks can arise from physical limitations, such as in individuals with upper limb differences, or neurological conditions, which may affect the motor control and coordination abilities [343].

Upper limb differences

Upper limb differences refer to variations in the structure, function, or presence of the upper limbs, which include the arms, hands, and fingers. These differences can be congenital, meaning present from birth, or acquired due to injury, disease, or amputation. Congenital upper limb differences may result from genetic factors, environmental influences during prenatal development, or a combination of both, and can range from minor anomalies, such as a missing finger, to more significant differences like the complete absence of an arm [440]. Acquired upper limb differences, on the other hand, often result from traumatic events, medical conditions such as cancer, or complications from other diseases [1430]. These differences, whether innate or developed, can significantly impact an individual's ability to perform daily activities, especially those requiring bi-manual coordination, and often necessitate adaptations or the use of prosthetic devices for functional assistance [125].

VR and disabilities of the upper limbs

Virtual Reality (VR) is an immersive technology that has shown potential to positively impact people's health and quality of life [1076]. However, research highlights critical gaps in the accessibility of VR for people with disabilities. Gerling and Spiel [422] examined the relationship between VR and disability, concluding that VR is predominantly designed for individuals without disabilities, which often excludes disabled people from fully engaging in these experiences. Similarly, Mott et al. [883] identified seven key barriers related to hardware that hinder the use of VR for individuals with limited mobility, particularly in manipulating dual motion controllers and inaccessible controller buttons for those with upper limb impairments. Naikar et al. [898] explored the accessibility features of free VR experiences and discovered that 36.8% of these experiences lacked any accessibility features. Specifically, they found that only 2 out of 39 experiences offered a one-handed mode for users with motor impairments. Yildirim's analysis of VR applications regarding one-handed use showed that only 5 out of 16 applications were fully usable with one hand, with an additional 2 being partly usable. Further research by Franz et al. [393] focused on locomotion techniques in VR for individuals with upper-body motor impairments. Their findings revealed that while certain techniques were more efficient and required less effort, users tended to prioritize factors such as enjoyment, exercise, and presence over efficiency. They concluded that offering a range of locomotion techniques would better serve users' varying preferences. Moreover, Franz et al. [700] developed a framework aimed at helping individuals with limited mobility orient themselves toward points of interest in a virtual environment. In another significant contribution, Yamagami et al. [1373] proposed a design space to map unilateral input to bimanual interaction in VR. They introduced three interaction techniques with varying levels of computer assistance, designed to accommodate different types of bimanual interaction motions, enhancing accessibility for users with mobility limitations.

These studies collectively underscore the need for more inclusive design and accessibility features in VR technologies to ensure that individuals with disabilities can fully benefit from the immersive and transformative potential of VR.

Input Systems for Mobility in People with Disabilities

In the study of interfaces designed for individuals with limb loss, input systems such as speech, eye gaze, and muscle activity sensors have become essential for enhancing control and interaction with prosthetics and rehabilitation technologies [178, 1260, 1174]. These input systems allow users to control devices with minimal physical effort, relying on biological signals and other natural inputs to compensate for the loss of limb function [1180]. Research into these interfaces focuses on improving the accuracy, responsiveness, and user experience to enable individuals with limb loss to regain mobility and independence.

One such interface is the electromyography (EMG) technique, which evaluates and records the electrical activity produced by muscles during contraction. EMG technique focuses on evaluating and recording the electrical activity produced by muscles during their contraction. The Electromyography (EMG) Trigno Light System [303] is an advanced technological tool used in the field of biomechanics and rehabilitation to measure and analyze muscle activity. This system utilizes wireless sensors to detect electrical signals produced by muscles during contraction and relaxation, delivering real-time, high-fidelity EMG data, essential for detailed analysis in clinical assessments, sports science, and ergonomic studies. Its precision and adaptability make it a crucial tool for improving mobility, designing effective therapies, and advancing research into disability rehabilitation [298], [849].

The Qualisys Motion Capture System is a state-of-the-art tool used extensively in biomechanics, sports science, and animation to accurately track and analyze movement [1197, 920]. This system employs a series of high-speed cameras that capture the three-dimensional positions of reflective markers placed on the subject's body or objects. The data collected is then processed to create a dynamic digital model of the subject's movements [1318]. Qualisys is renowned for its precision and high-resolution capture capabilities, making it an invaluable resource in detailed motion analysis [586]. Qualisys has played a crucial role in clinical settings, particularly in studies focused on people with disabilities. The system's ability to capture and analyze gait and movement patterns has been pivotal in rehabilitation research, helping clinicians to evaluate mobility impairments and develop targeted interventions for individuals with conditions such as cerebral palsy or stroke [866, 98]. Its high precision allows for a detailed assessment of motor function, enabling more accurate diagnosis and treatment planning [496].

Expert Interview and Development of the User Interfaces

This chapter describes the first phase of the user-centered design process. We conducted interviews we a person with upper limb differences and developed four prototypes based on the results.

Interview

Methodology

In the first phase of the study, we conducted a semi-structured interview with a male participant who has a congenital unilateral upper limb difference. The goal of this interview was to gather in-depth insights into the participant's experiences with conventional gaming and virtual reality (VR) systems, his interaction preferences, and his challenges. This qualitative data was essential in informing the design of the four interaction methods. Questions were designed to elicit information on the participant's daily use of input devices (e.g., keyboard, mouse, controllers, VR systems), his strategies for interacting with both conventional and VR systems, and the challenges they faced in various contexts. Additionally, we explored his preferences for avatar representations, control schemes, and feedback mechanisms in VR environments. The participant was encouraged to discuss his ideal VR experience, with particular attention to how control systems could be made more accessible for users with upper limb differences. To ensure thorough documentation, the interviews were audio-recorded and later transcribed for analysis.

Summary of Interview Results

The interview provided valuable insights into the participant's experiences with conventional gaming, VR systems, and input devices. The participant primarily uses a keyboard, mouse, and various controllers (such as the Switch Pro Controller, Joy-Con, and racing wheel) for PC and console gaming. He estimates using these devices for approximately 10 hours daily on his PC and smartphone, with an additional hour dedicated to console gaming. In terms of gaming experience, he is familiar with genres that require quick decision-making and precision, such as shooters, point-and-click games, and racing simulations. In PC gaming, often remaps controls to enhance usability, placing extra functions near the WASD keys or using buttons on the mouse. However, he encounters challenges with the Nintendo Switch, particularly with Mario Kart, where control remapping is not possible, limiting their ability to customize input methods. His VR experience is limited but includes demos on the HTC Vive. The participant expressed interest in newer VR systems like the Quest 3 due to its improved resolution. He found two-handed control setups in VR to be less accessible, particularly in shooter games where he could only use one of the available control options. This led to some frustration, as he was unable to experience the full range of gameplay features. Moreover, he expressed a desire for greater customization in VR systems, particularly in terms of control options and reducing motion sickness during locomotion. When it comes to avatars, the participant prefers abstract or creative representations over photorealistic ones, citing discomfort with the uncanny valley effect. He enjoys experimenting with unique or humorous avatars and are open to different types of controllers or hand representations depending on the game's setting. Overall, the participant values flexible control schemes, customization, and intuitive input methods, while also emphasizing the importance of clear feedback mechanisms in VR systems.

Application of Interview Results to the Design of Interaction Techniques

The insights gathered from the interview have directly informed the design of the four interface conditions, each tailored to address the participant's unique interaction needs and preferences. We developed a VR environment, using Unity [1287] and OpenXR [646] for the Oculus Quest. This environment includes virtual objects that are integral to the interaction tasks, allowing for targeting and selection. Within this VR scene, various objects serve as focal points for the user's interactions, enabling them to engage fully with the virtual setting. The user will be guided through four distinct interaction techniques specifically designed for bimanual interaction in a VR environment, with a focus on selection and targeting tasks.

- **Condition 1: No responsibility for Affected Hand (Control Condition)** This baseline condition leverages the participant's preference for customization and their ability to remap controls for efficiency. Since the participant is already comfortable with using one hand for control in conventional gaming setups, this condition ensures that the unaffected hand can take on full control responsibilities. The inclusion of button remapping mirrors the participant's approach in PC gaming, allowing them to optimize their control scheme without relying on the affected hand. This condition serves as a starting point for comparison against the other, more complex configurations.

- **Condition 2: Selection Responsibility for Affected Hand** In this condition, the affected hand is responsible for selection tasks using an EMG system, while the unaffected hand handles targeting. Based on the participant's openness to new technologies, this condition introduces EMG control, as a muscle-based input system for the unaffected hand.

- **Condition 3: Targeting Responsibilities Affected Hand** For targeting tasks, this condition incorporates a motion tracking system, allowing the affected hand to control motion in the VR environment. Since the participant has experience with precision-based tasks in gaming, such as targeting in shooters, this condition caters to their need for responsive and accurate control. The motion tracking system offers fine-tuned motion tracking, which aligns with the participant's preference for fluid and adaptive control. Meanwhile, the unaffected hand is responsible for selection.

- **Condition 4: Targeting and Selection Responsibility for Affected Hand** This most advanced condition assigns full responsibilities—both targeting and selection—to the affected hand using a motion tracking system and an EMG system for muscle-based input. Drawing from the participant's desire for more control options and customization in VR, this condition provides a comprehensive interface that allows the affected hand to fully participate in the virtual environment offering a more empowering experience.

System Architecture

The system architecture integrates VR, motion tracking, and EMG to create an adaptive bi-manual interaction framework for users with upper limb differences.

The VR environment, developed in Unity, features bi-manual tasks where users interact with virtual objects using a combination of motion tracking, EMG-based inputs, and VR controllers. The study employed the Meta Quest 2 headset, with Quest 2 controllers facilitating manipulation tasks. For motion tracking, the Qualisys Motion Capture System captured real-time movement data by tracking reflective markers placed on the affected arm (see Figure 3.21). The Qualisys system processed movement data through its proprietary motion capture software and streamed it to Unity for gesture-based control. For muscle-based interactions, the Delsys Trigno Avanti EMG system (see Figure 3.21) recorded electrical muscle activity from the affected arm. Using a client-server architecture, EMG signals were transmitted in real time to Unity via the Delsys API [304]. The Delsys EMG system operated on a client-server model, processing muscle activation before transmitting it to Unity. Wireless receivers ensured low-latency data transmission, while electrode placement targeted specific muscle groups for EMG-based interactions.

This integration of motion tracking, VR controllers, and EMG input enabled diverse interaction techniques. Motion tracking-based interactions used the Qualisys system to track hand positioning for selection tasks. EMG-based interactions allowed users to trigger actions through muscle contractions, while controller-based interactions relied on the Meta Quest 2 controller in the unaffected hand for navigation and hybrid input methods.

User Study I

In the first phase of the user study, which involved participants with upper limb differences, we aimed to evaluate the effectiveness and user preferences for various interaction techniques from their unique perspectives while performing tasks in a virtual reality environment. This evaluation provides valuable insights into which interaction methods are most accessible, effective, and user-friendly for individuals with upper limb differences.

Methodology

Materials

The study utilized a Meta Quest head-mounted display (HMD) for virtual reality immersion and hand-tracking controllers, along with additional sensors for specific interaction conditions. In each condition, participants held the controller in their functioning hand, while an EMG sensor (Delsys Trigno Avanti connected to Trigno Lite System [303] and motion capture markers (Qualisys Miqus M1) [1024] were placed on the affected arm. Both systems were connected to a desktop PC (Intel Core I9 3.70 GHz, 32 GB RAM, NVIDIA GeForce RTX 3090, Windows 10 Pro). The Oculus Quest 2 was used in Quest Link mode, which enabled real-time streaming of EMG and motion tracking data into Unity. The results were displayed inside the headset. In all conditions, participants held the corresponding Quest controller in their unaffected hands. The EMG Sensor and motion tracking markers were adjusted as needed, see Figure 3.21. The controller's virtual version was always visible in VR. When the motion tracking was used, a ray was visible, with its origin spatially registered to the position of the marker on the lower arm. If motion tracking was not used, the ray was attached to the VR controller. The EMG sensor was not visible in the VE. We designed a two-part task: A primary task, requiring higher dexterity, that was always done with the unaffected hand and a secondary task with less dexterity required, with different levels of responsibility for the affected hand. The primary task required participants to manipulate a virtual sphere through a pipe using a virtual pen. The Color of the ball changed regularly and to gain points, the color of the pen had to be changed accordingly (secondary task). The color could be changed by pointing towards the according color panel (either with the controller or with motion motion-tracked arm) and confirming the selection by either button press or tensing the biceps with the EMG sensor. The four conditions are described in detail in the following:

- ***C*** In the first condition the only input method was one VR controller in the unaffected hand. Participants grabbed the pen and moved the ball with it. When they wanted to change the color, they could keep the pen gripped. They then pointed toward the desired color panel and used the trigger button to select the color.
- ***C + EMG*** In the second condition, participants were equipped with an EMG sensor on their biceps on the affected arm. Again, they grabbed the pen and

moved the ball with it using the controller in the unaffected hand. For color selection, they pointed to the color panel with the controller, but to confirm the selection, the biceps of the affected arm had to be tensed.

- ***C + MT*** In the third condition, participants were equipped with a marker for the optical motion tracking system attached to the lower arm of the affected side. Grabbing the pen and moving the ball with it was again done using the controller in the unaffected hand. Color selection was done by pointing towards the desired color with the affected arm and confirming the choice was done using the trigger button of the controller.

- ***EMG + MT*** In the last condition, an EMG sensor and motion tracking system were used. Still, operating the pen to move the ball was done by the controller in the unaffected hand. Color changing now was done entirely by the affected side, using motion tracking to point to the color panel and EMG to confirm the selection.

Figure 3.21: One participant with unilateral upper limb differences illustrating the different bi-manual interaction techniques based on EMG and Motion Tracking: (a) control with only one controller, (b) affected hand is responsible for selection, (c) affected hand is responsible for targeting, and (d) affected hand has targeting and selection responsibility.

The sphere changed color every 5 seconds, and for each second the pen touched the ball with the correct color, a score on the scoreboard was increased. Participants explored each condition for about 2 minutes.

Participants

The study involved four participants, ranging in age from 25-34, all of whom had unilateral upper limb impairments. Three were male, and one was female. One male participant had a missing left hand, while another experienced right-hand and arm spasms caused by meningitis during infancy. A third male participant had Poland syndrome, resulting in a shortened right arm with limited finger development and no functional grasp. The female participant had a missing right hand. Participants were required to have unilateral upper limb impairment to ensure the study focused on evaluating bimanual interaction techniques for individuals with asymmetric motor abilities. Additionally, individuals with severe visual impairments or cognitive conditions that could affect task comprehension were excluded to maintain consistency in user performance. Regarding their experience with VR systems, three participants reported using VR less than once a year, while one participant reported using VR approximately once a year.

Procedure

The study began with a briefing on the objectives, consent, and a pre-test questionnaire to collect demographic data and prior VR experience. Participants then performed tasks under the four interaction conditions. After completing each condition, participants provided immediate feedback through verbal interviews and SUS and NASA-TLX questionnaires, discussing usability, comfort, and physical effort. In these interviews, participants reflected on their experiences in each condition, offering detailed insights into specific challenges and preferences. This allowed researchers to gather rich qualitative data at each stage, capturing evolving user perceptions. After all conditions were completed, participants took part in a final interview where they compared the different techniques, provided suggestions for improvement, and shared their preferences. Specifically, the participants were asked to put on the headset again, and the visualizations for the affected hand (black, white controllers, and wand) were shown to them one by one while wearing the glasses. The suggested visualizations are presented in the figure 3.22.

The qualitative data were collected through semi-structured interviews. These interviews were designed to be open-ended, allowing participants to freely discuss their experiences. The analysis employed a thematic approach, in which the transcribed interview data were systematically coded by two experimenters to identify key topics, challenges, and preferences articulated by participants. The resulting codes were then grouped into broader themes that captured recurring patterns and critical insights.

Results

Usability and Task Load Results

The average SUS score for the group was 71.88 (SD = 14.40). This indicates that overall, participants found the system moderately usable. The relatively high standard deviation suggests a notable variability in the participants' experiences, with some finding the system more usable than others. In addition to the SUS scores, the NASA Task Load Index (NASA-TLX) results for each of the four conditions are presented in the table 3.10. The table shows NASA-TLX results for four conditions, indicating varying mental, physical, and temporal demands, along with performance, effort, and frustration. Using the **C** as a baseline, the NASA-TLX results reveal distinct differences across the conditions. **C + EMG** increases mental, physical, and temporal demands, as well as effort, compared to the baseline. However, it notably reduces frustration, highlighting a trade-off where increased workload is balanced by greater user comfort. In contrast, **C + MT** improves perceived performance substantially but leads to moderate increases in mental and temporal demand, although it does not raise physical demand as sharply. The combination of **EMG + MT** appears to balance these factors effectively: it reduces effort, and frustration, while still maintaining a high physical and temporal demand. Overall, compared to the baseline, **EMG + MT** offers a more balanced workload, though it comes with higher physical and temporal costs.

Thematic Comparison Across Conditions

The study's evaluation provided valuable insights into how users adapted to and perceived each condition, highlighting both challenges and positive experiences. The

Table 3.10: Mean and standard deviations (SDs) of the NASA-TLX questionnaire

Metrics	C	C + EMG	C + MT	EMG + MT
Mental demand	30 (26.46)	45 (26.77)	41.25 (37.28)	27.5 (15.00)
Physical demand	20 (10.80)	51.25 (39.87)	27.5 (6.45)	43.75 (19.31)
Temporal demand	11.25 (16.01)	23.75 (21.36)	22.5 (13.23)	17.5 (6.45)
Performance	13.75 (10.31)	16.25 (8.54)	42.5 (31.22)	13.75 (11.81)
Effort	30 (12.91)	48.75 (31.19)	28.75 (14.93)	23.75 (4.79)
Frustration	36.25 (27.80)	21.25 (19.31)	38.75 (17.02)	16.25 (7.50)

following sub-sections explore these interactions, focusing on user feedback to compare the different techniques and identify areas for improvement in the design of interaction methods for individuals with upper limb differences.

User Experience

Across the different conditions, users' experiences evolved as they adapted to the various tasks and controls. In ***C***, although the initial learning curve for understanding the controller and grip function was steep, users eventually found the controls simple and satisfying. One remarked, "Once you have understood this to some extent and tried it out a bit, then it was quite simple to use. In ***C + EMG***, users appreciated the innovative approach of using both arms for different inputs and found the sensor's small and unobtrusive design appealing. One user noted, "The cool thing is that you somehow don't even notice the sensor... it's small and light and not bulky." This made the experience more engaging and fun, particularly due to the novelty of independent inputs for each arm. However, despite these positives, some users encountered difficulties with muscle tension and coordination, with one explaining, "I had a bit of a problem with relaxing my arm again." They found it hard to relax their arms and adjust to using muscles in an unfamiliar way for control, which affected their overall ease. ***C + MT*** introduced issues with the beam direction and intuitive control, making the experience feel less fluid than in previous conditions. One user commented that "the problem was that it was pointing in the wrong direction and it was a bit unintuitive." However, the use of both hands for different tasks was still seen as a positive aspect. Users enjoyed the cognitive challenge of dividing attention between tasks, with one noting, "It was fun because I could split the task more efficiently." Yet, this condition was physically more demanding, as users found it strenuous to keep their arms raised for extended periods. In ***EMG + MT***, users found the experience smooth and enjoyable, particularly appreciating the novelty of performing distinct tasks with each arm. One participant likened it to playing drums, saying, "It felt a little bit like I had two hands, like when playing drums, where each hand has a different rhythm." Despite the fun and ease of use, muscle tension remained a challenge, especially for users with less-developed muscle groups. One user pointed out, "Muscle tension is still not for me the go-to remedy," underscoring the physical difficulty of controlling the game through muscle contraction. In sum, while the user experience improved with each condition and users adapted more effectively, challenges related to physical effort, coordination, and muscle fatigue persisted, revealing key areas where further refinement could enhance both comfort and ease of use.

Learning Curve and Adaptation

The learning curve and adaptation varied notably across the different conditions, with users gradually becoming more comfortable and efficient as they progressed. In ***C***, users found the initial challenge to be understanding how the gripping function worked and which buttons on the controller were responsible for specific actions. One user explained, "Once you have understood this to some extent and tried it out a bit, then it was quite simple to use." While the learning curve was steep at first, practice allowed them to gain familiarity with the controls, making the task manageable over time. In ***C + EMG***, users found the experience required more adjustment. They commented that "it takes a bit more getting used to... so that you can do it more precisely." The primary challenge was mastering the precision of inputs, particularly understanding when the pressure or impulse was sufficient. This indicates that while the task was easy to grasp conceptually, it required ongoing practice to refine and perfect the control mechanics. ***C + MT*** posed even more difficulty in the beginning, as users expressed that "at the beginning, it was much more difficult... towards the end, it was a bit more familiar." While users found some aspects of the control system intuitive after initial use, the challenge lay in coordinating both buttons efficiently and accurately. One participant noted that "it was a bit of a challenge against yourself to get it right and quickly with both buttons," highlighting the increased cognitive and physical demands compared to earlier conditions. By ***EMG + MT***, the learning curve was smoother and more intuitive. Users acknowledged that practice led to greater proficiency, stating, "If you learn it again, you're probably faster... but it's another learning curve. You have to get used to it, but it works." The EMG sensor, which initially caused skepticism in earlier conditions, was described as much easier to use in this context. One user remarked, "It was just so much easier, worked much better." This suggests that the system improved in intuitiveness as users practiced, leading to a more seamless and fluid experience. In summary, while ***C*** required users to overcome the steepest initial learning curve,***C + EMG*** and ***C + MT*** introduced precision and coordination challenges that took time to master. By Condition ***EMG + MT***, users found the experience more intuitive and easy to adapt to with practice, highlighting an overall progression in user adaptability and efficiency across conditions.

Improvements and Suggestions

Across the conditions, users provided various suggestions and improvements, reflecting their evolving understanding of the system and their preferences for optimizing the experience. In ***C***, users emphasized the need for more ergonomic hand positioning, expressing a desire for controls that more closely mimicked real-life tasks. One user suggested, "The hand position would have been more ergonomic or more similar to real life," indicating discomfort with the current setup. In ***C + EMG***, users focused on the importance of feedback and threshold settings. One participant remarked, "If I had confirmed with my finger, then I think I would have more local feedback," suggesting that better haptic feedback could improve the experience. Additionally, users mentioned the difficulty of using the biceps for gaming inputs, which felt unnatural. There was a clear focus on refining the threshold system to make the task less physically taxing. One user highlighted the need to "lower the threshold" for triggering actions, which would have allowed them to complete the task more comfortably. ***C + MT*** suggestions revolved around fine-tuning the control system's physical layout. Users suggested adjustments to the control's positioning, saying, "So further to the left and further down... a little higher, closer," indicating that small spatial tweaks could enhance usability. There was also an imaginative improvement where a user suggested more interactive elements, like "having a machine gun on my right shoulder," indicating a desire for more dynamic and engaging use of the tracking system to fully leverage its capabilities. In ***EMG + MT***, users appreciated the ease of use but suggested that starting with both hands simultaneously would have made the experience smoother. One participant commented, "It would have been better to start with both at the same time." Moreover, they highlighted the importance of properly setting thresholds, stating, "The threshold seems to be good too," acknowledging the role of fine-tuned thresholds in making the experience more fluid and intuitive. Overall, users across all conditions pointed to the need for ergonomic adjustments, better feedback systems, and optimized threshold settings to improve overall usability.

Technical and Operational Issues

Technical and operational issues were prevalent across several conditions, with varying degrees of impact on the user experience. In ***C***, users experienced technical problems, with one participant noting, "the picture stops completely," and others reporting instances of lagging and stuttering. Users frequently encountered issues where the system became unresponsive, as illustrated by comments such as, "Now it is stuck" and "it's lagging quite a bit here." This unsteady behavior caused frustration and interrupted the flow of the task, as multiple participants mentioned that the system was simply "not working now." In ***C + EMG***, users encountered fewer outright system failures but still faced specific EMG sensor-related problems and technical difficulties. One user remarked that using the muscle for input was "still not my favorite," pointing out that the EMG sensor lacked the tactile feedback and speed of a traditional button. One participant reflected, "The impulse I was giving took a little longer until the ball changed color," which caused frustration and a lack of fluidity in the experience. Though ***EMG + MT*** marked an improvement in terms of overall system reliability, with more nuanced problems focused on the EMG sensor's responsiveness, ***C*** faced broader technical issues that significantly hindered performance. The absence of notable technical difficulties in ***C + EMG*** and ***C + MT*** suggests that these conditions may have been more stable, but the recurring issues in Conditions ***C*** and ***EMG + MT*** highlight the need for refinements in both system stability and the responsiveness of the EMG sensor to create a smoother, more efficient user experience.

Exemplifying

In terms of exemplifying and drawing parallels to daily tasks, the experiences in different conditions varied. In ***C***, users related the experience to familiar activities such as writing or everyday tasks that involve single-handed operation. One user noted, "Yes, I can do that when I'm writing my master's thesis." In ***EMG + MT***, users made a more specific comparison to complex activities that require independent hand movements. One participant likened the experience to "one hand making a movement or having a rhythm and the other hand in a completely different rhythm," drawing a parallel to playing drums, where each hand operates separately but in coordination. This analogy helped explain the novelty of performing distinct tasks with each arm, which felt unusual yet familiar in terms of multitasking. For ***C + EMG and C + MT***, no explicit comparisons to everyday tasks were mentioned. The lack of relatable examples in these conditions suggests that users may have found the actions less intuitive or less aligned with routine tasks in their daily lives.

Visualization of the affected Hand

The visualization of the hand significantly impacted users' experiences, with feedback highlighting the need for intuitive and immersive representations that align with the physical and virtual interaction. Many users expressed dissatisfaction when the visualization felt disconnected from their actual movements. For instance, one user noted that the controller felt as though it was "floating and not connected to my hand," which caused discomfort and a lack of embodiment. This disconnect between the visual feedback and physical control was a recurring issue, with users suggesting that the representation should feel more integrated with their movements. Additionally, there was a preference for a contextualized visualization based on the theme or setting of the virtual experience. Some users mentioned that in specific environments, such as fantasy games, using a wand or lightsaber would make more sense, while in other scenarios, a more realistic representation of the hand might be preferable. One participant explained, "If we are in a fantasy world… a magic wand or a lightsaber would make sense." This indicates that users value the flexibility of the visualization being adapted to the context of the task or game, enhancing immersion.

(a) Black Controller (b) White Controller (c) Wand

Figure 3.22: Suggested visualizations for the affected hand.

Discussion/Conclusion

The findings from this user study highlight the critical role of adaptive interaction techniques in enhancing the usability and accessibility of VR environments for individuals with upper limb differences. While participants initially faced a steep learning curve, particularly in conditions utilizing EMG sensors, usability improved with practice, indicating that familiarity with the system can mitigate some early challenges. The dual-hand tasks introduced cognitive engagement, which was generally appreciated by participants; however, muscle tension and coordination difficulties remained significant barriers to sustained use. Ergonomic considerations emerged

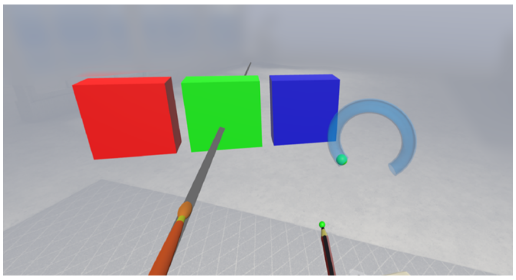


Figure 3.23: A screenshot from the perspective of a right-handed participant.

as a key area for improvement. Participants suggested that more natural hand positioning, along with fine-tuned input thresholds, could reduce physical strain and enhance overall comfort. Additionally, system stability played a major role in user experience. Technical issues such as lagging and misalignment disrupted task flow and contributed to user frustration, emphasizing the need for more reliable performance in future iterations. Another important factor was the visualization of the affected hand. Participants expressed a preference for visual feedback that felt intuitive and connected to their movements. Suggestions included context-sensitive visual representations, such as using a magic wand in fantasy environments, which would increase immersion and provide a more engaging experience.

User study II

In the second part of the user study, we investigated the efficiency and usability of the proposed prototypes.

Materials

The study setup was similar to the one used in Study I: Participants used a virtual pen to move a ball through a pipe. The sphere changed its color every three seconds, and the color of the pen had to change according to the color of the ball. Moving the ball with the pen was always done with the controller and the primary hand. Changing the color of the pen differed according to condition. In this study, no score was displayed inside the VR. The ball in the pipe did not move when the color of the pen did not match. We used 8 different tubes with different levels of curvature. Each appeared twice in each condition, resulting in 16 trials per condition. The virtual setup was adjusted to fit the handedness of the participant. The pen initially appeared closer to the primary side of the participant, and the color selection panel appeared on the contra-lateral side, facing toward the user's head at a 45-degree angle. This ensured that for the conditions including motion tracking (on the secondary hand), the hand would not interfere with the primary hand holding the pen. The ball always appeared on the left side of the tube and ended on the right side. The VR interface and sensor technology were designed to facilitate real-time interaction and adaptive feedback for bi-manual tasks. The system integrates motion tracking and electromyography (EMG) sensors to provide users with a responsive and immersive experience. The real-time feedback mechanism processes data from the motion tracker and EMG sensors to deliver immediate corrective feedback when users make errors or perform unintended actions. For instance, when users activate the EMG sensor, the system interprets the muscle signals based on pre-defined thresholds and displays visual feedback, such as color changes or arrows, to indicate successful activation. In addition to EMG inputs, the motion tracking component captures hand position and orientation, allowing users to manipulate virtual objects accurately. The system uses these inputs to provide continuous synchronization between physical movements and virtual interactions, ensuring a seamless experience. The setup for right handed participants can be seen in Figure 3.23.

Methods

We chose a within-subjects-design with four condition (***C*** , ***C + EMG***, ***C + MT***, ***EMG + MT***). Conditions were counterbalanced using the Latin Square design.

Procedure

After giving informed consent, participants filled out the demographics part of the questionnaire. The EMG sensor was attached to their biceps on the secondary arm and they could see the signal of the EMG sensor on a monitor in front of them. They were given as much time as necessary to practice flexing the biceps to produce a short signal. Then, also the tracker of the motion tracking system was attached to their lower arm on the secondary side. The participants then were asked to put on the HMD and get familiar with the task environment. In each condition the task was explained and the participants could asked question and practice the task until they felt ready to start. They then proceeded through 16 trials. After each condition, participants answered SUS and NASA TLX.

Participants

The study included 26 participants without upper limb differences, consisting of 19 men and 7 women. Participants were recruited through university mailing lists and local advertisements, with the option to choose between financial compensation (€20) or study credits. Participants were required to be between 18 and 44 years of age, with no history of upper limb injuries, chronic pain, or motor impairments, to ensure a baseline level of motor function for accurate assessment of the interaction techniques. The age distribution was as follows: 8 participants were 18–24 years old, 16 were 25–34 years old, and 2 were 35–44 years old. In terms of handedness, 23 participants were right-handed, and 3 were left-handed. This distinction was important as the experimental setup was adjusted to accommodate left-handed participants by reversing the placement of the pen and color selection panel in the virtual environment. Prior experience with VR systems was not required; however, participants were briefed on the task and given sufficient time to practice before beginning the trials.

Results

Task Completion Time

For analyzing the task completion time results, we calculated the sum of all 16 trials per condition for each participant. Figure 3.24 shows box plots of the data.

According to the Shapiro-Wilk test and inspecting the QQ-Plot, we found that the normality assumption for residuals was not met. We analyzed the data with the Friedman test and found a statistically significant difference in task completion

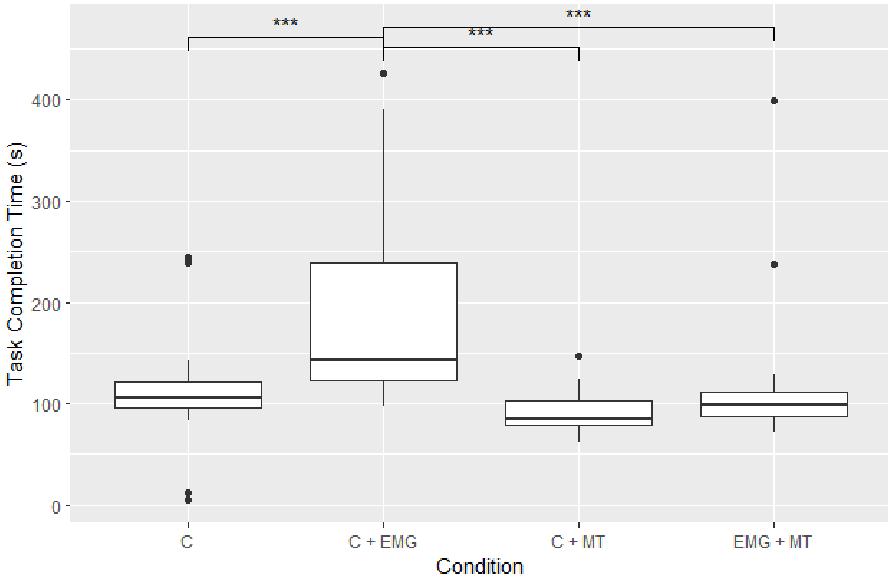


Figure 3.24: Task completion times for all conditions. "***" p < 0.001, "**" p < 0.01, "*" p > 0.05

time between the four tested input methods $\chi^2(3) = 41.585, p < .001$. A Pairwise Wilcoxon signed-rank test with Bonferroni correction indicated that task completion time was significantly higher for ***C + EMG*** compared to ***EMG + MT*** ($Z = -4.330$, $p < .001$), ***C*** ($Z = -4.153$, $p < .001$), and ***C + MT*** ($Z = -4.432$, $p < .001$). None of the other pairs are significantly different.

Usability

Mean SUS Scores can be found in Figure 3.25.

Shapiro-Wilk test and inspection of the QQ Plot showed that the normality assumption was met. A one-way repeated measures ANOVA was performed to compare the effect of the input method on System Usability. We found a significant difference between at least two groups ($F(3, 75) = 27.773$, $p < .001$, $\eta_p^2 = .526$).

A post-hoc test using Bonferroni correction revealed that the SUS score for ***C + EMG*** was significantly lower compared to ***C*** (p < 0.001), ***C + MT*** (p < 0.001), and ***EMG + MT*** (p < 0.001). Additionally, a significant difference was observed between ***C*** and ***C + EMG + MT*** (p = 0.033).

Task Load

We evaluated the NASA TLX results for each of the six sub-scales. The mean and SD values can be found in table 3.11.

According to the Shapiro-Wilk test and inspecting the QQ-Plot, we found that the normality assumption for residuals was not met in all cases. Analysis of the data with Friedman test showed a significant effect for interaction method on each sub-scale (Mental Demand: $\chi^2(3) = 13.74$, $p = .003$; Physical Demand: $\chi^2(3) = 21.23$, $p < .001$; Temporal Demand: $\chi^2(3) = 17.44$, $p = .001$; Performance: $\chi^2(3) = 31.89$, $p < .001$; Effort: $\chi^2(3) = 29.57$, $p < .001$; Frustration: $\chi^2(3) = 36.16$, $p < .001$). Post-hoc tests with Bonferroni correction revealed significant differences between interaction methods in each NASA-TLX sub-scale, as listed in Table **??**.

Table 3.11: Mean and SDs of NASA-TLX questionnaire and statistical comparisons

Metrics	C	C+EMG	C+MT	EMG+MT	Sig.
Mental demand	27.3 (15.2)	48.1 (27.4)	29.6 (23.2)	38.7 (27.0)	C vs. C+EMG ($Z = -3.399, p = .004$), C+EMG vs. C+MT ($Z = -2.965, p = .018$)
Physical demand	30.8 (26.0)	48.8 (27.0)	32.5 (24.7)	46.2 (29.0)	C vs. C+EMG ($Z = -3.436, p = .004$), C vs. EMG+MT ($Z = -2.762, p = .034$), C+EMG vs. C+MT ($Z = -2.749, p = .036$)
Temporal demand	42.5 (23.5)	53.5 (25.5)	33.7 (24.1)	43.1 (26.2)	C+EMG vs. C+MT ($Z = -3.180, p = .009$)
Performance	23.1 (22.2)	45.4 (23.8)	23.3 (22.5)	23.1 (15.4)	C vs. C+EMG ($Z = -3.998, p < .001$), C+EMG vs. EMG+MT ($Z = -4.052, p < .001$)
Effort	34.4 (25.5)	58.7 (25.1)	37.3 (25.0)	46.9 (25.7)	C vs. C+EMG ($Z = -4.008, p < .001$), C+EMG vs. EMG+MT ($Z = -2.908, p = .022$)
Frustration	24.4 (19.6)	49.8 (31.4)	20.6 (20.3)	28.5 (24.6)	C vs. C+EMG ($Z = -3.894, p < .001$), C+EMG vs. EMG+MT ($Z = -3.658, p = .002$)

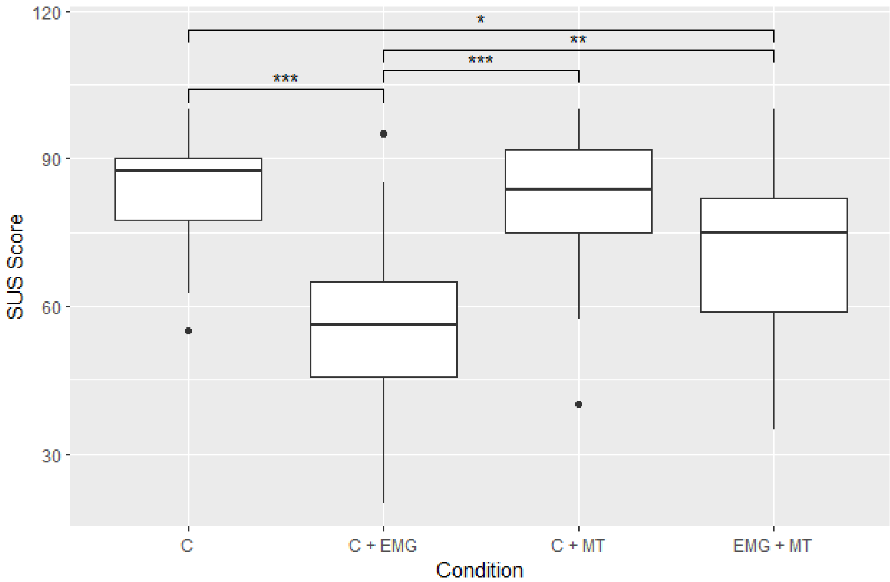


Figure 3.25: Boxplots for SUS scores. "***" $p < 0.001$, "**" $p < 0.01$, "*" $p<0.05$

Discussion

Task Completion Time

C + EMG resulted in the longest task completion times, with some participants taking over three seconds to change colors. Despite prior practice, some struggled to activate the EMG signal, particularly in the first and last trials, suggesting both a learning curve and muscle fatigue. However, EMG + MT had task times comparable to C and C + MT, indicating that EMG activation alone was not the main issue in C + EMG.

Participants sometimes changed colors unintentionally when returning their hand to the sphere, crossing other color panels along the shortest path. The low activation threshold, chosen to ensure accessibility, may have led to unintended activations. Some participants adapted by either carefully avoiding other colors or passively waiting for the correct color to appear. These behaviors suggest that a more refined activation mechanism, rather than a simple threshold, could improve usability.

Interestingly, EMG + MT had significantly shorter task times than C + EMG, as participants could keep the motion tracking pointer on the color panel while using their other hand for the pen. This reduced task-switching delays, allowing for more efficient interactions. Overall, all interaction methods except C + EMG had comparable task completion times. The efficiency of C may be attributed to familiarity with sequential input methods from everyday use, such as a mouse.

Usability

SUS results indicate that EMG-based interactions had lower usability ratings, with C + EMG being the most difficult due to activation and deactivation challenges. EMG + MT, however, did not suffer from deactivation issues, as users could keep the ray on the panel while operating the pen with the controller. Despite its improved task time, EMG + MT was still rated lower in usability than C, likely due to the difficulty of consistent EMG activation. This suggests that motion tracking is inherently more intuitive and easier to use than EMG. While the hypothesis that novel interaction methods would have lower usability scores than C is partially supported, differences between C + EMG and C + MT indicate that the distribution of tasks between hands affects usability.

Task Load

NASA TLX results showed that C + EMG had the highest workload, so comparisons focus on conditions excluding it. In terms of mental demand, C + EMG was significantly more demanding than C, but there was no difference between C + MT and EMG + MT, suggesting that the difficulty was specific to C + EMG. For physical demand, EMG + MT required more effort than C and C + MT, indicating that EMG input is more physically demanding than pressing a controller button. No significant differences were found in temporal demand or performance for conditions including C, but C + EMG had the lowest performance ratings, likely due to perceived failures. Effort ratings were highest for C + EMG, followed by EMG + MT, reinforcing the idea that EMG-based interactions add complexity. Frustration levels were also highest in C + EMG, confirming that participants found it the most challenging condition.

Conclusion and Future Work

Our findings from the prototyping phase with four participants with upper limb differences suggest that people do like to have some kind of bi-manual interaction technique in VR. To answer research question RQ1, users enjoyed performing tasks with different arms, showing the importance not only of software-based accessibility solutions like uni-manual input modes but also the users' desire to use their affected hand in VR. To answer research question RQ2, user satisfaction with bi-manual interaction techniques was similar or less, compared to uni-manual interaction, depending on condition. EMG seems be not as liked as motion tracking. Regarding efficiency, two bi-manual interaction techniques were on a similar level than the uni-manual technique, suggesting great potential to outperform uni-manual interaction in terms of efficiency after some practice time. We hypothesize that the positive feedback from the prototyping phase with people with upper limb differences could not be found in the usability scores in study two, because people without upper limb differences do not have the same level of positive feelings of being enabled to have bi-manual interaction in VR as people with upper limb differences have.

Several challenges emerged in implementing bi-manual interaction techniques effectively. First, EMG activation difficulties caused inconsistencies in control, with some participants struggling to maintain stable activation levels. This issue led to increased frustration and effort ratings, particularly in C + EMG. Second, motion tracking accuracy and latency affected the responsiveness of certain interactions, sometimes leading to unintended actions or delays. Third, adaptation time varied across users, with some requiring extended practice to achieve proficiency with bi-manual techniques, suggesting that initial usability limitations may improve over time. Future work should explore adaptive interaction models that dynamically adjust sensitivity and response times based on users' motor abilities, ensuring smoother and more precise control across different ability levels. To balance complexity and intuitiveness, developing customizable interfaces that allow users to adjust interaction parameters, such as gesture sensitivity or control modes, could enhance usability while maintaining accessibility. Addressing tracking latency and reliability will require advancements in sensor fusion techniques and machine learning-based error correction, which can improve EMG signal stability and minimize delays in bi-manual task execution. Additionally, incorporating haptic feedback or multimodal interaction methods could enhance user confidence and accuracy in VR-based bi-manual tasks. Taken together, we suggest that VR systems should be designed more inclusively, not only to enable all users to use them but also because everyone could benefit from novel input modalities and a variety of input techniques to choose from. Future research should further investigate the long-term usability and learning effects of bi-manual interaction techniques, assessing how familiarity and prolonged practice influence user preference and task performance. Expanding studies to larger and more diverse populations, including users with varying degrees of motor impairments, could provide deeper insights into accessibility and usability improvements.

3.2.10 Insights

Objective

This case study investigates how Virtual Reality (VR) bi-manual interaction techniques can be adapted for users with upper limb differences. The study focuses on creating equitable access by designing interactions that accommodate varying levels of responsibility for each hand. This includes evaluating how combinations of motion tracking and electromyography (EMG) can facilitate both efficient and accessible VR experiences for users with different capabilities.

Key Technologies

- **VR Environment in Unity**: A VR setup created in Unity and optimized for bi-manual tasks, specifically tailored to accommodate users with upper limb differences.
- **Motion Tracking (Qualisys System)**: Used to capture real-time movements.

- **Electromyography (EMG) Sensors**: EMG sensors were used to detect muscle activity.

Evaluation and Data Collection Framework

The study utilized both quantitative metrics and subjective assessments to gauge user performance, accessibility, and satisfaction:

- **Objective Metrics**: Task completion times was recorded across different bi-manual techniques to assess their efficiency and practicality.
- **NASA-TLX**: Used to measure cognitive workload, capturing mental and physical demands experienced during the interaction with each VR modality.
- **System Usability Scale (SUS)**: Provided insights into the perceived usability of each technique, comparing user preferences for EMG-based versus motion-tracking methods.
- **Semi-Structured Interviews:** Conducted post-experiment to gather qualitative feedback on user experiences, challenges, and adaptation strategies, offering deeper insights into usability and interaction difficulties.

Main Findings

- **Effectiveness of Combined Techniques**: Combining motion tracking with EMG proved more effective than EMG alone, showing improved task completion times and reducing user frustration by balancing functionality with accessibility.
- **User Preferences and Workload**: Motion tracking was preferred over EMG for ease of use, while EMG methods were associated with higher cognitive and physical demands. However, combining both methods reduced user effort, enhancing task engagement and reducing frustration.
- **Satisfaction with Control and Autonomy**: Users expressed a sense of empowerment in VR, particularly when they could engage both hands in tasks, indicating the value of inclusive design in enhancing VR accessibility.

Technical and Usability Limitations

- **Precision of Interaction for Different Abilities**: Ensuring smooth and precise control for users with various motor abilities posed a challenge, as response times and accuracy varied significantly.
- **Balancing Complexity and Intuitiveness**: Creating interfaces that were intuitive yet functional across different ability levels was essential to avoid overwhelming users with complex gestures.
- **Tracking Latency and Reliability**: Technical limitations such as minor latency in tracking and inconsistent EMG response impacted the seamless operation of bi-manual tasks, necessitating further refinement.

Future research should explore adaptive interaction models that dynamically adjust sensitivity and response times based on users' motor abilities, ensuring smoother and more precise control across different ability levels. To balance complexity and intuitiveness, developing customizable interfaces that allow users to adjust interaction parameters, such as gesture sensitivity or control modes, could enhance usability while maintaining accessibility. Addressing tracking latency and reliability will require advancements in sensor fusion techniques and machine learning-based error correction, which can improve EMG signal stability and minimize delays in bimanual task execution. Additionally, incorporating haptic feedback could enhance user confidence and accuracy in VR-based bimanual tasks.

3.2.11 N6: Preserving Family Album Photos

Objective and Context

In recent years, there has been a growing interest in analog family photo albums [1112, 591, 265]. Although the tradition of creating printed family albums is in decline, this reduction in practice has sparked increased fascination from both collectors and museums. Despite this renewed attention, there is a noticeable absence of readily accessible tools or infrastructures for users to digitize and catalog the vast collection of family album photos. Augmented reality (AR) technology offers a potential solution to this gap. To address this, we developed an application for the HoloLens 2 that: (a) digitizes photos as the user views them in a physical album, and (b) analyzes the digitized images, tagging them with metadata that infers their socio-historical context and possible date. This metadata is crucial for both cataloging and conservation purposes, as identifying the scene, individuals, and date of the photos enhances their preservation prospects [1112].

This work builds upon a body of research that has explored associating metadata with visual content through AR. For example, Marfia et al. [1088] demonstrated how AR systems can enrich real-world cultural experiences by embedding additional information. Similarly, the HyperReality AR application was designed to link physical environments with digital content to enhance everyday interactions [149, 209]. Such projects have laid the groundwork for the anticipated evolution of WebXR, where digital and physical spaces will merge, creating phygital environments where content seamlessly integrates with the physical world [788].

In this case study, we present a prototype developed for the HoloLens 2, combining AR with computer vision techniques to facilitate the preservation of family photo albums [1285].

Our research question is:

- How can AR technologies, such as the HoloLens 2, enhance the digitization and cataloging of analog family photos?

Materials and Methods

System architecture

The system will be based on the use of different tools: (a) an augmented reality device, namely Hololens2, used to track a user's view and to visualize photo metadata, (b) an image processing library to segment and process the pictures appearing in the scene, and, (c) two deep learning models to classify the segmented images.

The general application is based on a client/server architecture and is organized as follows:

- The **client application** runs on the Hololens2 device. The main aims of the client side are to capture the user view and visualize the information returned by the server about the date and the socio-historical context classification of each image in the view.
- The **server application** infers the best classes resorting to deep learning algorithms, taking as input the user view sent by the client. To make deep learning models work at best, a preliminary step of image isolation is required to feed them with the target images only. The inferred information are then sent back to the client to be visualized on its interface in AR.

The Hololens2 exploits its locatable camera (an RGB color camera) to access and control a user's real-time view by employing the Windows Media Capture and Media Foundation APIs. The usage of an image processing library is required to individuate, extract, and process the region of interest in the user's view. The image processing library that has been chosen for this project is one of the most popular ones: OpenCV [581].

On the client side of this system, video frames (as images) are captured from the device's camera live stream and sent to the server. At this point, the server isolates target images in the user view via OpenCV image processing algorithms and feeds them to deep learning models. The deep learning models, in turn, produce their classification. Finally, the server returns the classification results to the client side to be visualized on the HoloLens 2 interface.

Image pre-processing

Image pre-processing is a fundamental part of our project and it is applied to each frame extracted by the Hololens2 locatable camera. The main aim of this step is to detect, extract, and improve image targets before sending them to classification models. The first image pre-processing step consists in applying several transformation on the same frame to make the image target detection to be done properly: (a) a noisy removal and edge-preserved filter (e.g. bilateral filtering), (b) resizing and (c) conversion from RGB to grayscale space.

The second process includes detecting image target contours exploiting an automatic canny edge detector whose results are further improved with a closing operation to correct gaps between detected edges [197]. At this point the polygons, whose sides are defined by the detected contours, are approximated. To avoid bad polygons derived from noises or shadows in the scene, custom filters have been designed based on the area and the number of sides. For instance, only those polygons which can be approximated with 4 sides (i.e. rectangles) are assumed to be target images.

Despite we expect that the target images are placed on a planar surface (e.g. photo albums and walls), a user is free to move around the scene watching them from different perspectives. Therefore, these extracted images need to be adjusted before employing deep learning models. To do so, a perspective-warping transformation is applied to each target image. Finally the warped images are resized and evaluated by deep learning models. The warping algorithm returns the same image even when the user is watching the same picture from different points of view. This means that the entire process can be optimized by guessing only once for all the classifications related to a certain picture (e.g., a hash map is constructed where the key is the hash of the image and the value is its classifications).

Infer the date and the socio-historical context with deep learning models

As previously stated, once the images are available in a digital form, two deep learning models called, respectively, IMAGO DATING and IMAGO SOCIO HISTORICAL CLASSIFIER, developed by the authors of [1219], infer their most probable date and socio-historical context. These models were trained specifically on analog photos coming from family albums and are able to classify both the date and the socio-historical context of digitized analog pictures with an accuracy that falls slightly below the 70% threshold. In particular, the year range supported by the IMAGO DATING classifier is the [1930,1999] time frame, while the socio-historical classes were available through the IMAGO SOCIO HISTORICAL CLASSIFIER amount to work, free-time, motorization, music, fashion, affectivity, rites, school, politics. Once these two information are individuated, the server returns to the client a vector containing $n \times 2$ data, where n is the number of previously detected pictures.

User supported actions

A user is asked to choose and attach the analog images of interest to a planar surface, based on some general rules: (a) the background of the surface should be simple, (b) the photographs should be in rectangular shape, but they can vary in size, (c) the arrangement of the photographs, regarding their position and orientation on the surface, can be random as long as the pictures do not overlap, and, (d) all images should be observable in a single field of view of the device.

Respecting these rules, a given user can wear the Hololens2 device and start looking at the pictures. After a few seconds, the user can visualize the detected bounding boxes along with the classifications of each target image, as depicted in Figure 3.26. The user will see the classifications related to the date and the socio-historical context in which the photo was taken. Moreover, the system allows the user to interact with the visualized content. For example, the user can attach extra information to each particular image including a voice comment, suggesting a different date and/or socio-historical context. These interaction experiences have been designed adopting interaction models that are common in mixed reality apps that combine hand, eye gaze, and natural language to provide a multi-modal interaction experience that may potentially provide instinctual experiences for the user.

Proposed Evaluation Plan

This study aims to assess the usability, efficiency, and user experience of the AR-based system for digitizing and cataloging analog family photos. The evaluation will focus on system intuitiveness, task efficiency, and metadata accuracy while examining real-time processing performance.

The study will involve 12 to 15 participants from diverse backgrounds. Participants aged 25 to 65 years will interact with the system using their personal or historical family photos. The study follows a within-subjects design and consists of three phases:

- Training Phase (5–10 min): Participants receive a brief demonstration and hands-on practice with selecting and viewing photos in AR.
- Task Execution Phase (10 min): Users digitize and catalog photos, review and modify automatically generated metadata, and add annotations such as voice comments. System performance, processing latency, and user actions will be recorded.
- Evaluation Phase (10 min): Objective metrics include task completion time. Subjective assessments include NASA-TLX for workload, SUS for usability, and semi-structured interviews to gather qualitative feedback.

Findings from this study will guide future refinements, improving accessibility, interaction intuitiveness, and overall system efficiency to enhance AR-based archival processes.

Conclusions and future works

We introduced a novel approach for digitizing and cataloging old analog family photos using state-of-the-art technologies. Our work addresses key challenges in photography studies, particularly in the recovery and preservation of analog family albums. To this end, we designed and implemented a system that integrates an Augmented Reality (AR) device, the HoloLens 2, with Computer Vision and Deep Learning algorithms to enhance photo digitization, classification, and contextualization.

Despite the promising results, several challenges emerged in the development and implementation of our system. Real-time processing and latency issues affected the seamless integration of AR overlays, highlighting the need for optimized server-side processing and improved data streaming protocols. Variability in photo conditions, including differences in lighting, noise levels, and background complexity, impacted the accuracy of image detection and classification. Additionally, user interaction optimization remains an open challenge, as understanding user focus and intent when interacting with digitized photos requires more refined gaze-tracking and context-awareness mechanisms.

To address these challenges, future work will focus on integrating eye-tracking paradigms available in the HoloLens 2 to identify the user's focus of attention in real time. Analyzing gaze data will provide insights into user interests and enable the system to dynamically present contextualized historical and social information about the photos being viewed.

To improve real-time processing efficiency, we plan to enhance server-side optimization, implement asynchronous data handling, and refine data streaming protocols to reduce latency and ensure smooth AR interactions. Addressing photo condition variability will involve incorporating AI-driven image enhancement techniques, such as adaptive noise reduction, contrast balancing, and super-resolution algorithms, to improve detection and classification accuracy. Additionally, developing context-aware deep learning models will enhance adaptability to diverse lighting conditions and complex backgrounds, increasing system reliability in real-world applications.

By implementing these advancements, our system can further bridge the gap between analog photography and digital archival processes, offering a more immersive and context-aware exploration of historical family albums.

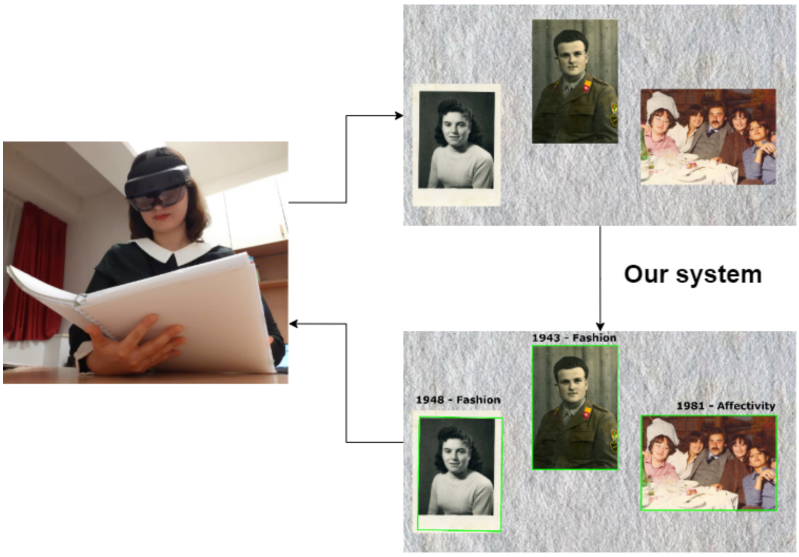


Figure 3.26: Application concept

3.2.12 Insights

The findings of this study have been published in [1224].

Objective

The primary goal of this study is to develop an AR application for digitizing and cataloging analog family photos. The solution leverages computer vision and AR technologies to facilitate the preservation and organization of family photo albums by enriching photos with metadata, such as socio-historical context and approximate dates. This approach aims to bridge the gap between analog and digital photo preservation, supporting both personal archiving and cultural heritage preservation.

Key Technologies

- **Microsoft HoloLens 2**: Provides an AR interface for overlaying metadata on digitized photos.
- **Image Processing and IMAGO DL Models**: OpenCV is used for detecting and cropping family photos, while the IMAGO-DATING and IMAGO SOCIO-HISTORICAL CLASSIFIER models estimate the date and socio-historical context of each photo.
- **Server-Based Processing**: Offloads image recognition and metadata tagging tasks to a remote server to ensure efficient, real-time analysis and AR overlay on the HoloLens.

Planned Evaluation and Data Collection Framework

The evaluation framework is designed to assess user experience, ensuring a comprehensive understanding of the system's effectiveness.

- **User Experience and Usability**: A user study will be conducted to gather feedback on the intuitiveness, ease of use, and perceived accuracy of the system. This will involve structured questionnaires, usability metrics (such as the System Usability Scale), and potential think-aloud protocols to capture real-time user insights.
- **Cognitive Load and Engagement**: To further understand user interaction, cognitive load measurements (e.g., NASA-TLX) may be incorporated to evaluate the mental effort required to use the system. Additionally, engagement levels will be assessed through self-reported measures and interaction logging.
- **semi-structured interviews**: Users will provide qualitative feedback on system usability, perceived accuracy, cognitive and physical effort, engagement, and suggested improvements, offering insights into interaction challenges and potential refinements.

Potential Findings

- **Enhanced Interaction with Physical Albums**: The AR overlay is expected to enrich the interaction with physical photos by displaying metadata, which could lead to heightened engagement as users explore historical context and additional insights about their family photos.
- **Improved Historical Awareness and Connection**: By providing socio-historical context and estimated dates, the AR system may foster a stronger personal connection to family history. Users are anticipated to gain a deeper appreciation for their heritage through contextualized information, which may encourage long-term preservation and sharing of family albums.
- **Engagement in Storytelling and Sharing**: The AR-enhanced family album could facilitate storytelling by encouraging users to share stories and memories linked to each photo. This interactive aspect may promote family bonding and engagement, as well as intergenerational sharing of family history.
- **Potential for Broader Cultural Heritage Applications**: The system's success in preserving personal photo albums could indicate its applicability in broader cultural heritage preservation. This AR-based approach may demonstrate value in digitizing and preserving historical artifacts beyond family photos, paving the way for museum or archival applications.

Technical, Usability Challenges and Future Directions

- **Real-Time Processing and Latency**: Achieving low latency in real-time AR overlay and maintaining a stable connection between the HoloLens and the server was challenging.

- **Variability in Photo Conditions**: Differing photo quality, lighting conditions, and backgrounds impacted the accuracy of detection and classification.

To address real-time processing and latency issues, future research should explore server-side optimization techniques, such as parallel processing and asynchronous data handling, to enhance response times. Additionally, implementing efficient data compression and streaming protocols could minimize transmission delays between the HoloLens and the server, ensuring a smoother AR experience. For challenges related to variability in photo conditions, future work could incorporate AI-driven image enhancement methods, such as adaptive noise reduction, contrast balancing, and super-resolution techniques, to improve the quality of images before classification. Additionally, context-aware deep learning models that dynamically adjust to different lighting conditions and background complexities could enhance the accuracy of photodetection and classification, making the system more reliable in diverse real-world settings.

3.2.13 N7: User Enactment in Virtual Reality

Objective and Context

The 21st-century technological revolution, particularly driven by advancements in Artificial Intelligence (AI), is reshaping every aspect of human life. AI has not only expanded machine capabilities but has also transformed daily experiences, from healthcare diagnostics [78] and autonomous vehicles [783], to personalized learning platforms [895] and smart homes [931]. Among these, smart homes, featuring interconnected and autonomous devices [29], stand out by creating adaptive environments that streamline and automate everyday tasks [1040].

At the heart of smart homes are AI assistants, which go beyond responding to commands by proactively predicting user needs and taking actions based on data from sensors and interactions. These AI systems enhance daily routines by offering solutions and suggestions before users request them, shifting from reactive tools to proactive partners [852]. In doing so, they create a personalized, responsive environment that anticipates user preferences and moods [751]. Understanding how users perceive and interact with these assistants is key to fostering acceptance and trust in these technologies.

User enactment is a valuable methodology for studying interactions with emerging AI technologies before they are fully developed. This approach involves carefully staged environments and scenarios to authentically assess future user-technology interactions [933]. However, traditional user enactment methods face challenges such as maintaining realism, managing participant control, and avoiding breaks in immersion due to artificial environments or researcher presence. Furthermore, budget constraints can limit the availability of appropriate interfaces, affecting the authenticity of the study [378].

Virtual Reality (VR) offers a promising solution to these challenges, as it allows for highly immersive and interactive environments that can closely replicate real-world settings [1235, 483]. The integration of VR into user enactment studies can address many of the limitations of traditional methods, though more research is needed to explore the full potential of this approach. We developed three VR simulations of a virtual smart home environment, focusing on two daily scenarios. We conducted a usability study to evaluate the user experience and analyzed the results.

In this paper, we aim to answer the following research questions:

- **RQ 1:** How can we create a feasible and immersive VR smart home experience for a user enactment study to explore user perception, interaction, and the impact of a proactive AI assistant in daily scenarios?
- **RQ 2:** How do participants perceive, interact, and give feedback about their interactions with the proactive AI assistant across these daily scenarios in this virtual smart home environment?

Related Work

This section reviews key studies and advances that have influenced the development of proactive AI assistants in smart homes and explores the potential of VR user enactment for investigating user interactions with these technologies.

Proactive AI Assistants in Smart Homes

Proactive AI assistants mark a significant advancement from traditional reactive systems by anticipating user needs and acting accordingly [1235]. Research shows that proactive AI can positively impact user emotions and behaviors by detecting stress or low mood through sensor technologies, such as voice tonality, facial expressions, and physiological signals [1135, 122, 998]. These systems can then support timely reminders or suggestions to uplift mood, such as recommending breaks or playing calming music [45], or adjusting ambient settings like lighting and temperature [480, 122]. Beyond emotional support, they can assist in household management by suggesting recipes and tracking expiration dates [469, 371]. These capabilities significantly enhance the ability of AI assistants to support everyday scenarios in smart homes.

User Enactment in AI-Assisted Domains

Foundational work by Odom et al. [933] has highlighted the effectiveness of user enactment methodology in understanding user experiences and informing design. To explore user interactions with AI assistants, user enactment has been applied in various domains. Neuhaus et al. [909] studied the impact of in-car AI assistants by comparing opaque systems (involving users only when necessary) with transparent systems (offering continuous task insights). Huff et al. [559] examined older adults' interactions with autonomous vehicles, understanding their specific needs. In the context of smart homes, user enactment has provided insights into how AI assistants impact daily routines. For example, Odom et al. [933] conducted a study with scenarios like "Family Conversation" (later redesigned as a trivia game), "Meal Planner" (smart fridge suggesting meals), and "What We Like To Do" (linking kitchen cleaning with vacation anticipation using family photos). These studies highlight user enactment's ability to simulate realistic environments, offering valuable data to improve AI system design.

Virtual Reality in User Enactment

Recent studies have explored VR's potential in user enactment across various domains, demonstrating its effectiveness in providing ecologically valid data and enhancing user experience and engagement. Niforatos et al. [917] used VR enactments for moral decision-making, showing that VR can replicate real-world decision contexts accurately. Meenaghan et al. [839] found that VR enactments improved offender recall in virtual environments, while Shultz et al. [1175] demonstrated VR mock-ups' effectiveness in healthcare design by assessing impacts on workflow and safety. Similarly, Kefalidou et al. [629] used VR enactments for early airport design testing, effectively reducing passenger stress and wait times. Simeone et al. [1184] showcased VR enactments' versatility in various scenarios, including "Virtual Parent" and "Smart Dog Monitoring." In the context of smart homes, Liu et al. [763] conducted a user-enactment study to explore users' behavior models in in-situ programming for AIoT (Artificial Intelligence of Things) automation, identifying dynamic interaction methods for configuring and testing smart home systems. Chiang et al. [232] used a user enactment approach to improve the communication effectiveness of AI-enabled smart home assistants. These studies collectively highlight VR's versatility and effectiveness in studying user experiences and interactions in different domains. Despite the advancements, a significant gap remains in understanding VR enactment's use for studying AI interactions in smart homes. Studies such as Liu et al. [763] and Chiang et al. [232] have applied VR enactment in this context, but further research is needed to explore its full potential and limitations. Our study takes this step and studies the flexibility of VR to address the potential challenges of user enactment in exploring AI interactions within smart homes.

Materials and Methods: User Enactment Study

In executing a user enactment study within a VR smart home setting, the process unfolds through three main stages: developing a virtual smart home environment, developing interactive scenarios, and a usability evaluation.

Virtual Smart Home Development

Prior research indicates that realistic VR experiments enhance presence and immersion, evoking stronger user responses [912, 1194, 597]. High immersion and low simulation sickness throughout the experience are essential to ensure a high-quality and comfortable VR experience. Based on this insight our VR-based user enactment experiment aims to provide a realistic, and effective platform for exploring user interactions with emerging AI technologies in smart homes. Our methodology focuses on enhancing realism, reducing costs, minimizing simulation sickness, maintaining immersion, minimizing immersion breaks, and managing participant control to tackle user enactment challenges.

High-Realism, Cost-Effective Virtual Reality Smart Home

Since the environment intends to meet the user's expectation of a real house, a one-room furnished apartment has been implemented in a Unity project, with a real blueprint being used during the modeling phase. The Unity ProBuilder tool has been used to create the building 3D model [10]. Next, the environment was populated with high-fidelity, freely available 3D models from Unity's Asset Store. Achieving high realism extends beyond high-quality objects to include meticulous lighting, where Unity's Global Illumination (GI) plays a pivotal role through both real-time and precomputed techniques to simulate natural light behavior. The project prototype employs a combination of directional, area, and point lights, alongside reflection probes, to achieve a lifelike illumination, particularly within the smart home model. Furthermore, the rendering process, crucial for defining the visual characteristics of 3D objects, benefits from Unity's shaders and materials within its rendering pipelines, with the Universal Render Pipeline (URP) being favored for its balance between graphical fidelity and performance, particularly in VR applications. Based on this, the smart home environment gained significant advancements in terms of realism, as shown in Figure 3.27, compared to the standard unity setup.

Realistic Virtual Reality Interactions and Reduced Immersion Breaks

This study applies two base interactions—movement and grabbing—by focusing on increasing their realism. Movement is facilitated through controller-based locomotion to overcome physical space constraints. Continuous movement was chosen despite potential motion sickness, due the need for comprehensive engagement with the scenarios. The brief VR experience (around 5 minutes) is expected to minimize discomfort. Interactivity is further enhanced by the Mecanim Animation System, which provides fluid hand animations that correspond to user actions, particularly during transitions between different hand poses, and by the grab action, enabling natural manipulation of virtual objects, both using built-in OpenXR scripts. This system ensures that hand movements are not only visually coherent but also dynamically responsive to user inputs. High-fidelity virtual hands play a pivotal role in enabling users to interact with the virtual world intuitively through precise tracking of user movements. The mechanics of doors and drawers are meticulously simulated to mirror real-world functions. By incorporating realistic interaction mechanisms and spatial audio, we minimized the risk of immersion breaks caused by external environments and researcher presence. Spatial audio enhances VR immersion and augments sensory cues [166, 528] by allowing objects to emit spatially realistic sounds through three setups: a watch alarm to signify time in the Smart Frames scenario, sound effects for collecting items into a backpack, and an AI assistant's voice generated via text-to-speech (TTS) in both scenarios to guide and maintain user focus. The TTS audio was produced using a freely available tool [5], utilizing the Microsoft TTS server with the Italian voice of "Elsa.

(a) Without post-processing (b) With post-processing

Figure 3.27: Comparison of standard and URP smart home environments with advanced lighting.

Managing User Control

By immersing users in a predictable, real-world-like environment, they can better anticipate outcomes and maintain control over their interactions with the virtual space and embedded smart technologies. Predefined workflows guide tasks while allowing for some flexibility, and preset customization options let users tailor their experience within set boundaries. Feedback mechanisms, such as prompts, alerts, and notifications, help users stay on track. These elements create an environment where users feel empowered to explore and interact confidently while maintaining control.

Interactive Scenarios Development

This study includes three VR simulations: one for familiarization and two main simulations. The main simulations focus on smart frames as reminders of positive events in stressful situations, and a smart kitchen, which assists in food preparation steps. Smart frames were chosen for their potential to alleviate stress, similar to the "Family Reminders" study by [933]. The kitchen was selected for its central role in the home and the insights can provide in transforming domestic chores. The design and implementation of these scenarios are based on scenario-based design principles by M.B. Rosson et al [912]. This method involves creating narratives with a user protagonist engaging in tasks to achieve specific goals.

At the start, a general introductory user script, as shown in Table 3.13, is presented to the participants to involve them in the scenarios. Each VR simulation will be discussed in detail in the following.

Simulation 1: Familirization

Before involving the user in the main simulations, a crucial familiarization simulation is implemented to orient participants within the virtual smart home setting. Initiated by the voice of the virtual assistant (Please see Table 3.13 for the assistant's script), this phase further extends to encompass a text-image-based introduction to the smart home's layout, particularly vital for participants who may be inexperienced with VR controllers. The familiarization process unfolds through a streamlined series of steps on a virtual touchscreen. Participants learn essential interactions such as pointing, moving, and grabbing objects, engaging in the practical task of transferring mugs from the bedroom to the kitchen. Once users press the "Complete" button, the tutorial ends (Please see Figure 3.28 for an overview of the steps).

Simulation 2: Smart Frames

The Smart Frames simulation aims to explore how the user feels about the experience of a simulated stressful situation where s/he is running late for transportation and needs to collect specific items within her/his home in a limited time frame. By this design, the study explores the potential of this digital technology to foster positive psychological states.

The AI assistant's script for the Smart Frames scenario (Please see Table 3.14) is crafted to immerse the user in a familiar task that might potentially induce stress. At the start, the AI assistant and a watch alarm jointly remind the user of an upcoming bus departure five minutes into the experience. The watch displays the

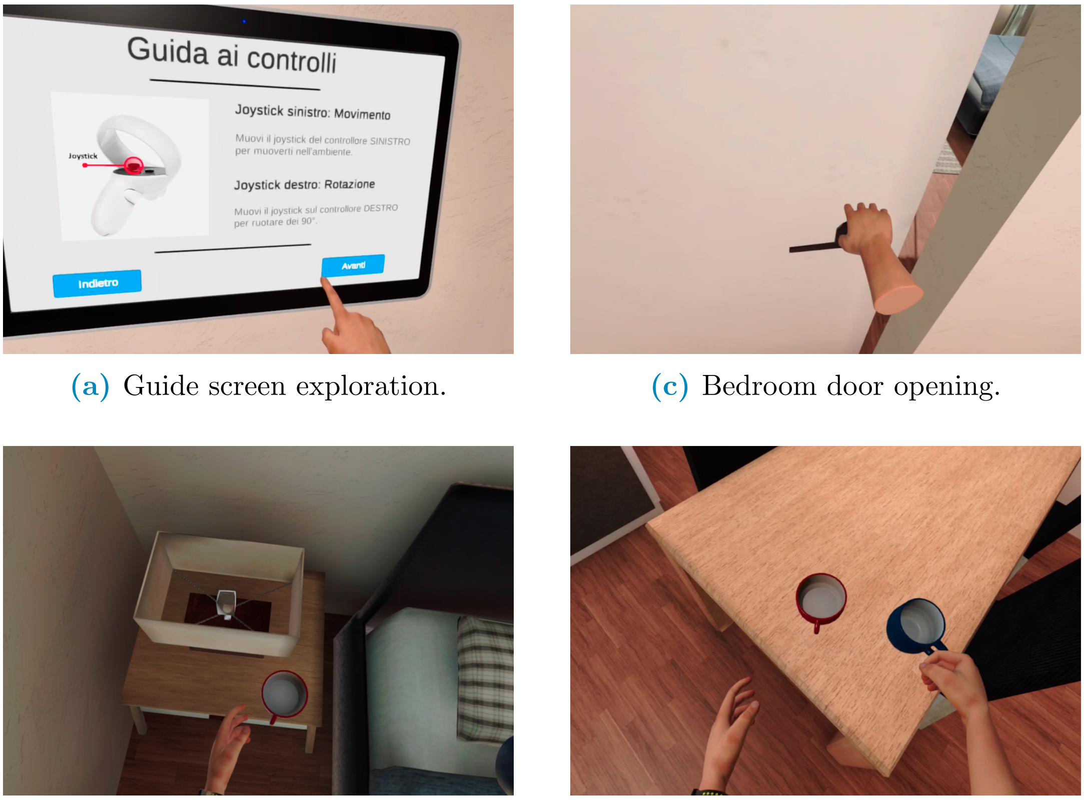
Simulation	Scripts
General	"You recently moved into a two-room apartment just outside the city center. Your new home has various smart devices connected to an AI named ARIA that controls them. ARIA spontaneously helps you with small household chores. Today, in particular, it will use the smart fridge and picture frames in the house to assist you with various tasks."
Smart Frames	"This is your last working week before your holiday starts, which you'll spend in Costa Rei, Sardinia. You've just woken up and realized that you didn't hear the alarm, so you're running very late for the bus departing in 10 minutes. You are already dressed; you just need to pack your backpack with various items needed for work. These items are scattered all over the house and include the following: Packed lunch (blue container), House keys (blue), Computer (gray laptop), Phone (red smartphone), and Water bottle (blue). You have to quickly gather all the items within 5 minutes, or else you risk missing the bus and being late for work. ARIA senses the situation and tries to reduce your stress by focusing on your upcoming vacation. As soon as you think you've collected all the items or the 5 minutes have passed, head towards the exit door."
Smart Kitchen	"It's 6:30 PM, and you've just returned home after a long day of work, still thinking about your upcoming vacation in Sardinia. You're already feeling hungry, so you decide to start preparing dinner. ARIA invites you to the kitchen and interacts with you, providing some suggestions. Together, you place the necessary ingredients for the chosen recipe on the kitchen counter."

Table 3.12: Smart Home introductory user's scripts

Script #	Script Text
1	*"Hello, I'm Aria, your home assistant. Take a look at the suggestions on the screen in front of you."*

Table 3.13: AI assistant's TTS scripts in the Familiarization scenario.

current time, helping users track their progress. Meanwhile, the user is exposed to smart frames around the house changing pictures and presenting pleasant moments to help alleviate potential stress. The user's task involves locating and collecting five specified objects placed strategically throughout the smart home (Please see Figure 3.29). Objects are gathered by placing them into a designated backpack object upon collision. If the user exceeds the allocated time, the watch alarm reminds them to leave promptly, signaling the end of the experience to prevent missing transportation (Please see Figure 3.30 for an overview of the steps). This simulation provides a platform that investigates users' opinions on the AI assistant's impacts in this context and whether they desire any changes in its behavior. Additionally, it allows users to share any further feedback about their experience with this setting.



(a) Guide screen exploration.
(c) Bedroom door opening.
(b) Retrieving the mugs.
(d) Placing mugs on the kitchen table.

Figure 3.28: Overview of the Familiarization scenario.

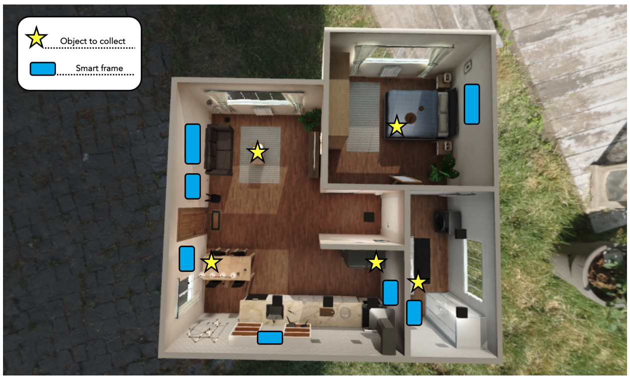


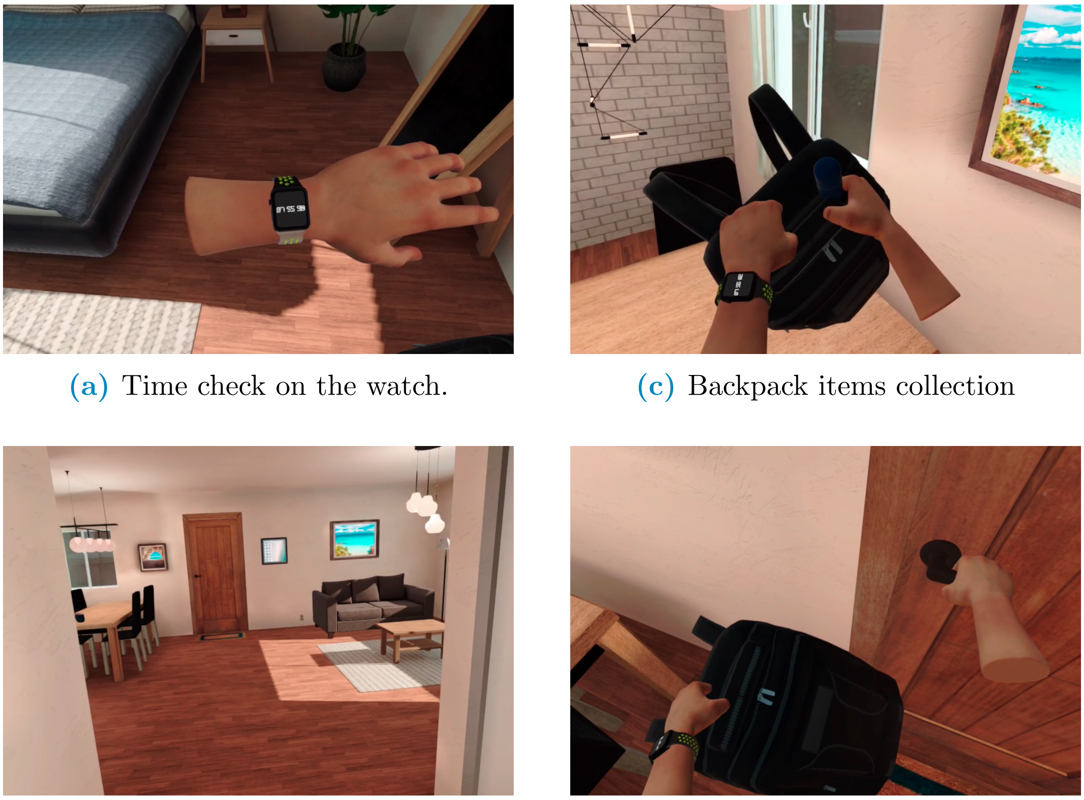
Figure 3.29: Smart frames and collectible objects arrangement.

Script #	Script Text
1	*"Your bus will arrive in 5 minutes."*

Table 3.14: AI assistant's TTS scripts in the Smart Frames scenario.

Simulation 3: Smart Kitchen

The Smart Kitchen simulation aims to explore how users feel about the interaction with a smart fridge and a scripted AI voice in the preparation steps of making



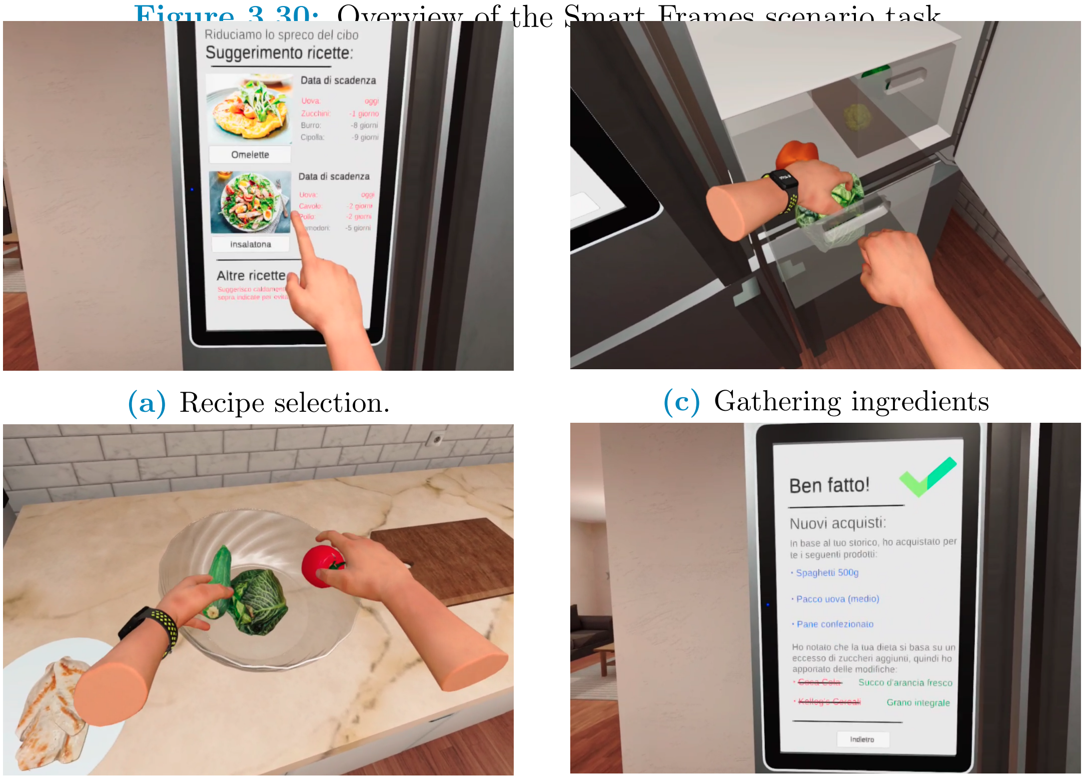
(a) Time check on the watch.

(c) Backpack items collection

(b) Observing the smart frames.

(d) Opening the exit door.

Figure 3.30: Overview of the Smart Frames scenario task.



(a) Recipe selection.

(c) Gathering ingredients

(b) Placing products on the countertop.

(d) Analyzing the AI assistant purchases.

Figure 3.31: Overview of the Smart Kitchen scenario task.

Script #	Script Text
1	*“It’s six thirty in the evening, it’s time to prepare dinner. Come in front of the fridge, and I’ll guide you to the best choice for your meal.”*
2	*“You have some products nearing their expiration date. On the screen, I’ve listed some great recipes that you can make using these products.”*
3	*“These recipes are not ideal. I remind you that food waste has a strong environmental impact, as well as an economic one.”*
4	*“Great choice! Take the ingredients shown on the screen and place each item on the kitchen counter in front of the fridge.”*
5	*“Take the ingredients shown on the screen and place them on the kitchen counter in front of the fridge.”*
6	*“Remember to consume the products nearing their expiration date as soon as possible.”*
7	*“Based on your tastes, I have purchased some products that have run out in the fridge. I have also made some small changes to make your diet healthier. Take a look at the screen for more details. I hope you’ll appreciate the modifications.”*
8	*“Great, I’ll let you prepare dinner. If you need a hand, don’t hesitate to call me. See you next time.”*

Table 3.15: AI assistant’s TTS scripts in the Smart Kitchen scenario.

dinner, experiencing suggestions from the AI, which recommends recipes based on product expiration dates and aims to encourage healthier eating habits.

The AI assistant consistently communicates through vocal scripts, outlined in Table 3.15, employing a Wizard-of-Oz approach for explicit activation. In this method, predetermined vocal scripts are delivered by the AI assistant in response to user interactions or commands. However, behind the scenes, a human operator controls the execution of these scripts, ensuring accurate and contextually appropriate responses [837]. The selection of the correct script, from Table 3.15, is given by the flow diagram in Figure 3.32. The user’s task involves navigating the touchscreen system, which initially displays recipes involving ingredients nearing their expiration date, emphasizing the remaining days until expiration. In case the user prefers different recipes, a dedicated button allows them to explore all the other available options. Once a recipe is selected, the complete list of ingredients is presented, prompting the user to prepare them on the kitchen countertop. After arranging all the required products, the user proceeds by pressing the ”Complete” button. Ultimately, the user experiences the AI assistant notifying them about the purchased missing products and the dietary alterations. Upon the user’s comprehension of the AI assistant’s actions, the experience concludes (Please see Figure 3.31 for an overview of the steps). Similar to the previous simulation, this one also creates a platform to explore users’ opinions on the AI assistant’s actions and any desired behavior changes, as well as gather feedback on their experience in the smart kitchen setting.

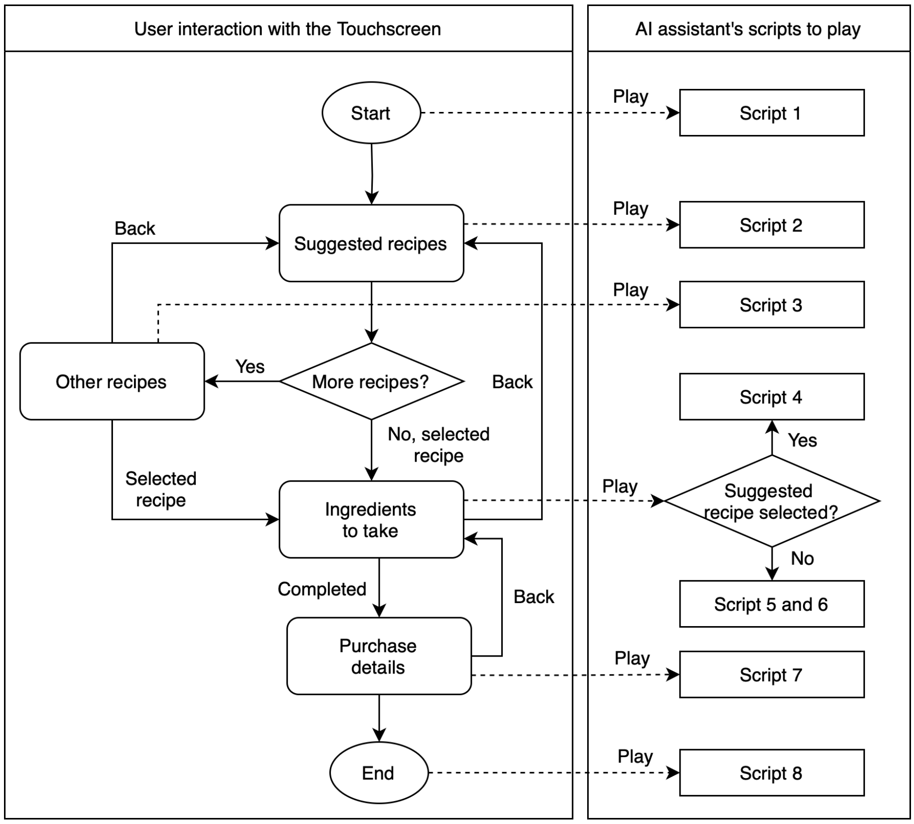


Figure 3.32: Flow diagram of AI script activation for the Smart Kitchen scenario.

Usability Settings

Apparatus

The study used an Oculus Quest 3 headset with Unity 2020.3.10f1. Participants completed pre- and post-experience questionnaires through Google Forms. Sessions ran on a VR-capable Alienware Aurora R15 (Intel Core i7, 16GB RAM, 512GB SSD, 1TB HDD, NVIDIA GeForce RTX 4080).

Methodology

We conducted a within-subject study, allowing every participant to engage in all the interaction scenarios. The study adopts a mixed-methods approach, integrating quantitative and qualitative analyses. The qualitative analysis employed a semi-structured interview method and an inductive analysis approach. The application language was set to Italian, and the open-ended questions were presented in the participants' native language (Italian) to ensure more comprehensive and accurate responses. To analyze participants' interview responses, we employed thematic analysis using Braun and Clarke's [164] framework, involving familiarization with the data, generating initial codes, searching for themes, reviewing and defining themes, and producing the final report.

Participants

We recruited 30 individuals (10 female, 20 male) to participate in our study. Participants were required to be adults (aged 18 and above) with no cognitive or physical impairments that could interfere with their ability to engage in the user enactment process. To ensure a diverse representation of perspectives, participants were selected from varied educational and professional backgrounds, with an emphasis on including individuals with different levels of familiarity with smart home technologies and interactive systems. Additionally, we aimed to balance prior experience with smart environments, ensuring a mix of both novice and experienced users to assess the usability and intuitiveness of the system across different familiarity levels.

Measures

In a structured evaluation of the experiment, several key measures were employed:

- Demographic Questionnaire: This questionnaire was designed to collect essential demographic details such as age, gender, and educational background, alongside assessing participants' previous experiences with VR technology with a head-mounted display. This scale aids in setting a contextual baseline for analyzing their experiences within the VR scenarios.

- Simulator Sickness Questionnaire (SSQ) [637]: The SSQ, with 16 items, was used to monitor and assess symptoms of simulator sickness (nausea, oculomotor, and disorientation) during VR interactions.

- Presence Questionnaire (IPQ) [570]: The IPQ, with 14 items, was used to measure participants' immersion and sense of presence (General Presence, Spatial Presence, Involvement, and Experienced Realism) during VR scenarios.

- Open-ended Questions: Following each main interactive scenario, participants were engaged with a set of open-ended questions. These inquiries are detailed in Table 3.16 for the smart frames scenario and in Table 3.17 for the smart kitchen scenario.

	Question
1	*"How did the task make you feel?"*
2	*"What impact did the smart frames have on you during the task?"*
3	*"Is there something you would like to change about the AI assistant actions regarding this task?"*
4	*"Is there something else you would like to say?"*

Table 3.16: Smart Frames open-ended questions.

	Question
1	*"How did the interaction with the AI assistant make you feel?"*
2	*"What do you think about the AI assistant actions?"*
3	*"Is there something you would like to change about the AI assistant actions regarding this task?"*
4	*"Is there something else you would like to say?"*

Table 3.17: Smart Kitchen open-ended questions.

Procedure

Before the start, participants received detailed information about the experiment. All participants signed a consent form and completed the Demographic Questionnaire at the beginning of the study. An initial SSQ was administered to establish a baseline for measuring simulation sickness in each condition, based on the participants' initial state. Subsequently, they engaged in the familiarization simulation. At the start of each scenario, each participant read the user scenario aloud. After each main VR simulation, participants completed the IPQ, and another SSQ, and answered four open-ended questions vocally. To minimize the potential for carryover effects—where residual symptoms such as nausea or discomfort from one scenario could influence the next—rest periods were incorporated between the scenarios. These rest periods were designed to allow participants sufficient time to recover from any simulator sickness symptoms before starting the next scenario. The experience concluded with gratitude for the participants' contributions.

Results

In this section, the results of the user study are presented.

Participant Demographics

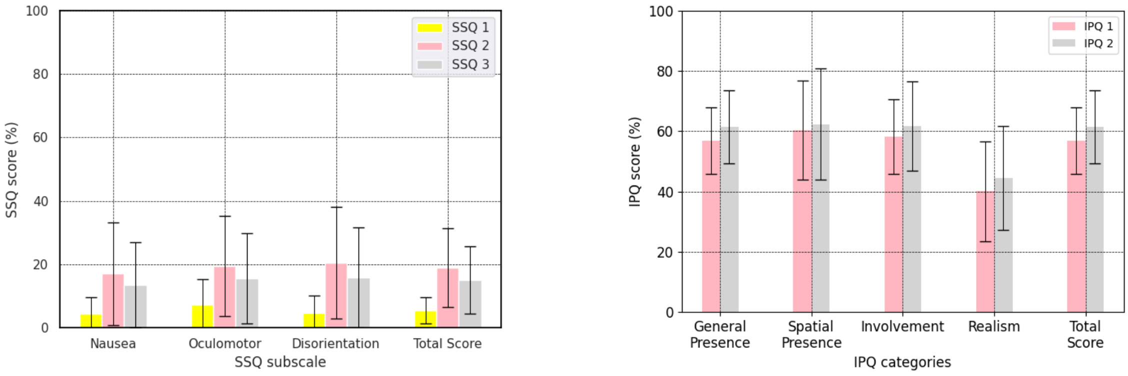
The study's participants were predominantly male, making up 66.67% of the sample. Most participants (86.67%) were between 25 and 39 years old, 10% were between 18 and 24, and 0.03% were between 40 and 60. A significant majority (60%) held a Master's degree, 16.67% held a high school diploma, 13.33% had a Bachelor's degree, and 10% had a doctorate, indicating a highly educated population. Concerning VR usage, 30% had used it a few times, while 26.67% had only experienced it once. Additionally, 23.33% had never used a VR headset, and 20% reported regular use, reflecting a wide spectrum of VR familiarity. This distribution indicates that the study reflects a wide spectrum of VR familiarity among highly educated younger adults.

Subjective Measures: SSQ and IPQ Findings

The Shapiro-Wilk test indicated that SSQ data did not follow a normal distribution. The Mann-Whitney U test showed no significant differences across SSQ dimensions: Nausea ($U = 18.0$, $p = 0.247$), Oculomotor ($U = 16.5$, $p = 0.178$), Disorientation ($U = 4.5$, $p = 0.532$), and Total Score ($U = 15.0$, $p = 0.114$). Although not statistically significant, SSQ2 (Smart Frame scenario) scores were consistently higher, indicating a tendency towards more simulator sickness symptoms in the Smart Frame scenario (Figure 3.33a). Previous research suggests SSQ scores below 20% are acceptable [130]. While SSQ2 approaches this threshold, SSQ1 and SSQ3 remain comfortably below it, indicating that SSQ2 shows potential discomfort.

For IPQ dimensions, the Shapiro-Wilk test showed that the General Presence score did not follow a normal distribution, while Spatial Presence, Involvement, and Experienced Realism adhered to a normal distribution. The Wilcoxon signed-rank test for General Presence ($W = 22.0$, $p = 0.025$) indicated a significant difference between IPQ1 (Smart Frame scenario) and IPQ2 (Smart Kitchen scenario). Paired t-tests for Spatial Presence ($t = -0.608$, $p = 0.548$), Involvement ($t = -1.439$, $p = 0.161$), and Experienced Realism ($t = -1.961$, $p = 0.060$) showed no significant differences. However, the paired t-test for the Total Score ($t = -2.887$,

$p = 0.007$) revealed a significant difference between the two conditions, indicating an overall variation in the sense of presence across the Smart Frame and Smart Kitchen scenarios. Figure 3.34b reflects these results. This suggests that while the VR experience maintained consistent levels of spatial presence, involvement, and realism across both scenarios, significant differences were observed in both the General Presence and overall presence (Total Score) between the Smart Frame and Smart Kitchen conditions.



(a) (b)

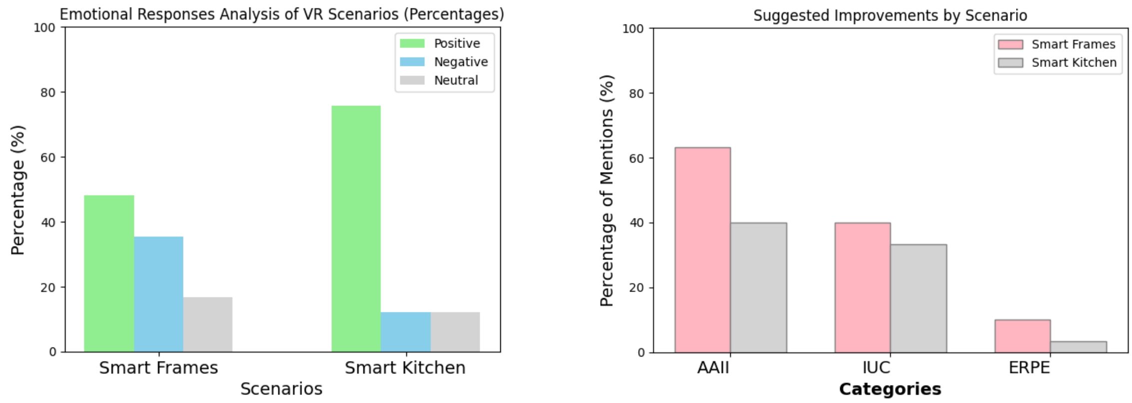
Figure 3.33: Comparison of SSQ and IPQ scores (%) at different stages of the experiment. Subfigure (a) presents the SSQ (Simulator Sickness Questionnaire) results, comparing scores across three experimental conditions: SSQ1 (Base), SSQ2 (Smart Frames), and SSQ3 (Smart Kitchen). Subfigure (b) shows the IPQ (Igroup Presence Questionnaire) results, comparing the sense of presence between two conditions: IPQ1 (Smart Frames) and IPQ2 (Smart Kitchen).

Thematic Analysis of Interview Responses

In this section, we aim to report key themes in participants' interview responses and provide actionable insights for enhancing AI-assisted VR smart homes. The process began with transcribing and processing responses from open-ended questions using Whisper [946], an ASR model by OpenAI. The transcriptions were translated into English by a native Italian speaker for consistency. Thematic analysis was conducted to identify recurring themes and patterns. The coding process revealed two primary themes for each scenario: "emotional responses" and "suggestions for improvement". Emotional responses were further categorized into three sub-themes: "positive," "negative," and "neutral." Suggested improvements were grouped into three sub-themes: "AI Assistance and Interaction Improvements," "Improving Usability and Control," and "Enhancing Realism, Presence, and Engagement." The results of the thematic analysis, detailing suggested improvements and emotional responses for Smart Frames and Smart Kitchen scenarios, are presented in Tables 3.19 and 3.18.

Emotional Responses Analysis

The percentages of positive, negative, and neutral emotional categories mentioned in each scenario were calculated to quantify the overall emotions of the participants. The analysis, depicted in Figure 3.34a, shows that the Smart Frames scenario elicited 49% positive, 36% negative, and 17% neutral emotional responses reflecting a mix of emotions. In comparison, the Smart Kitchen scenario garnered 56% positive, 9% negative, and 9% neutral emotions, highlighting a high level of positive emotions during the experience.



(a) Emotional Response Analysis for the scenarios.

(b) Suggested improvements: AI Assistance and Interaction Improvements (AAII), Usability and Control (UC), and Realism, Presence, and Engagement (RPE).

Figure 3.34: Emotional responses and suggested improvements results

Suggested Improvements Analysis

The analysis of participant feedback reveals key areas for improvement in both the Smart Frames and Smart Kitchen scenarios. The "AI Assistance and Interaction Improvements (AAII)" category was mentioned by 19% of participants for the Smart Frames scenario and 12% for the Smart Kitchen scenario. "Improving Usability and Control (IUC)" was highlighted by 12% of participants in the Smart Frames scenario and 10% in the Smart Kitchen scenario. Lastly, "Enhancing Realism, Presence, and Engagement (ERPE)" was mentioned by 3% of participants for Smart Frames and 1% for Smart Kitchen (Please see figure 3.34). The analysis identifies "AI Assistance and Interaction Improvements" as a primary focus for enhancement, with the Smart Frames scenario needing more attention than the Smart Kitchen.

Discussion

This study aimed to investigate how Virtual Reality (VR)-based user enactment can be used to explore user perceptions and interactions with a proactive AI assistant in a smart home environment. By addressing two research questions, the findings provide meaningful insights into the design and user experience of such systems.

RQ 1: How can we create a feasible and immersive VR smart home experience for a user enactment study to explore user perception, interaction, and the impact of a proactive AI assistant in daily scenarios? We developed an immersive VR smart home to study user perception, interaction, and the impact of a proactive AI assistant in two daily scenarios, overcoming fidelity, control, and environmental constraints. This VR environment offered valuable insights, demonstrating its feasibility for supporting such studies. Participants reported a high level of presence and immersion (See Figure 3.34b and Table 3.19), indicating that the design elements of the VR environment were successful in replicating a familiar and interactive home setting. The use of high-realism 3D modeling, realistic lighting, and spatial audio significantly contributed to the sense of immersion, making participants feel like they were in an authentic smart home environment. High level of immersion and presence are crucial for generating valid and reliable insights from user enactments in VR, as it allows participants to engage deeply with both the environment and the AI assistant [597].

RQ 2: How do participants perceive, interact, and give feedback about their interactions with the proactive AI assistant across these daily scenarios in this virtual smart home environment?

The interactions with the proactive AI assistant varied between the two scenarios, reflecting the different cognitive and emotional demands they imposed. As shown in Figure 3.34a, participants in the Smart Frames scenario exhibited a significant proportion of negative emotional responses (about 40%), with only around 50% expressing positive emotions. In contrast, the Smart Kitchen scenario received highly positive feedback (around 80%) with minimal negative responses. This divergence suggests that while the overall VR environment was immersive, the stress induced by the Smart Frames task hindered participant satisfaction.

Participants reported a wide range of emotions in both the Smart Frame and Smart Kitchen scenarios, with overall similar comments (Please see Table 3.19). However, the nature of negative emotions differed: task-related frustrations were common in the Smart Kitchen, while time-related stress was more prevalent in the Smart Frame scenario. The mention of competitiveness, determination, and social elements only in the Smart Frame scenario suggests it uniquely triggers a need for social support and a drive for success. Unlike in the Smart Kitchen, participants in the Smart Frame scenario did not express feelings of being supported. In the Smart Frame scenario, the AI assistant was present through voice at both the start and end of the task, as well as via the frames displayed throughout the environment. However, the lack of perceived support from the AI may be attributed to the added pressure of the time-sensitive task. The stress induced by the urgency likely limited the capacity for the AI assistant to be perceived as helpful or supportive, as participants were more focused on completing the task under pressure [1141]. Despite the generally accepted level of simulation sickness reported by users, a higher tendency toward simulation sickness was noted in the Smart Frame scenario (SSQ2) compared to the baseline (SSQ1) and the Smart Kitchen scenario (SSQ3) (See figure 3.33a). This suggests that certain elements, such as rapid movement or the stress-inducing nature of the task, caused physical discomfort despite the overall comfort. Adjustments to movement mechanics or visual stimuli, particularly under time pressure, could mitigate simulator sickness for prolonged use. For example, smoother transitions or reducing visual complexity during high-stress tasks might lessen discomfort [671]. The significant difference in General Presence and total presence score between the Smart Frame and Smart Kitchen scenarios likely reflects the design intent of the Smart Frame scenario, which introduced time-related stress. The lower presence in the Smart Frame scenario is expected, as participants were more focused on completing a time-sensitive task than immersing themselves in the virtual environment

[66]. Rather than indicating a flaw, this result suggests that the scenario effectively achieved its goal of creating a high-pressure, attention-demanding experience.

In the Smart Kitchen scenario, participants generally perceived the AI assistant as supportive and helpful, particularly in guiding them through the recipe selection process and offering suggestions based on product expiration dates. Many participants expressed feelings of comfort and satisfaction, reporting that they felt guided and supported by the AI. The assistant's ability to provide timely, relevant information contributed to a sense of comfort, suggesting that proactive AI systems can meaningfully enhance user experience when they offer contextually appropriate support [497]. In contrast, the Smart Frames scenario elicited more mixed feedback. Participants reported higher levels of stress and pressure due to the time-sensitive nature of the task, which detracted from their perception of the AI's effectiveness. While the AI assistant attempted to reduce stress by reminding users of pleasant memories through changing smart frames, participants felt that this support was insufficient to mitigate the urgency of the task.

Based on collected suggestions from participants (See Table 3.18), areas for improvement were systematically identified to enhance user interaction and experience. Figure 3.34 shows that participants suggested more AI Assistance and Interaction Improvements (AAII) in the Smart Frames scenario (60%), stressing the need for better context-sensitive prompts and adaptive behaviors in high-pressure tasks. Usability and Control (IUC) improvements were also mentioned (50% in both scenarios), reflecting a desire for more control over AI interaction frequency and style. Lastly, some participants highlighted the need for enhanced Realism, Presence, and Engagement (RPE), particularly in Smart Frames.

Given these findings, we identified several key areas where the design of VR-based user enactments, particularly those involving proactive AI assistants, can be refined to enhance user experience and interaction. Participant feedback, as detailed in Table 3.18, suggests that while the system was generally effective, there are significant opportunities to improve user comfort, control, and engagement. The following recommendations are derived from the feedback presented in the table:

- Adaptive Feedback Mechanisms: As noted by participants in the Smart Frames scenario, users felt that the AI assistant could have been more responsive in high-pressure situations by offering more detailed and context-specific prompts. For example, participants suggested that the AI could provide reminders of object locations or offer visual cues to help mitigate stress. Such adaptive feedback would allow the AI to better respond to user needs without being overly intrusive, which could enhance the perception of support during stressful tasks.

- Minimizing Simulator Sickness: In both scenarios, but particularly in the Smart Frames scenario, some users experienced discomfort due to rapid movement. To address this, participants suggested that VR environments should offer multiple locomotion options to reduce the risk of simulator sickness. Simplifying visual stimuli in high-stress scenarios could also help alleviate physical discomfort and extend user engagement in prolonged VR sessions.

- Multi-modal Interaction: Many participants expressed a need for more audio support during interactions, particularly in the Smart Kitchen scenario, where the AI's voice could provide real-time guidance and reminders. Incorporating multi-modal input—combining voice, visual cues, and even tactile feedback—would improve the realism and usability of the VR experience, reducing cognitive load and enhancing user engagement.

- Personalization and User Control: Users across both scenarios expressed a desire for greater customization in how the AI assistant interacts with them. Participants suggested the ability to control when and how often the AI offers suggestions, which could reduce feelings of intrusion and improve the overall experience. This desire for more user agency aligns with the broader goal of creating AI systems that are more flexible and responsive to individual preferences, particularly in domestic settings where personalization is key to user satisfaction.

Limitation and Future Work

Throughout this project, VR was applied as an extension of traditional user enactment methodology. While VR facilitates a wide range of experiences, its limitations are evident in scenarios requiring high tactile feedback, like cooking or slicing vegetables, where it struggles to replicate physical sensations. These functionalities are not included in this study. Therefore, it is crucial to conduct a thorough feasibility analysis of the intended scenarios and tasks when integrating user enactment with VR, to determine if the advantages of VR surpass those of traditional user enactment methods. Integrating VR in smart home user enactment offers further adaptation opportunities. For instance, creating a VR-based environment supporting multiuser experiences, as suggested by our participants, could yield deeper insights. Additionally, future research should explore haptic feedback technologies, such as wearable haptic gloves, ultrasonic mid-air haptics, or force-feedback systems, to enhance the realism of virtual object interactions. Advancements in physics-based object simulation and AI-driven predictive modeling could further improve the responsiveness and accuracy of virtual object behaviors. By addressing these limitations, future work can expand the applicability of VR-based user enactment, ensuring a more immersive and realistic interaction framework for studying smart home environments.

Conclusion

The integration of user enactment within VR heralds a significant advancement in design research methodologies, offering a novel lens through which to examine user interaction with emerging technologies. This study explored the feasibility of integration of VR in user enactment in the context of human-AI interactions in smart homes, demonstrating its potential to redefine the variables of environmental fidelity, user control, immersion, user interface limitations, and budget constraints. The achievements of this study are notably in the successful adaptation of VR into user enactment settings which allowed for a nuanced investigation into user behaviors and perceptions, providing valuable insights into recommended practices for future VR applications in user enactment studies within smart home contexts.

3.2.14 Insights

Objective

This case study explores how Virtual Reality (VR) can enhance user enactment by allowing users to experience and interact with proactive AI assistants in a smart home environment. The goal is to simulate realistic, daily AI-driven interactions in scenarios like the "Smart Kitchen" and "Smart Frames" settings, to gather in-depth user feedback that informs the design and improvement of AI systems.

Key Technologies

- **VR Smart Home Environment**: Developed using Unity and high-fidelity modeling, it replicates a one-room smart home with lifelike illumination and dynamic interactions for authenticity.
- **Proactive AI Assistant Prototype**: Designed to respond to users in real-time, the assistant offers contextually relevant prompts based on user actions within the VR environment.
- **HTC Vive Pro Headsets**: This headset was used for optimal VR immersion and control, with tools to simulate real-world interactions seamlessly.

Main Findings

- **Adaptive Feedback in High-Pressure Scenarios**: Users noted that the proactive AI assistant provided effective support, though they desired more adaptive feedback in high-stress moments. Participants suggested features such as reminders of object locations or visual cues, which could help alleviate stress and make interactions feel more supportive and responsive in real-time contexts.
- **Simulator Sickness and Comfort**: The study observed varying levels of comfort, with some participants experiencing mild simulator sickness, particularly in scenarios requiring rapid movements, like the Smart Frames. To address this, participants recommended offering alternative locomotion methods and simplifying visual elements in high-stress scenarios to reduce discomfort and extend engagement.
- **Multi-Modal Interaction Preferences**: Users expressed a preference for additional audio support during interactions, especially in complex scenarios such as the Smart Kitchen. Integrating multi-modal inputs—combining voice, visual cues, and potential tactile feedback—was suggested to improve realism and usability, potentially reducing cognitive load and enhancing overall user engagement.
- **User Control and Personalization Needs**: Participants indicated a strong desire for increased control over the AI assistant's interaction style, particularly in terms of when and how often assistance is provided. This feedback highlights the importance of customizable AI systems that are adaptable to individual user preferences, especially in domestic settings, where user autonomy can enhance satisfaction and trust.

- **Personalization and User Control**: Participants expressed a desire for customizable interactions with the AI assistant, highlighting the need to allow users more control over when and how the AI offers support to reduce feelings of intrusion.

Technical and Usability Limitations

- **Maintaining Realism and Immersion**: Replicating realistic, tactile interactions within the VR smart home, such as handling physical objects, presents a challenge due to VR's limitations in providing sensory feedback.

To enhance realism and immersion in the VR smart home, future research should explore haptic feedback technologies that simulate tactile sensations, allowing users to feel and manipulate virtual objects more naturally. Integrating wearable haptic devices, ultrasonic mid-air haptics, or force-feedback gloves could significantly improve interaction fidelity. Additionally, advancements in physics-based object simulation and AI-driven predictive modeling could refine virtual object behaviors, making interactions more intuitive and responsive.

3.2.15 N8: Real-Time Environmental Feedback

Objective and Context

This case study explores the integration of Internet of Things (IoT) sensors within a simulated environment to provide real-time environmental feedback, thereby enhancing user immersion and cognitive engagement. The project leverages temperature and humidity data collected from physical sensors to dynamically adjust visual and auditory elements within a Unity-based virtual environment. By synchronizing real-world environmental conditions with their virtual counterparts, the system creates an interactive and responsive space where the virtual room's weather conditions adapt in real time based on sensor inputs. This approach not only bridges the physical and digital realms but also demonstrates the potential of IoT technologies to transform abstract environmental data into meaningful, interactive experiences that can be utilized in educational and training applications. The primary objective of this project is to establish a seamless real-time feedback loop between physical environmental conditions and their virtual representations, thereby investigating the potential of such systems to enhance cognitive engagement and interaction. By linking real-world sensor data with a virtual environment, the system serves as a dynamic platform for demonstration, allowing users to experience and interact with environmental changes as they occur. By integrating IoT technologies with extended reality (XR) environments, the project exemplifies how context-aware feedback can be utilized to create immersive experiences.

This study aims to investigate the following research question:

- RQ: How can the design and development of an IoT-integrated virtual environment effectively synchronize real-time physical sensor data with virtual feedback to enhance user immersion and interaction?

Related work

The integration of Internet of Things (IoT) technologies with virtual environments has garnered significant attention in recent years, particularly in the context of enhancing user interaction and cognitive engagement. IoT enables the seamless collection and transmission of real-time data from physical environments, which can be leveraged to create dynamic and responsive virtual simulations. Previous studies have demonstrated the potential of IoT in various applications, such as smart homes, environmental monitoring, and interactive learning systems [63, 470].

In the realm of cognitive augmentation systems (CAS), the use of immersive technologies like virtual reality (VR) and augmented reality (AR) has been extensively explored to improve cognitive functions [74, 1071]. These systems leverage the immersive nature of VR and AR to create engaging environments that facilitate active learning and cognitive training. Real-time feedback mechanisms are crucial for maintaining user engagement and ensuring the responsiveness of virtual environments. Prior research has explored various methods for implementing real-time data processing and visualization within virtual simulations. For example, studies have utilized WebSocket and Hypertext Transfer Protocol (HTTP) protocols to facilitate continuous data transmission between physical sensors and virtual environments, ensuring minimal latency and high reliability [1257, 370]. The project employs HTTP requests at regular intervals to fetch sensor data, aligning with best practices identified in the literature to balance responsiveness with network stability. Moreover, the application of IoT in educational settings has been shown to enhance learning outcomes by providing students with interactive and tangible experiences. IoT-enabled simulations allow learners to visualize and manipulate real-world data, thereby fostering a deeper understanding of complex concepts such as environmental science and engineering principles [26, 786].

Despite the advancements in IoT and virtual simulations, there remain gaps in the seamless integration of real-time sensor data with highly interactive virtual environments tailored for cognitive augmentation. This project addresses this gap by establishing a continuous feedback mechanism between physical sensors and the virtual space, thereby potentially enhancing the interactivity and responsiveness of the simulation.

Material and methods

Selection of the tools

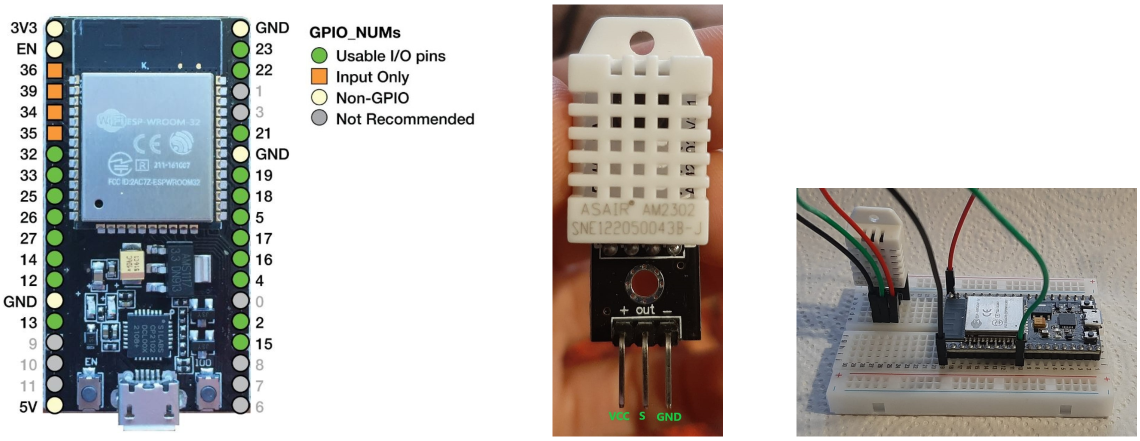
- **Hardware:**
  - **ESP-WROOM-32** (see figure 3.35a): The ESP-WROOM-32, also known as the ESP32, is a small electronic chip that allows devices to connect to the internet or other Bluetooth devices. It's popular for use in homemade gadgets and small projects because it's affordable and has the ability to handle many tasks at once. The ESP32 can connect to Wi-Fi networks and has Bluetooth, which means it can easily communicate wirelessly, making it perfect for things like smart home devices or fitness trackers. Its size is also very convenient, as it can fit into tight spaces, which is great for projects that need to be compact.

- **DHT sensor** (see figure 3.35b): The DHT sensor series is well-known for measuring temperature and humidity in various environmental monitoring situations. These low-cost digital sensors are known for their ease of interfacing with microcontrollers, such as the ESP-WROOM-32, and for their all-in-one ability to provide fairly accurate readings of both temperature and humidity. The DHT sensors, particularly popular models like the DHT11 and DHT22, work by incorporating a thermistor for temperature measurement and a capacitive humidity sensor for gauging moisture levels in the air. They communicate with a host microcontroller, using a proprietary protocol to transmit the sensor readings. Due to their simplicity, these sensors are extensively utilized in home automation systems, weather stations, and any application where basic environmental data collection is needed.

- **Software:**
  - **Unity**: A versatile game engine widely used for developing video games, simulations, and interactive experiences. It supports both 2D and 3D graphics, offers multi-platform deployment (PC, mobile, VR/AR), and uses C# for scripting. Unity's asset store provides pre-made resources, accelerating development.
  - **Arduino**: An open-source electronics platform designed for interactive hardware projects. It features microcontroller boards compatible with a vast range of sensors and actuators, making it ideal for applications in robotics, automation, and education.

Assembling the hardware and software components:

- **Components:**
  - ESP-WROOM-32 (ESP32) module
  - DHT-22 temperature and humidity sensor
  - Jumper wires
  - A USB cable to connect ESP32 to the computer
- **Connections:** We need to establish connections between the DHT-22 sensor (See figure 3.35c), and the PC. Generally, DHT-22 comes with three pins, which are labeled accordingly and should be connected as follows:
  - the VCC (+) pin of the DHT-22 to the 3.3V or 5V pin on the ESP32.
  - the GND (-) pin of the DHT-22 to a GND pin on the ESP32.
  - the S (out) pin of the DHT-22 to a digital I/O pin on the ESP32, such as pin 26.



(a) ESP-WROOM-32 (b) DHT-22 (c) Connections

Figure 3.35: ESP-WROOM-32, DHT-22, and their wiring setup.

System Architecture

The system architecture is meticulously designed to ensure seamless data flow and real-time responsiveness. It comprises several critical components, including the Espressif Systems Platform 32-bit (ESP32) microcontroller, Digital Humidity and Temperature sensor, model 22 (DHT22) temperature and humidity sensors, and a Unity-based simulated environment. These elements work in concert to create a robust data feedback loop that translates physical environmental conditions into virtual adjustments. The ESP32 microcontroller serves as the central hub, chosen for its cost-effectiveness, built-in Wi-Fi capabilities, and processing power. It facilitates the acquisition of environmental data from the DHT22 sensors and ensures reliable transmission of this data to the Unity environment over a local Wi-Fi network. The ESP32's versatility allows for future expansions, such as the addition of more sensors or integration with other IoT devices. The DHT22 sensor is selected for its accuracy and reliability in measuring temperature and humidity. Its ability to provide precise real-time data is crucial for accurately simulating environmental conditions within the virtual space. The sensor's compatibility with the ESP32 ensures seamless data integration and transmission. On the software side, the Arduino Integrated Development Environment (IDE) is utilized to program the ESP32 microcontroller. It manages the interaction between the ESP32 and the DHT22 sensors, enabling the collection and transmission of environmental data. The Arduino code is optimized to handle data sampling at regular intervals and to ensure efficient communication with the Unity application through HTTP protocols.

The virtual environment is meticulously crafted to reflect a realistic and responsive space that reacts to real-time environmental data. A virtual room is designed within Unity to simulate various weather conditions based on temperature and humidity readings from the DHT22 sensors. The system employs several distinct weather scenarios, each corresponding to specific environmental thresholds (See figure 3.36). When the temperature exceeds 20.9°C, the "sunny" scenario enhances the environment with brighter lighting, simulating sunlight. Visual elements such as sun rays and clear skies are activated, while auditory feedback includes ambient sounds like birds chirping and gentle breezes, creating a warm and inviting atmosphere. When the temperature drops below 0°C, the system initiates a snowy scenario. Unity's particle system is utilized to generate realistic snowflakes, and lighting is adjusted to reflect colder conditions with a bluish tint. Accompanying sounds, such as the howling of wind and the soft fall of snow, enhance the immersive experience. If the temperature remains above 0°C but humidity exceeds 57.9%, the environment simulates rainfall. Visual effects include animated rain particles and darkened skies, while auditory elements feature the sound of rain pouring and occasional thunderclaps, providing a dynamic and realistic representation of rainy conditions. In scenarios where temperatures range between 0°C and 20.9°C without triggering snowfall or rainfall, the system simulates a cold but dry environment. This is achieved through dimmed lighting and subtle environmental effects such as a slight breeze or the activation of virtual fans and heaters, maintaining a comfortable yet responsive virtual space. To further enhance realism and interactivity, objects within the virtual room respond to environmental changes. For instance, during cold weather, a virtual hot drink may appear on a table, and heaters might activate to simulate warmth. Conversely, in warmer conditions, fans could turn on, and drinks may appear chilled. These interactive elements not only add to the immersive experience but also provide tangible cues that help users connect real-world data with virtual responses.

(a) Example 1: Cold condition with a temperature of 10°C; Humidity: 14%.

(b) Example 2: Rain condition with a temperature of 18.9°C; Humidity: 62.5%.

(c) Example 3: Snow condition with a temperature of −5°C; Humidity: 80%.

(d) Example 4: Sunny condition with a temperature of 25°C; Humidity: 30%.

Figure 3.36: Weather Conditions for the Virtual Room

Planned Evaluation and Data Collection Framework

To evaluate the usability and effectiveness of the IoT-integrated virtual environment, a structured between-subjects study will compare user experiences in adaptive (real-time feedback) and static (non-responsive) climate conditions in VR. Participants will be randomly assigned to one of the two conditions, ensuring that each individual experiences only one type of environmental feedback. The study will recruit university students and professionals aged 18–45, maintaining a diverse sample with varying levels of familiarity with VR and IoT while excluding participants with visual or hearing impairments to ensure consistency in perception and interaction. The experiment will begin with a pre-study questionnaire to assess user demographics, prior XR experience, and baseline environmental awareness. Following a brief training session, participants in each condition will engage in a VR session tailored to their assigned group—either interacting with a static environment where climate conditions do not change or an adaptive environment where real-time sensor data dynamically alters climate conditions. They will perform exploratory and task-based activities, such as adjusting virtual objects to match environmental changes or identifying real-time climate variations. Data collection will include both objective and subjective measures. Task completion time, interaction accuracy, and response efficiency will be logged, while post-experiment surveys will assess immersion, usability, and cognitive engagement using Likert-scale ratings and open-ended feedback. Statistical analysis, including independent t-tests and ANOVA, will compare engagement and immersion levels between the two groups, while qualitative responses will inform usability refinements. Findings will guide future enhancements, such as improving system responsiveness, refining sensor integration, and expanding applications to educational and training simulations for environmental awareness and emergency preparedness.

3.2.16 Insights

Objective

This case study investigates the integration of Internet of Things (IoT) sensors within a virtual environment to provide real-time environmental feedback. By synchronizing physical environmental data—such as temperature, humidity, and air quality—with virtual elements, the study aims to enhance realism, immersion, and cognitive engagement within XR applications. This approach has potential applications in educational settings and training simulations where real-time environmental data could offer an interactive learning experience.

Key Technologies

- **IoT Sensors (Temperature, Humidity)**: Physical sensors capture real-world environmental data, which is then used to dynamically adjust the virtual environment in real-time.

- **Unity 3D and IoT Hub Integration**: Unity 3D serves as the primary platform for the virtual environment, while an IoT hub facilitates data collection and transfers sensor data to Unity for immediate adjustments within the XR space.

- **Real-Time Data Processing**: Data from IoT sensors is processed continuously, enabling the virtual environment to simulate real-world conditions, such as replicating outdoor temperature fluctuations or air quality changes.

Potential Findings

- **Increased User Immersion through Real-Time Feedback**: Integrating real-time environmental data, such as temperature and humidity, into the virtual environment is expected to enhance user immersion. Users may experience a more lifelike interaction as the virtual environment adjusts to reflect real-world changes, such as simulating rain or snow based on live sensor input.

- **Enhanced Cognitive Engagement and Awareness**: The dynamic changes in the virtual environment, synchronized with physical environmental conditions, are anticipated to boost cognitive engagement. This responsiveness can help users become more aware of environmental changes, making the experience more interactive and mentally stimulating.

- **Applications in Educational and Training Contexts**: The IoT-integrated environment may offer significant value in educational and training simulations by providing a realistic and adaptive platform. For instance, learners in environmental science or engineering could benefit from seeing real-time data translated into virtual representations, improving their understanding of abstract concepts through interactive visualization.

Technical and Usability Limitations

- **Latency in Data Processing**: Real-time synchronization between physical sensor data and the virtual environment presents latency challenges, especially with sudden environmental changes. Ensuring minimal delay between sensor detection and virtual adjustments is critical for maintaining realism.

- **Environmental Variability and Data Accuracy**: Variations in environmental data due to sensor sensitivity or external factors (e.g., rapid weather changes) can lead to inconsistencies in virtual responses, impacting user experience. Accurate calibration of sensors is essential to maintain alignment between real and virtual conditions.

To address latency in data processing, future work should focus on server-side optimization, including parallel processing, asynchronous data handling, and efficient data transmission protocols to improve real-time responsiveness. Implementing predictive modeling and data interpolation techniques could help mitigate sudden environmental changes, ensuring smoother virtual adjustments with minimal delay. For environmental variability and data accuracy, improving sensor calibration protocols and integrating machine learning-based error correction models could enhance the precision of environmental data interpretation. Utilizing sensor fusion techniques—combining temperature and humidity data—can improve the reliability of virtual representations. Additionally, developing adaptive filtering algorithms could help stabilize fluctuations in environmental data, reducing inconsistencies in virtual responses. By refining real-time synchronization, optimizing server performance, and improving data reliability, future iterations of the system could enhance realism and responsiveness, making it more effective for education, training, and environmental simulations.

3.3 Discussion and Conclusion

This chapter aimed to answer the research question: *How do cognitive augmentation systems impact individual learning, skill development, and cognitive processes?*

Through the presented case studies, we explored the role of these technologies in enhancing individual cognitive abilities.

Several case studies demonstrated how XR environments support cognitive augmentation by providing interactive learning and adaptive feedback. Systems designed for skill acquisition and problem-solving, such as Rubik's Cube Learning (N3) and Puzzle-Solving Assistance (N2), utilized spatially embedded guidance to help users follow structured learning steps. Similarly, the AI-driven Language Learning System (N1) provided adaptive instruction, tailoring feedback based on user performance. These studies highlight how XR-based context-aware instructional methods improve engagement and retention.

Ensuring equitable interaction for diverse users was a central focus in studies exploring bi-manual VR interaction (N5). The bi-manual VR study demonstrated that motion tracking and EMG sensor integration can create accessible XR experiences for individuals with upper limb differences. Meanwhile, enactment-based VR environments (Case study N7) provided insights into how users interact with AI-driven smart home automation, highlighting both the potential for proactive AI adaptation and the usability limitations imposed by simulated environments. Across these studies, the importance of customizable interaction techniques was evident, suggesting that future XR systems should focus on adaptive accessibility models, offering gesture, voice, and gaze-based alternatives to accommodate diverse needs.

Beyond direct user interaction, sensor technologies enabled real-time adaptation of XR environments based on external conditions. In the IoT-integrated XR study (N8), real-world sensor data dynamically influenced the virtual climate, demonstrating how multisensory integration can enhance immersion. Similarly, Outdoor AR Workouts (N4) used real-time sensor data to tailor exercise recommendations based on user conditions. These studies underline the potential of sensor-enhanced contextual adaptation, but they also exposed challenges related to data latency, environmental variability, and real-time synchronization. Improving edge computing and predictive sensor fusion techniques will be crucial for ensuring seamless, real-time adjustments in future XR applications.

The Family Album Preservation study (N6) explored the use of AR and computer vision to digitize and classify historical photographs, enhancing both personal and collective memory through automated metadata generation. This approach demonstrated the potential of XR technologies in archival preservation by seamlessly integrating digital information with physical artifacts.

While XR, AI, and sensor technologies offer substantial advancements in cognitive augmentation, they also pose challenges related to system stability, real-time synchronization, and usability. Future research should focus on integrating AI-driven personalization and refining multimodal interfaces to improve adaptability and accessibility. Additionally, leveraging edge computing, predictive modeling, and more efficient interaction techniques will ensure more responsive and seamless user experiences in cognitive augmentation applications. Expanding studies to diverse user populations and investigating long-term engagement effects will further contribute to the development of more inclusive, effective, and adaptive XR environments.

Table 3.18: Suggested Improvements for Smart Frames and Smart Kitchen

Category	Smart Frames	Smart Kitchen
AI Assistance and Interaction Improvements	**Proactive Help:** AI should offer assistance more proactively. E.g., "Maybe if it had seen me moving frenetically, I would have wanted it to ask if I needed its help." Others proposed features like the AI asking if they remembered where they had put their phone or offering to make the phone vibrate or play music. **More Non-Intrusive Guided Instructions:** More specific help and non-intrusive assistance. E.g., "a bit more specific help with some kind of drawing, a more detailed guide on how to start and perform the tasks," "I would prefer it not to be too invasive with the voice because otherwise, it would distract me and put me under unnecessary pressure, having already the pressure of limited time." **Highlighted Audio Integration:** Incorporating a voice assistant to perform the main actions within the experience. E.g., "If the purpose was to help me stay relaxed to facilitate the task, I would add some sort of voice assistant."	**Motivational Content:** Providing additional content to explain food choices. E.g., "I would provide more content to motivate and explain why some foods are not good." **Expiration Reminders:** Emphasizing the utility of reminders. E.g., "Having a reminder of what is expiring can be useful." **Precise Indicators:** Clearer guidance and fewer distractions. E.g., "It would be useful to have icons that more precisely indicate where things are." **Voice Repetition for Memory Aid:** AI voice repeating ingredients to eliminate the need for memorization. E.g., "If the voice repeated the ingredients, I wouldn't have to memorize them." **Enhanced AI Interaction:** More feedback from the AI and interactive system. E.g., "I would have preferred an AI that gives feedback, not only acting for my benefit but also based on what I told it," and "It could interact more, for example, by advising where things are located and maybe communicating more." **Voice Quality:** AI's voice should be more natural. E.g., "The quality of the voice could be less like Google Translate, more similar to the cadence of a human voice."
Improving Usability and Control	**Enhanced Gestures and Sensitivity:** Improvements to gesture recognition and sensitivity. E.g., "To be able to use gestures better," and "To have a quicker sensitivity in grabbing things." **Movement Options:** Offering multiple movement options to reduce motion sickness and improve control. E.g., "There might be less motion sickness if I could move in the space with my body," "Offer options for movement, both in steps and gradually, allowing us to choose our preference." **Visual Comfort:** Slowing down movement to reduce visual discomfort. E.g., "I would slow down the movement a bit."	**Session Spacing:** Spacing out sessions to reduce physical discomfort. E.g., "Compared to the first scenario, I experienced some headaches and dizziness in the second scenario. Maybe, it would be better to space out the two sessions a bit more." **User Approval:** Adding a step for users to approve the AI's choices. E.g., "It feels a bit too invasive. Adding a step where you can approve the AI's choices would be good." Another participant emphasized that the AI should not make decisions without user approval, especially in specific contexts like recipe preparation: "If it had proposed options to me, I might have considered them, but it shouldn't spend money without first asking for approval. You might be shopping to make a birthday cake for someone, and obviously, the recipe will have a large amount of sugar. I don't think it's okay for the AI to choose for you in that case."
Enhancing Realism, Presence, and Engagement	**Increased Realism:** Creating a more realistic and engaging environment. E.g., "It would be interesting to feel more the sensation of being there." **Social Presence:** Adding a social element. E.g., "It would be nice if there was a person inside the house to keep you company." **Interactive Environment:** Making the environment more interactive. E.g., "Opening the doors with the computer or a phone."	**Realistic Appearance:** Enhancements to realism and presence. E.g., "I would try to give a slightly more realistic appearance to myself." **Lighting Details:** Accurate lighting to avoid confusion. E.g., "I noticed a detail on the lighting where you could see the shadow of the hands and the controller, which could create confusion."

Table 3.19: Emotional Responses for Smart Frames and Smart Kitchen

Category	Smart Frames	Smart Kitchen
Positive	**Excitement, and Anticipation:** Participants expressed excitement and anticipation about the experience. E.g., "I was very excited to try a new experience." **Calming and comforting:** Many participants found the task calming and comforting. E.g., "I was able to complete the task calmly." **Immersion and Engagement:** Participants felt deeply immersed in the VR environment. E.g., "I did feel like I was in that reality." **Satisfaction, and Accomplishment:** Participants expressed feelings of satisfaction. E.g., "Once I followed the instructions, I was able to complete it calmly." **Simple, and Easy:** Many participants found the task simple. E.g., "The task was easy to perform." **Curiosity:** Participants expressed curiosity about the new experience. E.g., "I was curious to see what a virtual world was like." **Competitiveness and Determination:** Some participants felt competitive. E.g., "It made me feel competitive."	**Excitement, and Anticipation:** Participants expressed excitement about the experience. E.g., "I felt excited." **Calming, and comforting:** Many participants found the task calming. E.g., "I found the experience relaxing." **Immersion and Engagement:** Participants reported immersion in the experience. E.g., "Living the experience involved me a lot." **Satisfaction:** Participants mentioned feelings of satisfaction. E.g., "Very positive." **Utility and Convenience:** Participants found the AI assistant practical. E.g., "I think it's useful." **Support and Gratitude:** Participants felt supported by the AI assistant. E.g.," I felt supported this time."
Negative	**Anxiety and Pressure:** Many participants felt anxious due to the task's timed nature. E.g., "I was under pressure." **Frustration, Difficulty (technical):** Participants experienced technical frustration. E.g., "I had difficulty understanding how to grab and move within the space." **Confusion:** Confusion was common. E.g., "I was confused at the beginning because I couldn't find the objects I needed." **Disorientation and Tension:** Some participants felt tense and disoriented. E.g., "There was a dissociated impact between my reality and what the headset was proposing to me." **Physical Discomfort and Dizziness:** Physical discomfort was reported. E.g., "I had some problems with nausea." **Annoyance and Clumsiness:** Some felt clumsy during the task. E.g., "I felt clumsy navigating the virtual environment."	**Anxiety and Pressure:** Participants reported anxiety due to task pressure. E.g., "I have to look in the fridge and figure out what is about to expire." **Frustration, Difficulty (cognitive):** Participants experienced cognitive frustration. E.g., "I had to look in the fridge and figure out what is about to expire." **Discomfort and Alienation:** Participants reported discomfort and alienation. E.g., "I didn't feel comfortable." **Intrusiveness:** Participants felt the task was intrusive. E.g., "I was supervised."
Neutral	**Normalcy and Routine:** Some participants found the task routine. E.g., "It's a routine task." **Neutral or Indifferent:** Some expressed indifference. E.g., "I didn't feel particularly uncomfortable." **Unusual and Strange:** Some found the task unusual. E.g., "The experience was peculiar."	**Normalcy and Routine:** Participants felt a sense of normalcy. E.g., "It felt like normal." **Neutral or Indifferent:** Some expressed a neutral attitude. E.g., "The interaction was not significantly different." **Unusual and Strange:** Participants found the experience unusual. E.g., "It gave me a sense of alienation."

Chapter 4

Interpersonal Augmentation and Group Dynamics

The integration of extended reality (XR), artificial intelligence (AI), and sensor technologies can potentially offer spaces where humans can communicate, collaborate, and solve problems, regardless of physical location or cognitive abilities. In this chapter, we explore how these technologies foster ***social interaction and group dynamics***, enhancing cooperation through real-time feedback, and shared experiences. XR environments offer immersive, collaborative spaces where users can interact with digital objects and each other in real-time. In addition to facilitating human-human collaboration, AI systems within these environments adapt to dynamics and act as active collaborators. These AI systems can function as team members, guiding group decisions or performing specific tasks in coordination with human users. Meanwhile, sensor technologies monitor users' physical and emotional states, allowing the system to detect performance and engagement levels and adjust the collaborative experience. This feedback loop enhances the efficiency and productivity of both human-human and human-AI interactions.

4.1 Theoretical Background

Collaboration, social interaction, and group dynamics are essential elements for effective teamwork in everyday experiences. Recent technological advancements have opened new avenues for exploring how Extended Reality (XR), Artificial Intelligence (AI), and sensor technologies can enhance these social processes within virtual and augmented environments [1052].

Previous studies highlight that engagement and outcomes are significantly enhanced when individuals participate in dialogue, negotiation, and co-construction of ideas within a group [1313]. XR technologies offer platforms that support such collaborative interactions by allowing users to work together on shared activities, regardless of physical location. For example, Billinghurst et al. (2001) introduced the MagicBook, an augmented reality (AR) system that facilitates collaboration by enabling users to interact with both real and virtual worlds, allowing for shared experiences that improve collective task performance and engagement [129]. In Mixed Reality (MR) environments, users can manipulate virtual objects, share resources, and interact with each other. For instance, Steptoe, Steed, and Slater (2010) explored the use of Virtual Reality (VR) for collaborative environments by integrating eye-tracking technologies, which enhance social presence and coordination among users during group tasks. The use of eye-tracking sensors in this study allowed for more natural interactions, significantly improving the sense of collaboration and the effectiveness of group decision-making. By tracking where users are looking and how they engage with virtual objects, the system was able to provide a more cohesive and engaging collaborative experience [1238].

Social Presence Theory, which examines the degree of awareness and connection between users in mediated communication environments, is particularly relevant [1172]. Slater et al. (2000) demonstrated that social presence in VR environments can closely mirror real-world interactions, showing that users engaged in collaborative tasks experienced a heightened sense of co-presence. This sense of co-presence directly contributed to improved group dynamics and task performance [1195]. AI-driven virtual assistants have been shown to support collaborative tasks in AR settings. Chang et al. (2013) explored how AI, combined with sensor technologies such as gesture recognition, can enhance educational collaboration by offering real-time feedback and adaptive task support. This integration of AI and AR facilitated group problem-solving by ensuring that all participants received contextually relevant assistance, thus improving both learning outcomes and group cohesion [215]. These advancements demonstrate the potential of these technologies to revolutionize social interaction and cognitive augmentation in various collaborative settings.

In this chapter, we aim to further explore how the integration of these technologies can impact collaboration, social interaction, and group dynamics within immersive environments by examining case studies that highlight shared virtual and augmented experiences. Specifically, this chapter addresses this key research question:

- RQ: How do cognitive augmentation systems enhance social dynamics, teamwork, and collaborative experiences in shared virtual environments?

4.2 Case Studies (N9 - N11)

In this chapter, the potential of XR, AI, and sensor technologies in supporting collaboration and social interaction is illustrated through the design and development of case studies. By addressing the question of how these advanced tools can bridge the gap between remote users, these examples reveal both the benefits and challenges of fostering social presence and teamwork in virtual environments.

4.2.1 N9: Virtual Office Experience for Experiencing Uncertainty

Objective and Context

Most of us would agree that uncertainty, in many circumstances, is not something we like to experience. For example, we do not wish to be uncertain about our ability to pay bills at the end of each month, our work and educational prospects, and our health [268]. Some studies in neuroscience also support this claim by providing evidence that the human brain is hardwired to interpret uncertainty as a danger and respond to it with fear and stress [990, 863]. A human brain under uncertainty tends to overestimate and dramatize danger [642], jump to conclusions [111], and underestimate its ability to handle it [673, 468, 818].

Following this approach to uncertainty, the goal has been to reduce it [1240, 1239]. For example, people are encouraged to reduce the uncertainty of loss of income in old age or of possible unemployment with saving money, paying taxes, and buying insurance policies [268]. In education, traditionally, uncertainty is often seen as a threat and removed by exposing students to clearly defined problems, following predefined methods of solving them, to reach expected outcomes [721]. The reality is that we live in an uncertain and complex world [268]. Despite our best efforts, things do not always go as planned, and unexpected events may happen. Hence, one should strive to accept uncertainty, performing tasks aware of its existence instead of amplifying its fear with the risk of arguing with life rather than living it. The recent experience with COVID-19 supports such an idea [72]. This is why many educators have recently sought the best ways to provide a structured and supportive learning environment to prepare young students to respond productively to the challenges originating from dealing with uncertainty [333, 1003]. As described by Beghetto [102], novel learning environments should structurally offer uncertainty, engaging students with it, teaching them how to sit with its difficulty, how to explore, how to generate and evaluate new possibilities, and, most importantly, take action based on them [104]. In this way, uncertainty may act as a catalyst for creative answers rather than an unbeatable barrier. This approach motivates the idea of designing and implementing platforms to support the study of the behavioral responses that the uncertainty may trigger [1000, 1264, 72].

The broad concept of uncertainty is, in fact, closely connected with that of information which, in turn, is at the core of interpersonal communications [661, 116]. Interpersonal communication concerns the study of social interaction between people and tries to understand how verbal and written dialogues, as well as nonverbal actions, are used to achieve communication goals [115]. Studies show individuals facing different levels of uncertainty have different behavioral responses, from negative to positive [669, 675, 155]. The ways a human being may deal with an uncertain situation may differ based on individual differences [48], culture [537], and the level of expertise [692]. Hillen et al presented a conceptualization of an individual's experience of uncertainty based on a categorization of potential responses [526]. In such a model, ambiguities or/and complexities generate(s) stimuli to the information system. Uncertainties appear when individuals perceive (consciously become aware of) their existence. Cognitive, emotional, and behavioral responses then follow such a perception.

Virtual Reality (VR) systems may act as feasible platforms to assist in understanding behavioral responses to the uncertainty of interpersonal communications, as they may provide 3D spaces involving the same kind of navigational and communication challenges experienced in the real world [800]. With VR, it is possible to create structured environments where the ability of people to cope with challenges can be observed, behavioral data gathered, eventual achievements and feedback engineered, and strategies for skill improvement applied in a top-down fashion [301, 172, 148, 1306]. In VR, people can express their ideas, feel in control, and accomplish tasks and communicate with others [472, 255, 1208, 535]. This raises the potential to enjoy and engage in activities in the digital space and then apply them to the real world to improve one's social well-being [153]. In addition, creating such an experience in the context of a serious game can support situated cognition by contextualizing a player's experience in an engaging and realistic environment [296]. In addition, it can benefit from those game design techniques that support the idea that uncertainty could potentially maintain a user's attention and engagement, providing the motivation to continue even in challenging moments [268].

Considering this domain, we propose the design and development of an immersive virtual reality experience whose scope is to support the investigation of how people manage uncertainty while performing tasks in a workplace scenario. This experience, implemented as a serious game, aims at simulating a workplace scenario, a social environment where success in managing effective interpersonal communication appears very important [886, 1404, 92, 812, 471].

With this work, we aim to contribute to the research community by providing answers to the research questions below:

- RQ1: How do the participants rate their experience with different tasks in terms of perceived uncertainty?
- RQ2: How do different degrees of uncertainty affect users' behavior and performance in this immersive virtual workplace scenario?
- RQ3: How are the users' subjective responses to uncertainty related to the objective responses?
- RQ4: How does the user evaluate the quality of his/her experience?

Related Work

In this section, we present and discuss the works that fall closest to our contribution.

A good body of research has focused on the study of "Navigational uncertainty" and its effect on the user's spatial navigation performance and behavior [1230, 175, 174, 518]. In this area of research, uncertainty has been mostly introduced into the system by creating a perception of disorientation [225] and curing conflict [527] for the user, resulting in an increase in his/her information-seeking behavior. In their recent review, Keller et al. [631] proposed that collecting and analyzing continuous navigational data obtained from the participants in virtual reality experiences that create navigational uncertainty can potentially provide important insight into their information-seeking behavior. For example, in this research [175], the authors focused on the "Looking around behavior" as a common type of information-seeking behavior of participants when experiencing navigational uncertainty. They recorded continuously the heading direction and tried to find its relation to navigational success measures. From this body of literature, we could conclude the potential and importance of the data that could be captured from VR experiences to provide insights into the behavioral responses of people, especially in the study of the effects of a variable, such as uncertainty, on behavior.

Another area in which the study of uncertainty has received a lot of attention is gaming. As Costikyan et al. [268] claim, games could improve by purposefully applying the concept of uncertainty in their designs. Uncertainty could act as a catalyst to hold users' attention and interest; mastering it may help pursue a game's goal in an efficient and non-threatening way [1231]. In addition, Costikyan et al. [268] support these claims by citing the sociologist Roger Callios [192] "Play is... uncertain activity. Doubt must remain until the end, and hinges upon the denouement... every game of skill, by definition, involves the risk for the player of missing his stroke and the threat of defeat, without which the game would no longer be pleasing. The game is no longer pleasing to one who, because he is too well trained or skillful, wins effortlessly and infallibly".

In the following, we review some examples of games that exploit uncertainty in their design and present a comparison of their features in Table 4.1:

- Gone Home [1380] is a first-person exploration game designed to put players in unknown situations, engaging them to stay and accomplish some tasks, such as uncovering the narration by non-linear progression through searching the space. This game puts a player in the shoes of a young woman who returns home and finds that her family is absent. As Veale et al. [1301] also discussed, Gone Home is a video game that uses effective storytelling to create empathy and a sense of responsibility in users by placing them within a recent historical moment. In this way, it exposes the user to the positive and negative elements of the past and encourages him/her to stay in the game and reflect on these elements [1198]. While not strong on interactivity, the game through a careful visual, spatial, and audio design of the environment leads its users to explore the house along a twisting, uncertain path and find out what happened to the woman's family through an analysis of imperfect clues from the memorabilia, journals, and other items left around the various rooms. During the experience, there are notes, voices, and letters from or to her family that motivate and guide her in the exploration. These items of cues can be kept in the inventory and reviewed whenever desired [1380]. Considering an interest in the study of navigational behaviors of users, Bonnie Ruberg [1091] argues that with a deeper analysis of the interactive elements of the game, the player path is linear instead of meandering despite what it seems the game encourages players to do. The path is already set and the locked, or hidden doors prevent the user to have access to some areas unless they trigger an event or find an object that unlocks this barrier in a predefined order.

- Don't Starve [348] is a survival game that places the user in the role of a scientist who finds himself in a strange and unfamiliar world. The goal is to collect and effectively use survival tools. An uncertain scenario amounts to the interaction with the frogs in the game, as this creates ambiguity, as it is unclear whether they are hostile. For example, they can represent food, but different outcomes may result from eating them. The game successfully engages the user to accept this ambiguity till effectively able to develop higher-level strategies to interact with them. Farah et al. [362] studied the multiplayer expansion of the game to track cooperative features and teamwork behavioral markers.

- Wenge xu et al. [1370] developed a motion-based survival game, GestureFit, that involves the user in a fight with a monster. They induced uncertainty in the system through three uncertain game elements: false attacks (creating the perception that there would be a chance that the system is tricking the player to waste a defense move by defending against a false attack), misses (creating the perception that there would be a chance that the actual hit will be interpreted as a miss), and critical hits (creating the perception that there would be a chance that an attack would be a critical attack and produce more damage than a normal one). In this way, they created two different levels of uncertainty, one with inducing these uncertain elements into the game and the other without. After, they conducted a study to measure the effects of levels of uncertainty (certain and uncertain), the display type (VR and LD), and age (young adults and middle-aged adults) on the game experience, performance, and exertion level. Their results showed that for the kind of game they designed, virtual reality could improve game performance. In addition, they found that the uncertain elements that they applied in their design might not help enhance the overall game experience, but could help increase the user's exertion.

- RelicVE [764] is a virtual reality (VR) game that gives the user a similar role to an archaeologist and engages him in an exploration process of an archaeological discovery experience. It exploits uncertainty in the design of their exploration process by placing the user in a situation where s/he does not know the shape and features of the target artifact and only can discover it by gradually and strategically using available tools and physical movements. In this way, when the user hits specific triggers, a new part of the information about the artifact will be uncovered. They also managed the complexity of the game by the complexity of the shape and volume of the artifact. They integrated VR interaction techniques in the design of their virtual system to create an experience close to the real-world experience of archaeologists and in this way increased the immersion and physical activity of the user during the experience. In addition, they used a timer and a health bar to add the element of time pressure to the experience. To evaluate the experience, the authors also conducted a usability study that found the experience to be innovative as it can improve players' learning and motivation by adding the elements of uncertainty into the design.

To the best of our knowledge, no previous work took full advantage of the available technologies, such as virtual reality, to induce structured uncertainty and investigate the influence of uncertainty levels on human behavior with a focus on interpersonal communications. Our study tries to take this step from within the design and development of such an application by applying some of the design techniques inspired by the previous games in this area and virtual reality techniques that improve the user experience and the study of behavior.

Table 4.1: A comparison of the elements in the proposed platform with those in the Amelia Bedelia story.

Name of the Element	Description of the Element in Amelia Bedelia Story	Description of the Element in our platform	Reason for Use
Absence of guidance	The housekeeper is asked to accomplish tasks based on the given instructions while does not have access to anybody to communicate her doubts.	The same situation is true here for the user but also s/he can save in the system the type of problem s/he is facing (a problem with the interface and/or a problem with the instruction).	This design choice limits the access to the sources of information, asking to focus and rely on the already provided knowledge or may come after, from sources such as panels and phone calls.
Specific means of communicating instruction	Textual on a printed paper	Both textual and verbal that comes from the panels and voice calls	Communicating instructions in both verbal and textual forms would be in favor of cognitive load and managing the attention of the user during the experience [1258].
Specific instruction communication patterns and sources of ambiguity	Instructions are presented in sequences of sentences, as appearing in step-by-step construction manuals. These instructions include lexical ambiguity coming from each sentence.	The same is followed here. In addition, the complexity of instructions also changes with increasing the degree of interconnectivity among parts of the sentences. In addition, available tasks and information change with unpredictable phone calls coming from the boss.	This design choice provides the possibility for the experiment designer to purposely reduce the amount of available information and change the complexity of the sentences to control the amount of ambiguity and complexity in the system. In addition, the possibility of applying lexical ambiguity, as another potential source of confusion, is provided.
A friendly environment supporting understanding and empathy in interpersonal communications	A nice house with friendly relationships between Amelia and the family	A nice virtual office and the friendly voice of the boss	Experiencing this environment potentially keeps the user's interest to stay till the end of the experiment and accept the challenges.

Experimental Setting

In this section, we describe the experiment we conducted to study the effects of different levels of uncertainty on behavioral responses, performance, and quality of the experience of the participants resorting to objective and subjective measures.

Participants

We recruited 17 participants (3 female, 14 male, age: 20–35, M = 25.05, SD = 1.75). Participants were required to be university affiliates within the age range of 20–35 years to ensure a sample with relevant academic backgrounds. To account for potential variability in VR experience, individuals with diverse levels of familiarity with head-mounted displays (HMDs) were included, as measured on a Likert scale (1 = never, 5 = every day, M = 2.88, SD = 1.36). Since the study involved elements requiring language comprehension, participants were also screened for English proficiency (M = 3.47, SD = 1.01, measured on a 5-point scale) to ensure they could fully engage with experimental tasks. Participants were recruited from within the university. However, individuals with severe visual impairments or motion sickness sensitivity were excluded to prevent discomfort and ensure reliable participation in the VR-based experiment.

Setup

In our experiment, participants navigated in a virtual office via an HTC Vive Pro HMD (refresh rate: 90 Hz, resolution: 1440 × 1600 pixels, FoV 110°) connected to a workstation (Intel(R) Core(TM) i7-6850K CPU @ 3.60 GHz, 3.60 GHz). The environment was developed using Unity 3D version 2019.4.35 f1. Unity 3D is a game engine developed by Unity Technologies (SF, USA). It is a very famous platform that has been used by game developers across the world. The data analysis was performed using R version 4.2.2 and RStudio version 2022.07.2+576. R is a programming language and software environment for statistical computing and graphics, developed by the R Development Core Team and maintained by the R Foundation (Vienna, Austria). RStudio is an integrated development environment (IDE) for the R programming language, developed by RStudio, Inc. (BST, Mass, USA).

Experience Design

The experience was designed as a role-playing serious game where a user, in the role of a new employee, is exposed to two different levels of uncertainty in the context of interpersonal communication in a workplace scenario. To this aim, the story plot that develops within the experience takes inspiration from Amelia Bedelia, the protagonist and title character of the children's book series authored by Peggy Parish [969]. Amelia Bedelia is a housekeeper who takes her instructions literally because her boss could not be present in the house on the first day of her work. The instructions include lexical ambiguity coming from each sentence. Despite such ambiguity, Amelia stays positive and expresses her excitement to do her job well and make her boss happy, but she repeatedly misunderstands the guidance. Inspired by this storyline, our application implements:

- An absence of guidance when a user is following and executing given instructions. This design limits the access to sources of information, asking the user to focus and rely on the already provided knowledge or information that may come after from sources such as panels and phones;
- Specific means of communicating instructions, which may be textual with the use of panels (and sometimes verbal, e.g., through phone calls) as a result of the absence of guidance;

- Specific instruction communication patterns in the form of sequences of sentences, such as what appears in step-by-step construction manuals. At the same time, it enables an experiment designer to purposely reduce the amount of available information and change the complexity of the sentences to control the amount of ambiguity and complexity in the system;
- The possibility of applying lexical ambiguity, as another potential source of confusion;
- A friendly environment supporting understanding and empathy in interpersonal communications.

The application includes two phases: the "Familiarization" phase and the "Main" phase. The goal of the "familiarization" phase is to remove any uncertainty arising from unfamiliarity with VR interfaces and the related context. For this purpose, it provides information and a step-by-step tutorial with feedback to familiarize the user with the context and allow the user to feel confident with the interactions that will then be executed. The user in this phase will get to know the boss, his/her role, the space s/he will be working in, the means of communication, and the way s/he can accomplish the tasks indicated by the boss using the available interfaces. At the end of this phase and when the system confirms the user has successfully executed all steps, s/he will reach the virtual office by pressing the "Move to the office" button from the panel on the left hand (see Figure 4.1 for some screenshots taken from the familiarization phase).

The main phase starts with the user finding himself/herself inside a virtual office in front of a door. After 10 s, a phone starts ringing, and s/he should answer. The boss is on the phone, welcoming and asking the player to follow some instructions, explaining three options that will be available during the experience: submitting the task, suppressing it, and requesting help using the buttons on the panel. The boss also says that if something important comes up he will call again. By pressing the "I am ready" button on the panel, a description of the first task appears. The user can now teleport to move within the office environment, removing objects based on the instructions. The removed objects then become visible in the "Item" tab of the panel. The user can cancel a previous removal by pressing the close button near each image. The user will be asked to complete a second task either by pressing the "Submit task" button or the "I do not do this task" button. After removing a specific number of objects, in the middle of the second task, the phone will ring. The boss warns the user that it may be necessary to cancel previous removals to follow a new set of instructions. Task 2 finishes either by pressing the "Submit task" button or the "I will not do this task" button. The user can also decide to exit the game by pressing the "Exit the game" button.

The virtual office is hence furnished with interactive and non-interactive objects as well as two dynamic blackboards as two sources of information (See Figure 4.3 for some screenshots showing the virtual office environment). As described in Figure 4.2, there are five possible sources of information in the experience: 1. a small blackboard displays the name of the current task; 2. a big blackboard communicates the current status; 3. a small blackboard attached to the panel is a closeup of the big one; 4. a phone that blinks and rings when the boss calls; and 5. a task board showing the instructions for each task. The different parts of the panel are shown in Figure 4.4. An example of teleporting and removing interactive objects may be viewed in Figure 4.5. In addition, to increase the immersion, during the main phase an ambient sound is played, simulating the sounds coming from nearby offices to help reduce the confounding effects of noises coming from the real world.

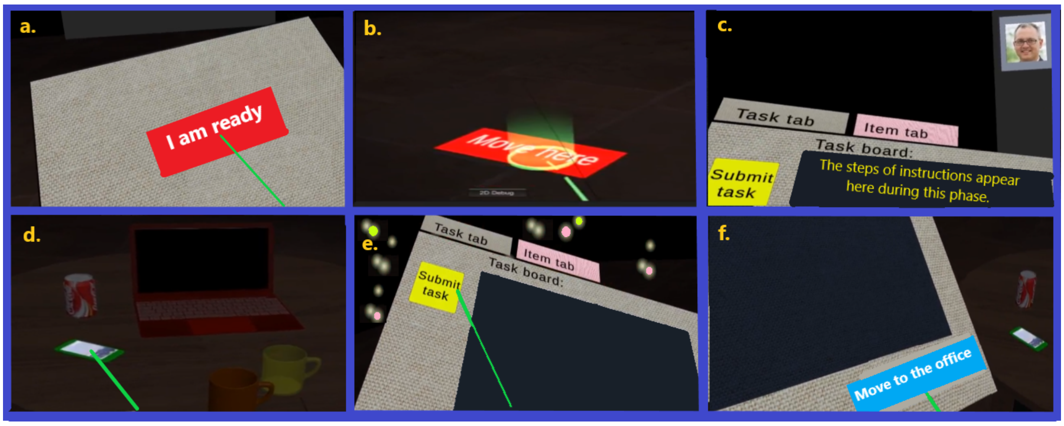


Figure 4.1: Familiarization

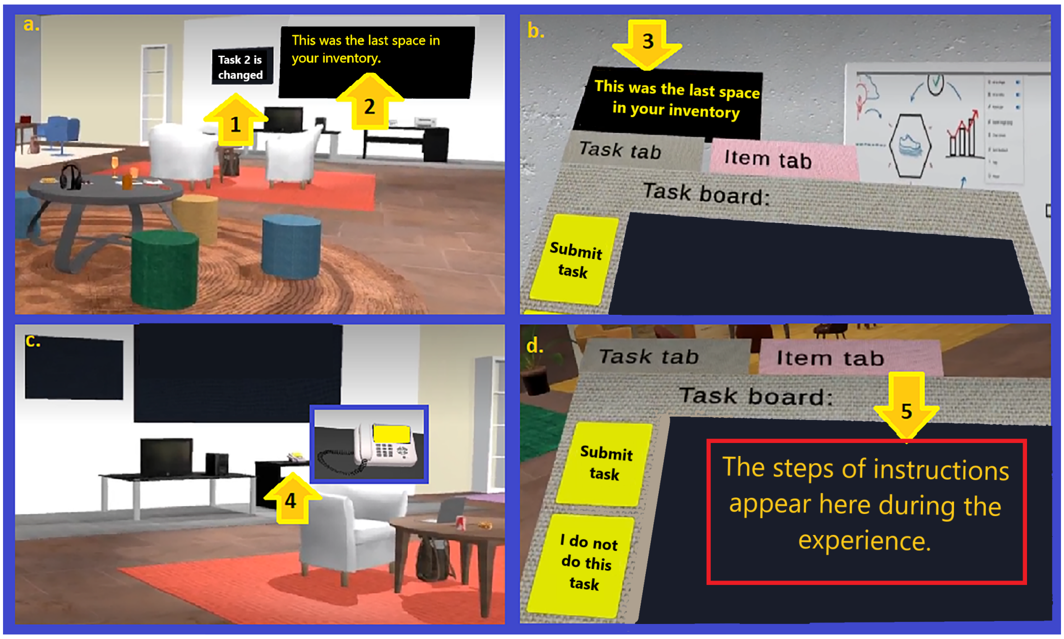


Figure 4.2: Sources of information

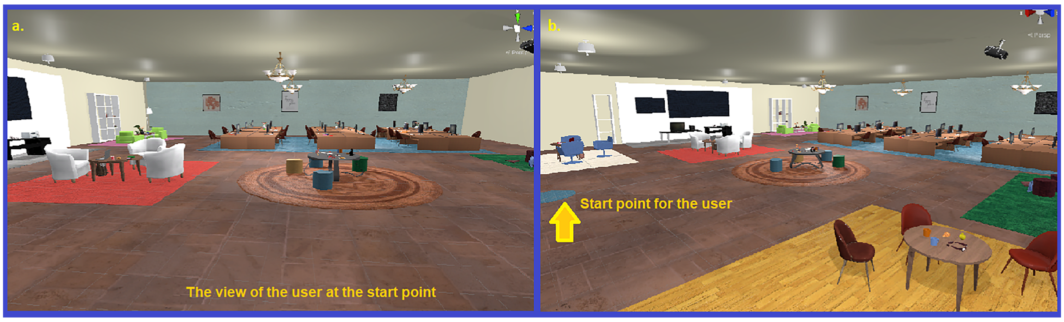


Figure 4.3: Screenshots showing two views of the office: (**a**) the view of the office from the perspective of the user at the beginning; (**b**) Another view of the office.

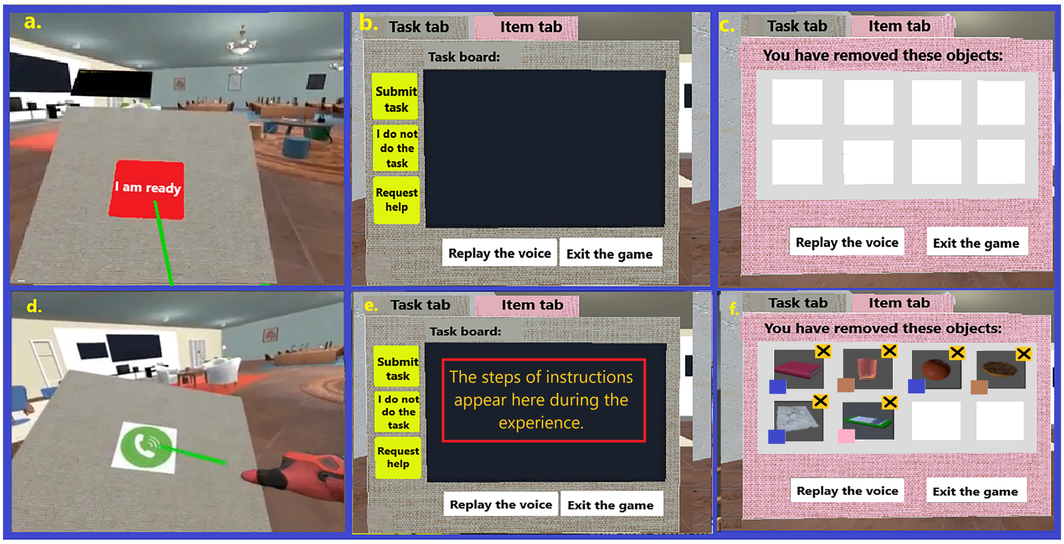


Figure 4.4: Interaction with panels

Figure 4.5: Interactions for moving and selections

The tasks amount to sequences of instructions to search and remove objects expressed in written form or verbally at different moments in the experience. The tasks include two levels of uncertainty, as inspired by the definition of Hillen et al. [526]. As explained before, uncertainty appears in terms of ambiguity, probability, and complexity. Ambiguities result from incomplete guides and instructions. Probable situations appear as unexpected task changes and complexity as a change in the number of causal factors in the instructions.

Following this guide, we proposed these two tasks to represent two levels of uncertainty:

Task 1 (Base Task): Includes clear, step-by-step instructions. Each step specifies the number, location, and color of objects to remove.

Instructions for Task 1:

- Step 1: Go to the blue rug area. Remove the red glasses and green smartphone from the desk.
- Step 2: Go to the blue rug area. Remove the apple and orange from the tables.
- Step 3: Go to the brown rug area. Remove the blue cup from the table.
- Step 4: Go to the red rug area. Remove the green wallet and the sandwich from the table.
- Step 5: Go to the white rug area. Remove the pink book from the table.

Task 2 (Intermediate Level of Uncertainty): Adds complexity with lexical ambiguity, missing information, and potential instruction changes (see Figure 4.6 for layout).

Instructions for Task 2:

- Step 1: Go to the brown rug area. Remove any food not on a plate from the table.
- Step 2: Remove the glasses from the brown rug area.
- Step 3: If there are mugs in the pink rug area, remove the orange one.
- Step 4: Go to the green rug area. Remove the pillows closest to the hat.
- Step 5: If calculators are on the table and a bag is under the table in the white rug area, remove the calculators.

Instructions for Task 2 (After Change):

- Step 1: Go to the brown rug area. Remove any food on plates on the table.
- Step 2: Remove the glasses (if present) from the brown rug area.
- Step 3: If there are books in the blue rug area, remove pencils near them.
- Step 4: Go to the red rug area. If a bag lies under the table, do not remove the smartphone.
- Step 5: If there are mugs on the table in the yellow rug area, remove them.

Figure 4.6: Screenshots from seven different areas for the placements of objects characterized by the color of their associated rugs.

Methods

Procedure

After the participants read the consent form and provided their informed consent, we briefly explained that the experience would develop in a virtual office and that they would be asked to perform some tasks there. Then, a short introduction of the HTC Vive Pro headset, controllers, sensors, and their applications for this study was provided. Then, the users started with the familiarization phase and were guided to the main phase of the experiment. Afterward, the users answered demographic and evaluation questions that will be analyzed later.

Measures

In this section, we describe the objective and subjective measures used to test our hypotheses.

The application records behavioral responses that could be inferred from the HTC Vive controllers and the headset log data. The following variables were measured:

- Variables related to the time:
  - Time to submit Task 1;
  - Time to submit Task 2;
  - Response time to new messages in Task 1;
  - Response time to new messages in Task 2.
- Variables related to the position: Position of the user in each moment.

Subjective measures:

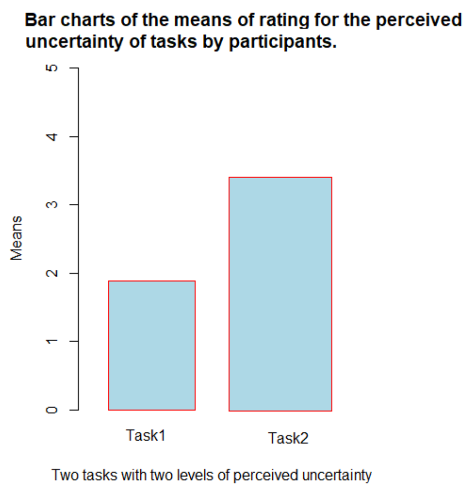
We utilized multiple questionnaires to evaluate participants' subjective experience with the application as detailed below.

- The Demographic questionnaire: This questionnaire asked participants about their nationality, sex, age, and education level.
- Level of English proficiency questionnaire: A five-point Likert scale was used to rate the level of English proficiency of participants.
- Previous Experience with immersive VR: A five-point Likert scale was used to rate the previous experience with immersive VR of participants.
- Perceived uncertainty questionnaire: In this questionnaire, using a five-point Likert scale, participants were asked to rate their level of perceived uncertainty for each task after the experiment.
- System Usability Scale (SUS) questionnaire: This questionnaire [171] consists of 10 items and utilizes a scale of 1 (Strongly disagree) to 5 (Strongly agree) to provide a "quick and dirty" reliable tool for measuring usability.
- Slater–Usoh–Steed presence questionnaire (SUS): This questionnaire [1291] consists of five items and utilizes a scale of one to seven to assess participants' sense of being there in a virtual office.
- The immersive experience questionnaire (IEQ): This questionnaire [1067] comprises 31 items and utilizes a scale of 1 (Not at all) to 7 (A lot) to measure the subjective experience of being immersed while playing a virtual serious game.
- Motion sickness questionnaire (MSAQ): This questionnaire [428] comprises 16 items, utilizes a scale of 1 to 9, and is a valid instrument for the assessment of motion sickness.
- Intolerance of Uncertainty Scale (IUS): This questionnaire [181] consists of 27 items and utilizes a scale of 1 (Not at all characteristic of me) to 5 (Entirely characteristic of me) that assesses emotional, cognitive, and behavioral reactions to ambiguous situations, implications of being uncertain, and attempts to control the future.

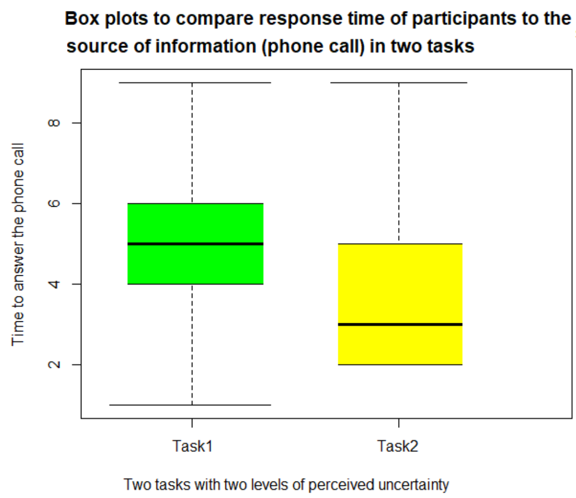
Results

In this section, we present the objective and subjective results of our experiment concerning our research questions:

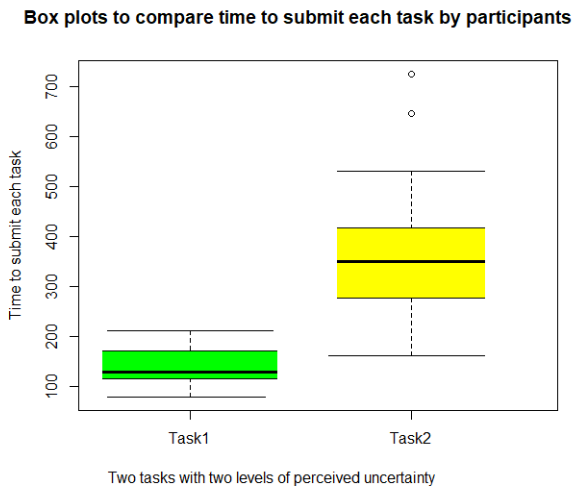
We compared the ratings that the participants gave to the perceived uncertainty of two tasks with the Wilcoxon Signed-Ranks test. The result found a significant difference between them ($v = 0$, $P = 0.0003553 < 0.05$) suggesting that overall, the participants rated Task 2 with higher perceived uncertainty than Task 1 (See also Figure 4.7a for visual comparison of the ratings).



(a) Perceived uncertainty.



(b) Response time.



(c) Task completion time.

Figure 4.7: Overall results.

To find the effects of different degrees of induced uncertainty on the user's behavior, first, we confirmed the normality of the data with the Shapiro–Wilk test at the 5% level. Then, we conducted the Paired T-Test. The results did not find a significant difference between the response time in the two tasks $t(16) = 1.44$, $p = 0.084 > 0.05$. However, the box plot in Figure 4.7b visually shows a lower response time to pick up the phone in Task 2 when compared to Task 1.

Since the normality of the data was rejected by the Shapiro–Wilk test at the 5% level, using the Wilcoxon signed-rank test $v = 0$, $P = 0.00001526 < 0.05$ we found a significant difference between the task completion time for Task 1 and Task 2 (See also figure 4.7c to see a visual comparison between the amounts).

To report the differences in change of position in task 1 in comparison to task 2, figure 4.8 and 4.9 present a visual comparison of participants' change of position.

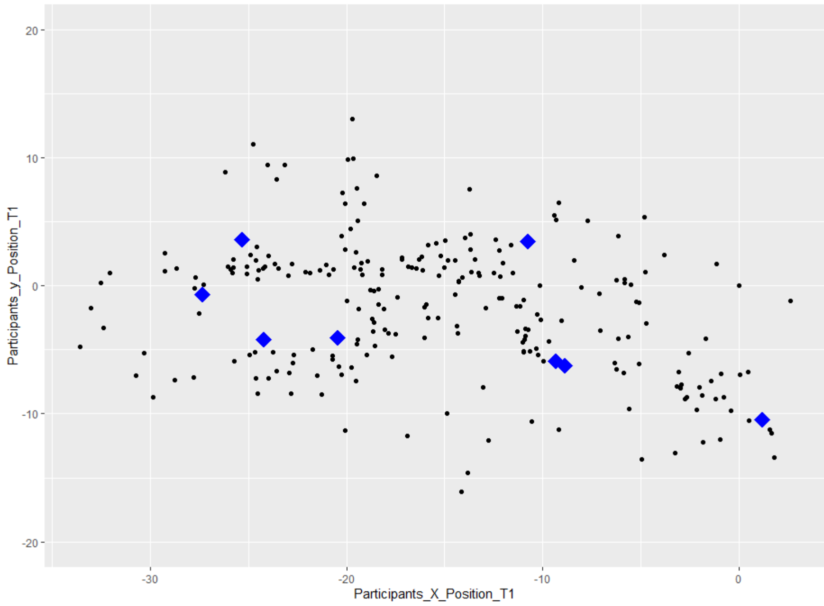


Figure 4.8: A visualization of participants' change of position in task 1; The 8 task targets are shown in blue color.

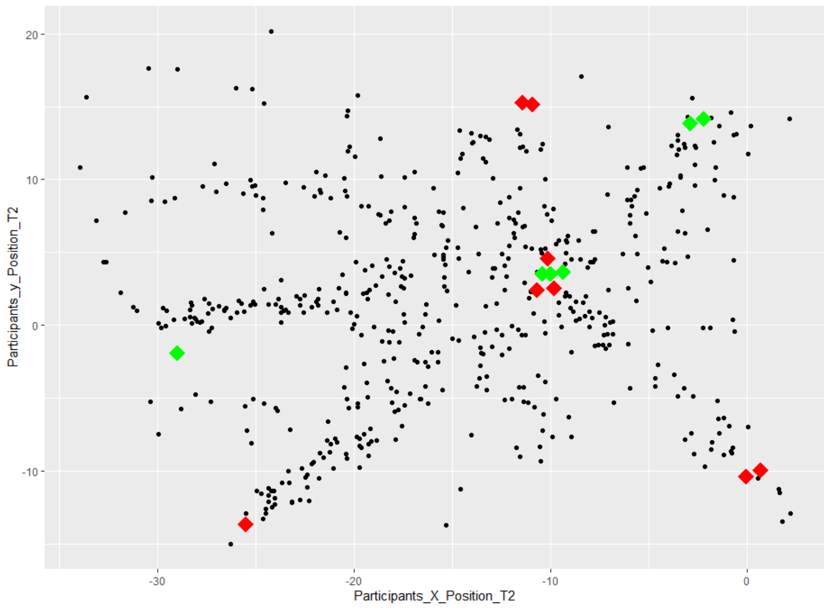


Figure 4.9: A visualization of participants' change of position in task 2; The task targets related to before the change of the task are shown in red; The task targets related to after the change of the task are shown in green.

We used Pearson's r-test to measure the strength and direction of the possible linear relationship between the scores received from the participant's answers to the system usability, immersion, presence, motion sickness, and intolerance of uncertainty questionnaires and the recorded time to answer the second call (i.e. response time to the source of information in task 2). We also used this test to find the possible relationships between the scores of these questionnaires and the time spent on the second task. See table 4.2 for the results of these tests.

Table 4.3 reports the mean and standard deviation of scores obtained from the questionnaires about the quality of the participants' experience and their intolerance to uncertainty.

Table 4.2: Correlation values between subjective and objective measures.

Questionnaire Name	Time to Answer the Call in Task 2	Task Competition Time for Task 2
The System Usability Scale (SUS)	r = −0.38	r = −0.15
Immersive Experience Questionnaire (IEQ)	r = 0.15	r = 0.4
Slater–Usoh–Steed presence questionnaire (SUS)	r = 0.24	r = 0.29
Motion sickness questionnaire (MASQ)	r = 0.21	r = 0.16
Intolerance of Uncertainty Scale (IUS)	r = −0.09	r = 0.07

Table 4.3: Mean and standard deviation of scores received from participants' answers to the questionnaires.

Questionnaire Name	Mean	SD	Range
The System Usability Scale (SUS)	76.32	9.89	[1–100]
Immersive Experience Questionnaire (IEQ)	65.84	7.13	[1–100]
Slater–Usoh–Steed presence questionnaire (SUS)	64.37	14.50	[1–100]
Motion sickness questionnaire (MASQ)	22.18	12.48	[1–100]
Intolerance of Uncertainty Scale (IUS)	59.48	11.63	[1–100]

Discussion

In this section, we present and discuss the main findings of the experiment in more detail.

The main purpose of this study was to design and implement a VR platform capable of simulating uncertainty in interpersonal communications at two levels, while also recording and analyzing human behavioral responses to this exposure. We addressed the following research questions:

RQ1: Is there any significant difference between subjective ratings of participants for perceived uncertainty of Task 1 and Task 2?

Our findings from post-experiment ratings indicate that the proposed design successfully generates at least two levels of uncertainty in the user experience.

RQ2: How do different degrees of induced uncertainty affect users' behavior and performance in this immersive virtual workplace scenario?

- Does the response time of the user to reach the source of information (the phone call) differ between the two tasks?
- Does the task completion time for the user differ between the two tasks?
- How does the change in participants' position differ between Task 1 and Task 2?

We focused on studying the differences in behavioral responses under two levels of uncertainty, particularly in terms of real-time records of participants' response time and position.

In terms of response time, we were particularly interested in how quickly participants reacted to new information from a significant source (a phone call from the boss). We expected that increasing the level of uncertainty would affect response time; however, statistical tests did not reveal a significant difference between the two tasks.

Regarding task completion time, we examined how long participants persisted in completing each task as an objective measure of their tolerance for varying uncertainty. Participants were free to end tasks at any time without pressure or feedback. Our expectation was that participants would spend more time completing Task 2, which had a higher level of uncertainty, and this was confirmed by the results, with Task 2 showing a significantly longer completion time.

Position data for participants was recorded every 4 seconds during both tasks. The distribution of these positions along the X and Y axes, compared with target positions for each task, is visualized in Figures 4.8 and 4.9. A visual comparison shows that participants in Task 2, where uncertainty was higher, exhibited more changes in position. This finding aligns with our expectations.

In summary, our experiment suggests that adding uncertainty to a task negatively impacts task completion time but does not significantly affect response time.
RQ3: How are users' subjective responses to uncertainty related to their objective responses?

We anticipated stronger correlations between subjective and objective measures; however, we found only small correlations. Specifically, we observed a small negative correlation between System Usability Scale (SUS) scores and the time to answer the second call, small positive correlations between presence scores and both task completion time and response time for the second call, and a small positive correlation between Motion Sickness Questionnaire (MASQ) scores and the time to answer the second call. Increasing the sample size may reveal stronger correlations.
RQ4: How do users evaluate the quality of their experience through subjective measures?

Another aim of the study was to assess participants' subjective evaluations of their experience with the system. The mean System Usability Scale (SUS) score was higher than the average SUS score of 68, indicating good system usability, though there is room for minor improvements [170]. The average scores for the Immersive Experience Questionnaire (IEQ), the Slater–Usoh–Steed Presence (SUS) Questionnaire, and the Motion Sickness Questionnaire (MASQ) also fell within acceptable ranges, suggesting that participants had a generally positive experience.

In conclusion, the system, supported by the designed environment and storyline, successfully created an engaging virtual experience. Using HTCVive Pro controllers and headset tracking, we were able to capture participants' behavioral responses, including their response times and positions, in real time, providing valuable insights into their interactions with the system.

Conclusions and Future Works

In this study, we investigated the effects of uncertainty level in a virtual office on participants' objective and subjective responses through a controlled human-subject study. We designed an experimental scenario inspired by a famous story named Amelia Bedelia written by Peggy Parish [969]. For the design of our system, we first investigated and carefully selected the virtual reality interfaces and environments that supported our research needs. In addition, we were inspired by previous games which applied uncertainty in their designs. The goal was to develop a system that supports a pleasant 3D immersive experience with real-world-like interactions and rich data-collecting techniques. In our usability study, participants were asked to complete two different tasks inside a virtual office where they were also involved in interpersonal communication with their boss on the first day of work. We measured the participants' objective responses through the log data captured from the tracing of HTCVive pro controllers and headsets as well as assessed their subjective experience through questionnaires. We determined that the two proposed versions of tasks received significantly different ratings from the participants for their perceived uncertainty after the experiment. In addition, our results supported that the time taken to submit different tasks differs significantly. In addition, results from the usability, immersion, presence, and motion sickness questionnaires conveyed that overall, the participants were satisfied with the experience by scoring the usability, presence, and immersion of the experience on average higher than 50% and the motion sickness of the experience less than 30%.

This study suggested that our proposed VR system can manipulate the levels of uncertainty to study it. In the design of this system, we inspired ourselves from real-life situations. An example workplace scenario could be what happens regularly for one in the role of a manager. S/he may receive multiple unpredictable inputs at once and has to constantly monitor and choose what to do first, stay productive, and successfully monitor time allocations to be able to work with everyone involved [1424]. To indicate how effectively our system replicates such real-life happenings under the same conditions, an evaluation of our proposed system against real-life baseline conditions is required. We decided not to consider this system evaluation in this study because of our limitations in controlling the confounding factors coming from real-world settings that make it hard for us to have a valid measure of the effects of uncertainty. So, we leave it for future work.

Future research should focus on refining realism in ambiguous scenarios by exploring AI-driven procedural content generation to dynamically adjust uncertainty levels based on user interactions. Enhancing behavioral tracking through eye-tracking, physiological monitoring, or machine learning-based uncertainty modeling could further improve the system's ability to measure and respond to user uncertainty in real time. Additionally, incorporating multisensory cues, such as haptic feedback, and spatialized audio, could deepen immersion and make ambiguous situations feel more realistic. Further studies should also investigate a broader range of behavioral responses, including stress levels, cognitive load, and decision-making strategies, to gain deeper insights into uncertainty processing in VR. Expanding the study to diverse participant populations and real-world decision-making contexts could also provide deeper insights into how uncertainty perception varies across different user groups and domains.

4.2.2 Insights

The findings of this study have been published in [483].

Objective

This case study aims to explore how varying levels of uncertainty within a virtual office setting impact user behavior and information-seeking actions. By simulating an office environment with different uncertainty scenarios, this VR-based study examines how users adapt to ambiguous instructions and how their interpersonal communication strategies are affected.

Key Technologies

- **Virtual Reality (VR) Environment**: A VR system utilizing HTC Vive Pro headsets to simulate a collaborative office experience with varying uncertainty levels, offering controlled ambiguity in tasks.

Main Findings

- **Perceived Uncertainty, Task Completion, and Response Time**: Users reported significantly higher perceived uncertainty in the second office scenario, where instructions included ambiguous elements. Task completion times between the two scenarios showed statistically significant differences, with an increase in completion time for tasks in the second scenario.
- **Usability and User Satisfaction**: The VR office system received a mean usability score of 76.32 (SD = 9.89) on the System Usability Scale (SUS), suggesting that participants found the interface intuitive and engaging.

Technical and Usability Limitations

- **Maintaining Realism in Ambiguous Scenarios**: Ensuring that the simulated uncertainty felt authentic required careful calibration of task instructions and realistic interaction tracking to mirror real-world uncertainty dynamics in a virtual setting.

Future work should explore adaptive scenario generation using AI-driven procedural content creation to dynamically adjust uncertainty levels based on user interactions, making ambiguity more contextually relevant and realistic. Enhancing behavioral tracking through eye-tracking, physiological monitoring, or machine learning-based uncertainty modeling could improve the system's ability to measure and respond to user perception of uncertainty in real-time. Additionally, incorporating multisensory cues, such as haptic feedback, and spatialized audio, could further immerse users in ambiguous scenarios, enhancing realism and engagement. Expanding the study to diverse participant populations and real-world decision-making contexts could also provide deeper insights into how uncertainty perception varies across different user groups and domains.

4.2.3 N10: Shared Virtual Reality for Experiencing Uncertainty

Objective and Context

Uncertainty is a ubiquitous concept. It means we can find it everywhere and everybody can experience it or at least be affected by it [236]. Each person perceives uncertainty with most of the things about the past and present, and almost everything about the future [1138], [806], [610]. The relationship between the person and the environment characterizes the kind and degree of uncertainty that is experiencing [1288]. There would be self, others, and relationships that create uncertainty that results in cognitive and behavioral responses to it. This introduces interpersonal communications as a potential context for the study of uncertainty since the study of social interaction between people and the way they use verbal and written dialogues, as well as nonverbal actions are the main focus of this field [115]. In this regard, uncertainty appears closely connected with the concept of information [661, 116]. A conceptualization proposed by [526] suggests inducing the uncertainty of information into a communication system can be done in three ways: creating any kind of information deficit that makes the target message unclear for the receiver, creating some requested changes that the receiver could not predict, and creating the content of the message so interconnected and complex that limits understanding. In these situations, one may perceive uncertainty when not sure about the content of a message but accepts it assuming that having enough information would resolve this doubt. The person may try to reduce this kind of uncertainty by referring to the information sources that could be accessed through available information channels [524]. This is where information-seeking behaviors may appear.

Human information behavior (HIB) studies have been focused on investigating different aspects of human information-seeking behaviors such as the kind of choices, searching performance, and emotions of the users, when exposed to a variable of interest [1085], [631]. Belkin [107] suggests that someone experiencing the uncertainty of information first recognizes an anomaly in the state of knowledge that could only be resolved in the process of information seeking by communicating information with others. In this way, uncertainty may trigger information-seeking actions like asking questions. In this regard, a systematic study of the relationship between uncertainty and information-seeking behavior is highlighted [579], [509], [885], [441], [1348]. such a study will concern the investigation of whether uncertainty will be perceived by people in a situation and how it influences their information-seeking behaviors.

Virtual reality experiences traditionally have been restricted to being experienced by only one user at a time interacting with the environment [1043]. Recent studies have focused more on creating a virtual multi-user experience that gives multiple persons the possibility of experiencing the same content together and interacting with each other similar to what one experiences in the real world [431], [725]. On the other hand, when experiencing a shared experience, an important way to measure if a communication system is successful in providing a proper platform for the user to have social interactions is to measure the degree of experienced co-presence. Co-presence is a variable that has been used to measure the degree that the participants think they are not alone [687].

Considering this domain, we propose the design and development of an immersive virtual reality experience to create an enjoyable shared experience. Also, it supports the investigation of how uncertainty affects the performance and information-seeking behavior of the person performing tasks in a social workplace scenario that is characterized by the elements of uncertainty.

With this work, we try to examine these hypotheses:

- **H1:** Participants rate the perceived uncertainty of experience in office 2 more than in office 1.
- **H2:**: Participants show more information-seeking behavior like asking questions in the experience in office 2 compared to office 1.
- **H3:**: Participants spend more time executing the task in office 2 in comparison to office 1.
- **H4:**: Participants give a different score to the presence and co-presence of the experience in office 2 compared to office 1.
- **H5:** Participants will have a good evaluation of the usability of the system.

Related work

Applying the concept of uncertainty in game design could potentially improve the user's experience by holding his/her attention and interest during the experience[268]. For example, "Gone Home"[1380] and "Don't Starve" [348] are two examples that incorporate uncertainty in their gameplay to increase tension and keep players engaged. This creates a sense of unpredictability and adds to the overall experience of playing the games. In "Gone Home," uncertainty is created through the mystery surrounding the disappearance of the family. As the player explores the house and learns more about what happened, they are faced with a sense of uncertainty and unease, which adds to the suspense of the game. In "Don't Starve," uncertainty is created through the unpredictability of the game's randomly generated wilderness. The player never knows what challenges or dangers they might face, and must constantly adapt to new situations to survive. This creates a sense of uncertainty and keeps the players on edge, as they must always be prepared for the unexpected.

Uncertainty also has been the subject of study in virtual reality games. For example, Wenge Xu, et al [1370] in their studies explore the effect of different factors such as gameplay uncertainty, display type, and age on the players' enjoyment, motivation, and engagement when playing their designed VR game. The study's results suggest that gameplay uncertainty, or the unpredictability of the game, has a positive effect on player motivation and engagement, while display type, or the type of VR headset used, has a relatively small effect on player experience. Additionally, the study found that age did not significantly affect player experience with the experienced VR game. In RelicVE [765] the authors aim to create an experience that is both engaging and educational, and uncertainty is used as a tool to increase player engagement and promote learning. In the "RelicVR" game, uncertainty is introduced in several ways. For example, players are given limited information about the relics they are exploring, and they must use their knowledge and skills to uncover the history and cultural significance of the relics.

Social VR is also a potential context that could target the study of uncertainty, especially in interpersonal communications. Since it targets the study of multi-user platforms that allow two or more users to co-experience and interact with one another in a virtual space and social scenario [1288]. For example, such applications may target social activities like co-experiencing virtual mortality [84], dancing [1215], puzzle-solving task [1236], prototyping procedure of a product[666], and learning experience [741], [1096].

A recent previous study by the authors of the current paper, [483], suggested the design, development, and evaluation of a first version of a VR platform that challenged users to accomplish tasks with two levels of uncertainty. Their results showed that they created a pleasant virtual experience and reported some meaningful measures related to the participants' behavioral responses about the frequency, time of actions, and user position when exposed to uncertainty. In the above-mentioned version, the user was alone in the virtual office during the experience and did not have any possibility to communicate with somebody to express his/her doubts during the experience. Since, to the best of our knowledge, no previous work targeted a study of the effects of the elements of uncertainty in the interpersonal communication of a social VR experience, we will take this step and propose an extended version of our previous application. This extension suggests the design and development of such an application by adding the possibility of the user being able to communicate with an assistant during the experience. Also, we added to the complexity of the previous environment by creating more spaces that give the possibility for the objects to be hidden and as a result could not be found easily. In addition, we created two office rooms each with a different representative task, which gives us the possibility of conducting a better comparison between the variables of interest in two different situations.

Experimental Setting

In this section, we describe the experiment we conducted to study the behavioral responses of participants to perceived uncertainty in two virtual offices.

Participants

We recruited 6 participants (1 female, 5 males, age:20-40, M=26.33, SD=5.28) who are master's students at the University of Bologna to participate in our study. To account for variability in VR experience, individuals with different levels of familiarity with head-mounted displays (HMDs) were included, as measured on a Likert scale (1 = never, 5 = every day, M = 2.83, SD = 0.75). Since the study involved verbal communication and comprehension in English, participants were screened for English proficiency (M = 3.17, SD = 1.17, measured on a 5-point scale) to ensure they could effectively engage with the experimental tasks. Individuals with severe motion sickness or known discomfort with VR environments were excluded to prevent interruptions during the experiment.

Materials

In this section, we will provide more details to explain the design and implementation choices of the proposed virtual environment.

Setup

In our experiment, participants navigated in a virtual office via an HTC Vive Pro HMD (refresh rate: 90 Hz, resolution: 1440 × 1600 pixels, FoV 110°) connected to a workstation (Intel(R) Core(TM) i7-6850K CPU @ 3.60 GHz, 3.60 GHz) and an HTC Vive (refresh rate: 90 Hz, resolution: 1080 x 1200 pixels, FoV 110°) connected to a workstation ("Intel(R) Core(TM) i7-9750H CPU @ 2.60GHz, 2.59 GHz"). The environment was developed using Unity version 2019.4.35 f1 and the avatars were designed with the "Ready Player Me" tool [2]. The data analysis was performed using R version 4.2.2 and RStudio version 2022.07.2+576. To build our multiplayer experience we used the Photon software development kit (SDK) which was developed by Photon Engine, a leading provider of cloud-based network infrastructure to help game developers and application builders reduce the complexity of networking and simplify the process of building and deploying online experiences. Also, this experience required a woman who played the role of assistant in the experience.

Design of the experience

In the experiment described in this study, we utilize a VR system that creates a shared experience between the participants and an assistant in a workplace scenario. They are each represented by a virtual humanoid body and they can see virtual representations of the other people present in the virtual world. Data communication is shared across a network, and consistency of the shared world is maintained, so that all involved perceive the same environment from their unique viewpoints, and can interact with one another. We uploaded three photographs of three people (two women and a man) randomly collected online and uploaded them into the "Ready Player Me" platform to create three half-body avatars with facial features similar to those photographs. These avatars were used in our experiment representing an assistant and two participants.

The experience includes the familiarization room, office room 1, and office room 2. It starts and will lead to the familiarization phase. The familiarization room is furnished with simple items of furniture, some interactive and non-interactive objects, two boards for communicating instructions, and a mirror that helps the user to feel more present in the experience representing his/her movements and actions in the familiarization room [1316]. The left board shows the how-to instructions and the right one the task instructions. When the user enters, first the boss's voice will be played introducing himself, explaining that this is the first day of work for the participant, telling that he (the boss) could not be present in the office, and asking him to follow the instructions from the boards to execute some tasks during the experience. Then, the experience will proceed first by experiencing Office Room 1 and then Office Room 2. For all the room experiences, there would be an assistant which accompanies the user in the experience by standing near a desk, watching the user, and answering his/her questions.

For accomplishing tasks, inside the rooms, the user rays a cast on the object and presses a trigger to remove an interactive object. For each room, the user is asked to press the blue button on the table when finishing the task (Please see the figure 4.11 for some screenshots of the participant's experience in room 1).

The presented task in each room amounts to sequences of instructions to search and remove objects which are expressed in written form and will be communicated by the blackboard on the left wall of the room. Inspired by the definition of Hillen et al. [526], uncertainty in our experience appears in terms of ambiguity, probability, and complexity. Ambiguities result from incomplete guides and instructions. Probable situations, such as unexpected task changes, can also increase the uncertainty of the user's experience, and complexity can increase uncertainty by adding a large number of causal factors or elements that must be considered in the instructions. This can make it more challenging for the user to understand the situation and make decisions.
Following this guide we proposed two office room experiences each representing a different level of uncertainty (Please also see figure 4.12 for the placements of objects in both offices in seven different areas of the environment with their associated rugs):

- Room1 (with a base task): The instructions in this room experience express simple and clear task steps in which the number, place, and color of objects that should be removed could be understood easily.
Instructions for Task 1:

- Step 1: Remove the green mug and pink book from the white rug area.
- Step 2: Remove the bag and the sandwich from the blue rug area.
- Step 3: Remove the apple and the red book from the gray rug area.
- Step 4: Remove the tart and the blue mug from the red rug area.
- Step 5: Remove the red pillow and paper punch from the green rug area.
- Step 6: Remove the blue mug and glasses from the yellow rug area.

Room 2 (with an intermediate level of uncertainty): The instructions in this room are more complex compared to Room Office Experience 1 including some uncertain elements like some missing information and the possibility of change during the experience.

Instructions for Task 2:

- Step 1: Remove any foods not positioned on the plates from the pink rug area.
- Step 2: If there are two bags in the white rug area, just keep the blue and orange mugs and remove the others.
- Step 3: Remove all the glasses from the yellow rug area.
- Step 4: Remove only the pillows that are close to the shelves in the red rug area.
- Step 5: Remove any kind of bread from the gray rug area.

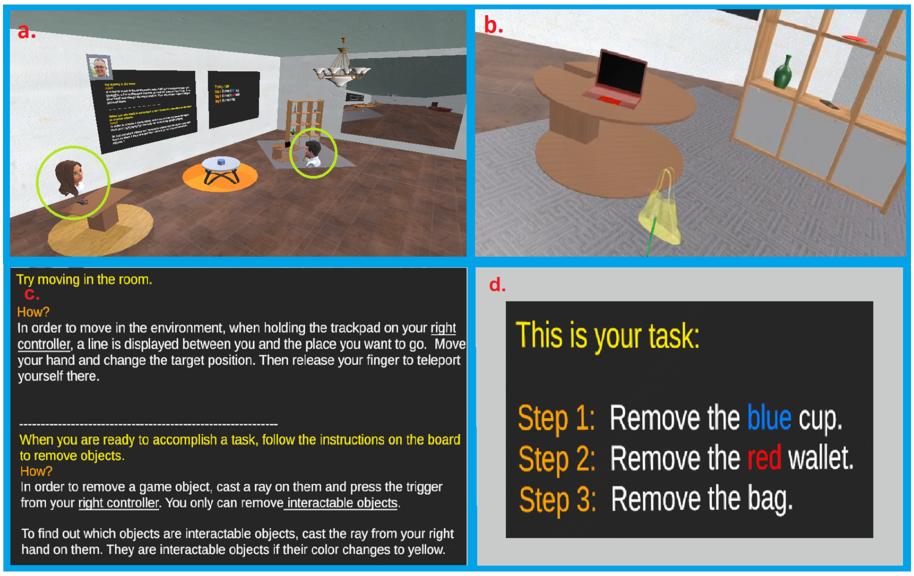


Figure 4.10: Screen shots from the familiarization phase. a. showing the positions of the objects in the familiarization room, and the avatars in a moment of the experience. b. a close-up screenshot from the interaction of the user with an interactive object by casting a ray on it and pressing the trigger from the controller. c. a close-up of the board's instructions that appear in part a.

- Step 6: Remove all the glasses from the green rug area.

After the 30s, the task will be changed by adding some lines to the instruction requesting to also remove the orange mug from the white rug area and the blue mug from the gray rug area.

Methods

Procedure

First, the participants read the consent form and provide their informed consent form, Then, they will be asked to listen to a short tutorial about the HTC Vive headset, controllers, sensors, and their applications for this study. The participants then will experience the familiarisation phase, room office 1 and room office 2 in a sequence. Finally, they will answer some questionnaires related to their experience with the system.

Measures

In this Section, we describe the objective and subjective measures used to test our hypotheses.

- **Objective measures** In this experience, we captured behavioral responses related to exposure to different levels of uncertainty by measuring some variables related to performance (task completion time) and frequency of requesting social interactions (asking questions).

- **Subjective measures** We utilized multiple questionnaires to evaluate participants' subjective experience with the application as detailed below.

Figure 4.11: Some screenshots from room 1 (a similar situation would happen also in room 2). a. shows the position of the assistant in the office room. b. shows the participants when accomplishing tasks in the office room 1. c. shows the participant when selecting an interactable object.

Figure 4.12: A screenshot showing the two office rooms characterized by seven associated areas for accomplishing the steps of the task each with a different colorful rug; a. shows office room 1. b. shows office room 2.

- **Demographic questionnaire:** A questionnaire to ask our participants some demographic questions like sex and age.
- **Level of English proficiency questionnaire:** A 5-point Likert scale to ask our participants to rate their level of English proficiency.
- **Previous Experience with immersive VR:** A 5-point Likert scale to ask our participants to rate their previous experience with immersive VR.
- **Perceived uncertainty questionnaire:** A 5-point Likert scale to ask participants to rate their level of perceived uncertainty for each task after the experiment.
- **System Usability Scale (SUS) questionnaire:** A 5-point Likert scale [171] to provide a "quick and dirty" reliable tool for measuring usability.
- **Slater-Usoh-Steed presence questionnaire (SUS):** A 7-point Likert scale [1291]to assess participants' sense of being there in a virtual office.
- **Copresence questionnaire:** A 7-point Likert scale [502] to measure co-presence which people experience with their digital counterparts as actual people in a social VR experience measuring the dimensions of Attentional Allocation (Atn), Perceived Message Understanding (MsgU), Perceived Affective Understanding (Aff), Perceived Emotional Interdependence (Emo), and Perceived Behavioral Interdependence (Behv). For this experience, we focused on CoPresence (CoP), Attentional Allocation (Atn), and Perceived Message Understanding (MsgU) dimensions.

Results

In this section, we present the objective and subjective results of our experiment concerning our research questions:

In order to compare the participants' ratings to the perceived uncertainty of two office room experiences we used the Wilcoxon Signed-Ranks test. The result found a significant difference between them (v = 0, $p = 0.035 < 0.05$). These results suggest that the perceived uncertainty of task 2 was rated significantly higher than office room experience 1.

To find the effects of different degrees of induced uncertainty on the user's behavior, we were interested in investigating the effects of uncertainty on variables related to performance and information-seeking behavior. Related to performance we measured the effects on the task completion time of each room office experience. First, we confirmed the normality of the data with the Shapiro–Wilk test at the 5% level. Then, we conducted the Paired T-Test. The results did not find a significant difference between the task completion time in the two office room experiences (t(5) = -3.2916, $p = 0.9892$). However, the box plot in part (a) from figure 4.14 visually shows a higher task completion time for Office Room Experience 2 when compared to Office Room Experience 1. Also, we measured the effects on information-seeking behaviors like asking questions. First, we confirmed the normality of the data with the Shapiro–Wilk test at the 5% level. Then, we conducted the Paired T-Test. The results did not find a significant difference between the number of asking questions

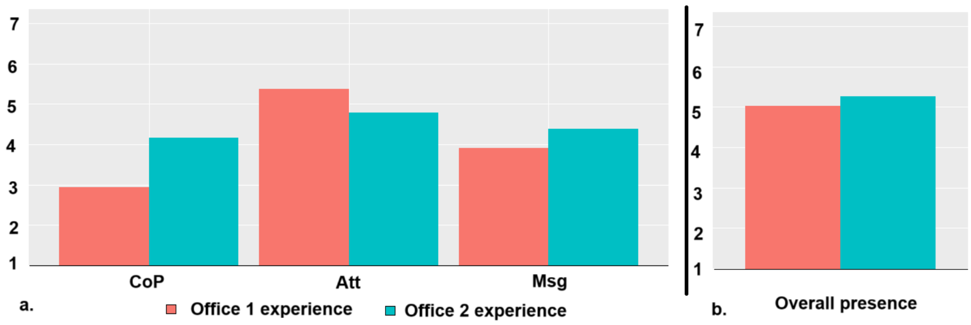


Figure 4.13: Results for a comparison between the means of a. social presence dimensions and b. for Presence in office room experience 1 and office room experience 2.

in the two office rooms (t(5) = -1.1125, p = 0.8417). However, the box plot in part (b) of figure 4.14 visually shows a higher number of asking questions in office room experience 2 when compared to office room experience 1.

The data obtained from the SUS questionnaire showed a mean score of 77.91 (SD = 12.84), indicating overall usability levels.

We calculated scores to find a significant difference in a comparison of different co-presence dimensions. The results for co-presence (V = 1, p = 0.05917), attentional allocation (V = 6, p = 0.4017), and perceived message understanding (V = 3, p = 0.1411) did not show any significant difference. Also, we could not find any significant difference between the scores of presence in office room experience 1 and office room experience 2 (V = 1, p = 0.1056). Figure 4.13 shows a visual comparison between the results of social presence dimensions and presence in two different levels of experiences.

Discussion

In this section, we present and discuss the main findings of the experiment in more detail. In this study, we contributed to examine the following hypothesis:

- **H1:** Participants rate the perceived uncertainty of experience in office 2 more than in office 1. Our findings from a comparison of the post-experiment ratings of the participants to the perceived uncertainty of two tasks indicate the potential of the proposed design to successfully produce at least two levels of uncertainty in the experience of the system.

- **H2:**: Participants show more information-seeking behavior like asking questions in the experience in office 2 compared to office 1. We were expecting that with an increase in the perceived uncertainty, the information-seeking behavior will be increased. Although our statistical test could not find a significant difference.

- **H3:**: Participants spend more time executing the task in office 2 compared to office 1. We were expecting that with an increase in the perceived uncertainty, the task completion time would be increased. Although our statistical test could find a significant difference.

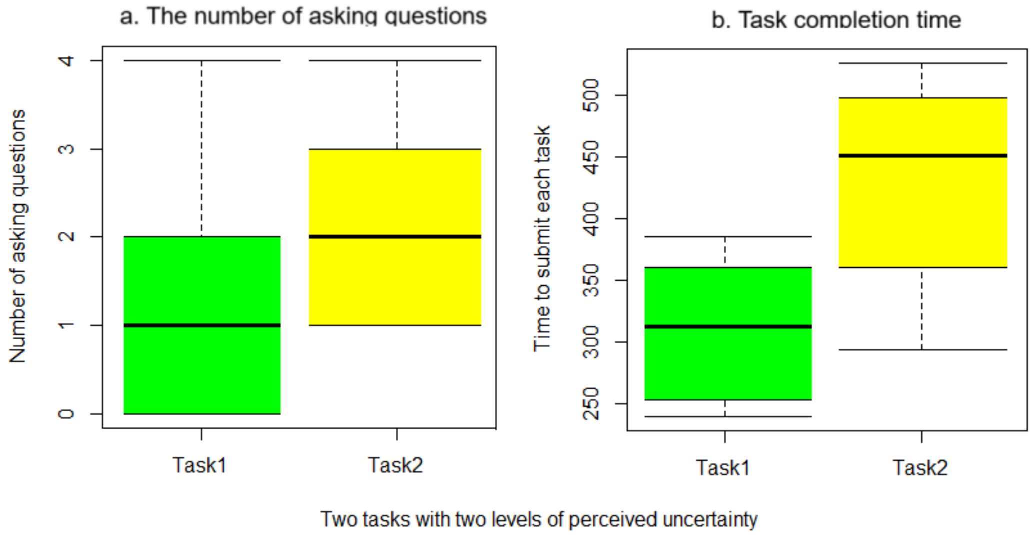


Figure 4.14: A comparison in the a. number of asking questions by participants and b. time to submit the task in Office Room Experience 1 and Office Room Experience 2.

- **H4:**: Participants give a higher score to the presence and copresence of the experience in office 2 compared to office 1. We were expecting that with an increase in the perceived uncertainty, the information-seeking behavior will be increased. Although our statistical test could not find a significant difference.
- **H5:** Participants will have a good evaluation of the usability of the system. Another purpose of the study was to report the results of the participants' evaluation of their experience with the system. The mean score of our results from the System Usability Scale (SUS) (M = 77.91, SD = 12.85) reports an acceptable average score (the minimum acceptable average score is 68). This means that the system overall got a good usability score and needs some minor improvements [170].

Conclusions and future works

In this study, we suggested the design and development of a shared VR experience and investigated the effects of uncertainty levels on the information-seeking behavior and performance of the user in a virtual office. We measured the participants' objective and subjective responses through a controlled human-subject study. The results did not convey any significant difference between the task completion time, the performance, the sense of presence, and the co-presence of the user in two different office rooms. But, we were able to confirm that the system can create two different levels of uncertainty and the participants gave a good score to the usability of the system. We plan to increase the sample size in a future study that gives us the possibility to have more statistical power to detect and report the behavioral responses from the proposed experience. To enhance real-time synchronization in multi-user VR environments, future research should explore network optimization techniques, including low-latency data transmission protocols, predictive synchronization algorithms, and adaptive buffering to minimize delays. Implementing edge computing solutions could further reduce lag by processing critical data closer to users rather than relying solely on a centralized server. Additionally, exploring AI-driven synchronization models that anticipate user actions and dynamically adjust system responses could improve interaction fluidity. Future research should also investigate how different network conditions, such as bandwidth limitations or varying connection speeds, impact shared VR experiences and develop adaptive synchronization strategies to ensure consistency across diverse setups.

4.2.4 Insights

The findings of this study have been published in [485].

Objective

This case study investigates how virtual reality (VR) can simulate uncertainty within a collaborative communication setting. The goal is to examine how participants respond to uncertain and ambiguous information in a shared immersive VR environment, focusing on their communication strategies, and social dynamics in collaborative tasks.

Key Technologies

- **VR System for Shared Communication**: A VR system developed to simulate a collaborative office experience with varying uncertainty levels, offering controlled ambiguity in tasks. The system utilizes two HTC Vive Pro headsets to enable an immersive multi-user experience.

- **Photon SDK**: Supports real-time, multiplayer VR interactions, enabling synchronized actions and seamless communication for a realistic collaborative experience.

Main Findings

- The VR system effectively created experiences with distinct levels of uncertainty, with participants perceiving higher uncertainty in the more complex scenario.

- Despite this, there was no statistically significant difference in task completion times or information-seeking behaviors between the scenarios.

- Participants rated the system's usability positively, indicating an engaging and functional design for studying social VR and uncertainty in communication.

Technical and Usability Limitations

- **Ensuring Real-Time Synchronization**: Maintaining real-time synchronization of actions and communication in the shared VR space was critical for a seamless user experience, requiring robust network connectivity and optimized data handling.

To enhance real-time synchronization in shared VR spaces, future research should focus on network optimization techniques, such as low-latency data transmission protocols, predictive synchronization algorithms, and adaptive buffering to minimize delays in multi-user interactions. Implementing edge computing solutions could further reduce lag by processing critical data closer to the users rather than relying on a centralized server. Additionally, exploring AI-driven synchronization models that anticipate user actions and pre-load relevant data could improve responsiveness, ensuring seamless interactions in collaborative virtual environments. Further work could also investigate the impact of different network conditions, such as bandwidth limitations or varying connection speeds, to develop adaptive strategies that maintain synchronization under suboptimal conditions. Expanding studies to include larger participant groups and cross-device compatibility would provide deeper insights into optimizing shared VR experiences across diverse platforms.

4.2.5 N11: Collaborative memory sharing in Augmented Reality

Objective and Context

The interest in human heritage has recently gained a lot of attention [8]. This interest has grown significantly since the advent of the COVID-19 pandemic, which forced people to stay at home, away from places of interest, families and friends. In such context, among all the human heritage materials, emerges the role of photographs, as they are a unique way to share any kind of visual information. Particularly, historical and analog photos have gained momentum, since they provide an unrepeatable chance to revive old memories about social events, affections, relatives, friends, special events, etc. During the 20th century, people printed and collected such kinds of pictures in photo albums, namely family albums. Even if this phenomenon is not as popular as before, due to the advent of digital photography and the spread of social media, such kinds of photos are still of interest, for all those who like to look back and discover their families' pasts, but also for academic research [1112]. Such photo albums may so represent a link for those people who are forced to stay away from each other, as well as a distraction from worries and fears.

Despite the growing attention to these topics, digital technologies often lack tools apt to individuate, digitize, and share elements of human heritage in an easy and portable way. Rosner et al. have posed particular attention to this topic, exploring the opportunities and the criticalities that emerge with the use of computational systems to preserve cultural resources and local traditions (i.e., Bolognese tortellini food making) [1088]. Taking inspiration from this idea, we decided to extend the system introduced by Stacchio et al. in [1223], where a system was developed for the digitization and cataloging of collections of analog family album photographs exploiting: (a) the HoloLens 2 [1284] as a wearable device, (b) Augmented Reality (AR) paradigms to implement our interface, and, (c) Deep Learning (DL) algorithms to catalog the pictures observed by the user. With respect to such work, our system also includes (a) the chance to share with remote users the HoloLens 2 scene view, while (b) exploiting a well-known object detector, namely YOLO [1049], to improve the performances in the cataloging process. Our work has been validated through a simple assessment model, asking a group of ten people to provide their comments regarding the use of our prototype.

We make use of a cultural heritage dataset composed of analog family photo album pictures called IMAGO [1219]. The IMAGO dataset is a digital collection of analog family photos taken between 1845 and 2009, belonging to ca 1500 family albums. It comprises 16.642 digitized images, labeled by their shooting date and socio-historical context class by expert historians. The socio-historical context classes have been defined according to socio-historical literature and are meant to describe the scene portrayed in a picture (e.g., free time, school, rites, etc.). Putting to good use such pictures and labels, Stacchio et al. in [1219] described the architectures and the training strategies, providing also two pre-trained classifiers, namely IMAGO-DATING and IMAGO SOCIO-HISTORICAL, able to predict, respectively, the date and the socio-historical context of an analog family album photo, with about 70% accuracy.

It is important to note now that the creation of such classification models required, in the first place, the digitization of those images, a process that needed hours of manual work. For this reason, we saw the opportunity to exploit AR, especially if experienced through a head-mounted display, as an easy-to-use tool that may be used to digitize and share analog photos.

In this study we aim to answer these research questions:

- How can AR and DL enhance the digitization, recognition, and classification of historical family photographs?
- What is the user experience when sharing augmented family photo albums remotely through the HoloLens 2 interface?

Related Work

A known problem with cultural heritage amounts to its digitization and archiving, to make it subsequently available to all. Many different research projects have hence worked on such a problem, in the following we cite a few relevant examples published in the literature. In OmniArt [17] the authors digitized the dataset belonging to a museum, labeling each artwork with its author(s), period, gender, and style (the authors also provided their baseline). Another example may be found in The Newspaper Navigator Dataset [719], where the authors describe the digitization of over 16 million pages of historic American newspapers, containing not only metadata related to their textual contents but also to the spatial regions of interest and their semantic meaning. Such kinds of datasets are not only useful from an archiving point of view but also may be exploited to increase the corpus of knowledge a unique source to learn and produce knowledge about unknown material. It is possible to identify a clear workflow in such works: (a) digitize specific cultural heritage assets, (b) build a dataset, and, (c) share it with the world. It is also possible to find research projects that have focused on only step (c). For example, Zhicong et al. explored the possibility of using the camera feed to live stream artistic performances or cultural traditions and customs [774]. Our work builds upon these contributions by integrating AR and deep learning to enhance the digitization, recognition, and classification of historical family photographs. Unlike previous approaches that primarily focus on dataset creation and classification models, our system enables real-time, immersive sharing and interaction with analog photo albums through HoloLens 2. By bridging digitization with AR-based remote collaboration, our study aims to provide a novel perspective on how extended reality can facilitate cultural heritage preservation, sharing, and engagement.

Augmented Reality system design and implementation

As previously stated, we here aimed to extend the work introduced in [16], concentrating on improving the detection performance and also on providing an authentic experience of sharing family memories exploiting AR and DL techniques. To reach these goals, we designed an AR system architecture that pipelines: (a) the HoloLens 2 interface, and, (b) the deep learning processing. Such steps are visually represented in Figure 4.15.

Hololens 2 interface and sharing stage

The application sends all of the frames within the user's view to the DL models which, in case one or more historical pictures are detected, provides the bounding box(es) and the label(s) that can be then visualized in AR.

Such information is utilized to augment the visualization of the family photographs resorting to the HoloLens 2 interface. In addition, the application also supports the sharing of the augmented HoloLens user' view to other devices (e.g., smartphone, tablet, pc).

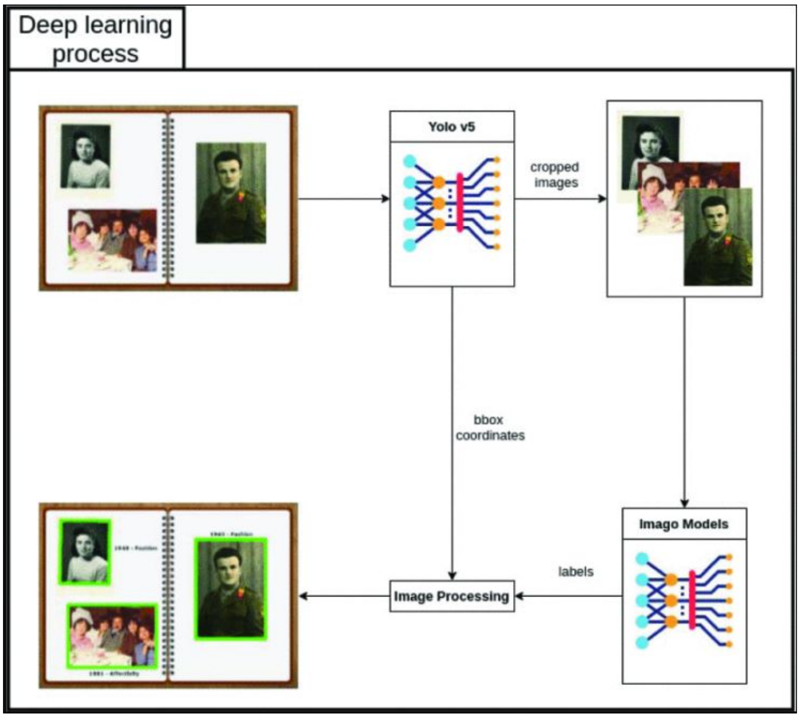


Figure 4.15: Deep learning processing architecture.

Photograph detection stage

With respect to [1224], the detection module of the photographs implemented in our system has been improved. In our previous work, in fact, we resorted to a classical computer vision pipeline to implement the task of recognizing the area in which family album photos were located. The latter was composed of stacking pre-processing image algorithms (i.e., bilateral filtering), edge-detection (i.e., canny edge detector), and contour-detection ones (i.e., Sobel). However, a more recent trend, amounts to the exploitation of the performances of DL-based object detectors, as they can learn how to manage more varied and complex situations [7]. Within the DL object detectors zoo, the YOLO architecture has emerged, since its newest version (v5) [1049]. In particular, we resorted to YOLOv5s, because it amounts to a good compromise between performance and memory usage, making it a good candidate to jointly work with the HoloLens 2.

The YOLO architecture, however, is not sufficient to solve the task of recognizing photos within family albums, as in its original version it is trained with the IMAGENET dataset [1092]. This motivates the decision to synthesize a new one, which results from a random pasting, on random backgrounds, of n pictures (with n ranging between 0 and 4), casually picked from the IMAGO dataset (e.g., paper, wall, grass backgrounds). Images might also partially overlap.

With this process, 9,006 images were obtained. These have been subsequently partitioned in training (7,372) and test (1,634) sets.

We then proceeded to fine-tune the YOLOv5s model, exploiting data augmentation techniques (e.g., random brightness, horizontal and vertical flipping) for 10 epochs, with a batch size of 32 and the adam optimizer, setting a learning rate of 1e-3 with a weight decay equal to 5e-4. The result of this stage is a DL model capable of cropping historical pictures appearing in family albums (as shown in Figure 4.15).

Picture-inference stage

The IMAGO DL models (i.e., IMAGO-DATING and IMAGO SOCIO-HISTORICAL CLASSIFIER) are at this point exploited to predict the date and the socio-historical context of each picture. As specified in [1219], the model is capable of dealing with pictures whose date falls within the 1930-1999 interval and whose socio-historical context belongs to one of the following Work, Free-time, Motorization, Music, Fashion, Affectivity, Rites, School, Politics, according to the definition specified in [1219]. Such labels, along with the ones provided by YOLO, are then sent to the HoloLens 2 to augment the view of the photographs with such information.

User-view sharing

The labels obtained are also leveraged as a piece of information that may be shared, following a collaborative style, and hence sent to the interfaces of those users who are viewing photo albums from a remote location. To this aim, we built a simple HTTP server to continuously stream, to any kind of device (e.g., smartphone, tablet, pc), the augmented view of the HoloLens 2. In brief, the server processes the video stream captured by the HoloLens 2 and adds to each of its frames the labels returned by the YOLO and IMAGO DL models. The use of HTTP is a design choice meant to support easy access to the stream, from any type of device. A real-world example of the augmented view, as seen from the HoloLens 2, is provided in Figure 4.16.

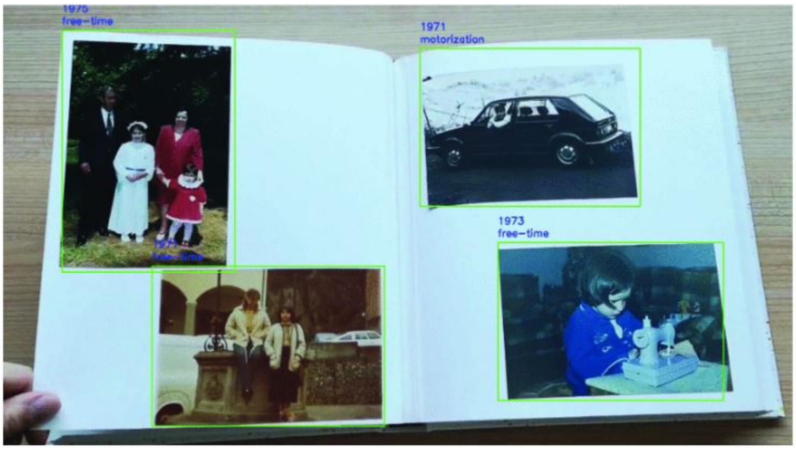


Figure 4.16: Real-world example of Augmented HoloLens 2 view.

Human Interface Evaluation

Participants

To evaluate the effectiveness of the proposed AR application, we asked a group of ten participants to answer some additional questions regarding their experience. This group had an average age of 26 years and was composed by 3 females and 7 males.

The number of participants has been chosen as a trade-off between the necessity of acquiring sufficient feedback data from a population and the time spent for the evaluation phase. Moreover, ten participants have repeatedly proven to be a sufficient population to discover over 80% of existing interface design problems [6, 1105].

Ethics

Written consent to participate in this experimental study was collected from each subject. The experimental session was possible thanks to the full compliance with the COVID-19 sanitary protocol adopted by the University of Bologna.

Assessment model

As aforementioned, once our participants tested the experiences, they were asked to complete a survey. This has been designed to assess four constructs, namely, Perceived Ease and Enjoyment of Use (PEEU), Deep Learning Gain (DLG), HoloLens Perspective (HLP), and Receiver Perspective (RP).

Perceived Ease and Enjoyment of Use (PEEU) and Deep Learning Gain (DLG) constructs

The first chunks aimed to investigate the PEEU constructs and the DLG ones (both evaluated through a 5-point Likert scale). For simplicity, a general overview of these constructs is reported in Table 4.4.

Individuals' satisfaction and acceptance of a technological innovation, such as an AR application, may be analyzed through different theoretical approaches. The Technology Acceptance Model (TAM) [292] amounts to one of the most popular assessment approaches, as it allows to measure user intentions in terms of their attitudes, subjective norms, perceived usefulness, perceived ease of use, and related variables. In our case, we want to concentrate on the perceived usefulness and ease of use. Perceived usefulness is defined as the degree to which individuals believe that adopting one particular technology will improve an aspect of their life, whereas perceived ease of use is the degree to which an individual thinks that adopting a particular technology will be easy to use.

Starting from these definitions we composed the PEEU construct:

A1. I found the new interface easy to understand;

A2. I would prefer watching an Augmented Family Photo Album with respect to a normal one;

A3. I enjoyed the overall experience.

The A1 sentence immediately gets to the point; item A2 has been introduced as a further investigation, to understand if the users prefer to live an augmented experience with respect to a classical one. Through A3, we ask for a broad evaluation of the experience.

Following this path, we also want to evaluate the usefulness of the three DL models that have been developed to carry out the three different computer vision tasks present in this work: family album photo recognition, date, and socio-historical context estimations. For such reason, we also designed the chunk of question items defined as Deep Learning Gain (DLG), which is thought to measure the utility of our DL models:

B1. I appreciated the automatic identification of the pictures;

B2. I appreciated the automatic estimation of the pictures' dates;

B3. I appreciated the automatic estimation of the pictures' socio-historical context.

HoloLens Perspective (HLP) and Receiver Perspective (RP)

The second chunk of question items regards the HLP and RP constructs are defined in Table 4.5.

This additional set of questions was defined to explore the different perspectives of users enjoying our application (i.e., the one of the HoloLens 2 wearer and the remote one). In particular, they are based on the concept of Behavioural Intention, that is the individual intention to use a particular technology. Such items are an adaptation of the most significant elements used in [1058]. However, different from the first constructs, which were meant to exclusively measure the usefulness of our system, these questions aim at inspecting more intimate aspects of the users' intentions, i.e., the use they would make of this application and its impact on their daily lives.

In particular, both constructs were investigated by exploiting two groups of questions: the C and D groups. The C group is formed by Yes/No question scale questions, to avoid neutral scores:

C1. Would you use the HoloLens application to share your memories?

C2. Nowadays, would you use the HoloLens application to share your family photo album with a distant friend or relative?

C3. Nowadays, would you prefer to share your memories with the HoloLens, rather than sharing them in presence?

C4. Would you use this application to revive memories with a distant affection?

C5. Do you think this application would push you to contact your affections?

This group of items appears sufficient to answer and evaluate our constructs. Indeed, they face the problem of sharing memories from different perspectives: C1, C2, and C3 regard the intentions of the HoloLens 2 user while C4 and C5 are about the remote user. Nevertheless, we also wanted to explore deeper aspects of the Behavioural Intentions. For this reason, we also introduced the D group, evaluated through a Likert scale ranging from 1 to 5, in order to capture all the nuances of the user's intentions. It is formed by the following questions:

D1. Would you use the HoloLens 2 application to share with anyone your family photo album?

D2. Do you think this HoloLens 2 application would push you to contact your affections?

D3. Do you think this HoloLens 2 application would push you to spend more time visualizing your photo family album?

D4. Would you use this application to visualize family photo albums of strangers?

D5. Nowadays, may this application help create bonds between strangers?

The D-items group formed by D1, D2, and D3 reinforces the opinion regarding the role of our AR application in the revival of the family photo albums' cultural phenomena. The second group, which is composed of D4 and D5, regards instead the possible role that our design could have in socialization, inspecting the possibility of sharing such intimate material with complete strangers.

Results

All the collected data have undergone a reliability check to test their internal consistency and validate our research, through the widely used Cronbach's alpha index. However, Cronbach's alpha may result in low values for constructs when the tested population is equal to or less than ten items [960]. Therefore, we have also analyzed the Mean Inter-Item Correlation (MIIC), which is appropriate for our case [995]. In a range from 0 to 1, the MIIC confidence interval is 0.15 to 0.50, whereas higher values denote the items overlap.
As reported in Table 4.6, all scales demonstrate to be reliable with respect to the MIIC measure (all MIICs > 0.15). As you can see, our analysis doesn't take into consideration the group C4-C5. This is due to the fact that such questions concern very different aspects. The first one regards the application we are proposing, while the second involves family and personal aspects which are beyond the scope of this research.

Survey analysis: Perceived Ease and Enjoyment of Use (PEEU) and Deep Learning Gain (DLG) constructs

In Figure 4.17 are reported the survey results about the Perceived Ease and Enjoyment of Use (PEEU) and the Deep Learning Gain (DLG) construct items. In particular, we have detailed the mean and the standard deviation for each of them.

From such responses, it is evident that there is a strong agreement about the usefulness and ease of use of our application. Indeed, only the A2 item highlights a mean lower than 4 (where 5 is the maximum). This is due to the fact that some of the respondents continue to prefer reviving their old memories physically with their affections.

Surprisingly, all the questions regards the DLG construct have a mean of 4.5. This outcome was not so obvious, since the respondents are clearly suggesting their preference for the use of modern technologies in the given application scenario.

Survey analysis: HoloLens Perspective (HLP) and Receiver Perspective (RP)

Figure 4.18 and Figure 4.19 report the survey results for the HoloLens Perspective (HLP) and the Receiver Perspective (RP). In particular, the first Figure depicts the percentage of agreement with respect to the C-x items of the two groups, while the second describes the likelihood with respect to the D-x ones, evaluated with the mean and the standard deviation of Likert scores.

Given the percentage of agreement on the C-x items, reported in Figure 4.18, we can infer that the considered population, from both the HoloLens 2 user and the remote perspectives, would use our AR application to contact their effects and revive together their memories, when physically distant. This is of great importance since our work could be useful to bring back to life the tradition of family reunions in front of a family album, even when a family is geographically spread. However, we can notice from the answer to C3, in line with the discussion in Section 4.2.5, that our respondents were equally divided when asked whether they'd prefer to live such a moment physically or virtually.

The results described in Figure 4.19 follow the trend of the previous ones. Nevertheless, even if there is great uncertainty (due to high standard deviation), the D2 answer highlights the fact that our proposal may not be sufficiently convincing to contact an affection, in some way linked to the photo album, more than usual. Moreover, D4 and D5 scores underline that a large part of our respondents are not so comfortable regarding the sharing of such intimate materials with anyone who wants to appreciate it. Nevertheless, these answers may provide additional inspiration for future works.

Conclusions and future works

We here presented an AR system to revive one of the biggest family traditions, i.e., family photo album exploration, putting to good use the HoloLens 2. To reach such a goal, our AR system includes a trained version of the most known DL-based object detector, namely YOLO, to recognize pictures within a family photo album and two additional DL models, namely IMAGO-DATING and IMAGO-SOCIO HISTORICAL CLASSIFIER, already introduced by Stacchio et al. in [1219]. Such models served the purpose of providing the information needed to augment a given HoloLens 2 user's view. Moreover, we also implemented a simple streaming service, allowing users to access shared photo albums from any kind of device. The system has been assessed with the interview of 10 users who found the interface easy to use and who provided enthusiastic feedback regarding the proposed experience. Based also on the users' comments, we were able to individuate possible future directions of work. Firstly, we aim to include an active collaboration between HoloLens 2 users and remote ones, letting them synchronously manipulate the augmented and shared view, through any kind of non-AR device (e.g., smartphone, tablet, pc) and AR devices (e.g., HoloLens 2). Such kind of manipulation amounts to provide: (a) data annotation capabilities through vocal recognition, and, (b) affine transformations such as moving, flipping, rotating etc. With these extensions we aim at incrementing the level of interest, possibly enhancing the quality of the experience. Secondly, we want to augment the capabilities of the examined IMAGO DL models, giving them the possibility to infer richer details, such as the people's identity, the country, any symbolic objects (e.g., chairs, cars), and/or specific events (e.g., weddings, birthdays). Additionally, to address real-time synchronization and latency challenges in shared experiences, future work will focus on network optimization strategies such as latency compensation algorithms, predictive synchronization models, and adaptive buffering to maintain seamless interactions, particularly in remote collaboration scenarios. Exploring edge computing solutions could help reduce reliance on centralized servers, enhancing real-time responsiveness. By implementing these advancements, our system has the potential to elevate family photo exploration into a deeply interactive, historically enriched, and collaborative experience, bridging the gap between traditional photo albums and AI-driven augmented reality.

Category	Question	Evaluation Method
PEEU	(A1) I found the new interface easy to understand	5-point Likert scale
	(A2) I would prefer watching an Augmented Family Photo Album respect to a normal one	5-point Likert scale
	(A3) I enjoyed the overall experience	5-point Likert scale
DLG	(B1) I appreciated the automatic identification of pictures	5-point Likert scale
	(B2) I appreciated the automatic estimate of pictures' date	5-point Likert scale
	(B3) I appreciated the automatic estimate of pictures' socio-historical context	5-point Likert scale

Table 4.4: Evaluation of the Augmented Family Photo Album

4.2.6 Insights

The findings of this study have been published in [1218].

Objective

This case study explores how Augmented Reality (AR) can facilitate collaborative memory sharing within a shared environment. The study aims to understand how AR technology can create an immersive and engaging experience that enables individuals to recall, share, and interact with visual memories together. This approach

Category	Question	Evaluation Method
HLP	(C1) Would you use the HoloLens application to share your memories?	Yes/No question
	(C2) Nowadays, would you use the HoloLens application to share your photo family album with a distant affection?	Yes/No question
	(C3) Nowadays, would you prefer to share your memories with the HoloLens rather than sharing them in your presence?	Yes/No question
	(D1) Would you use the HoloLens application to share with anyone your photo family album?	5-point Likert scale
	(D2) Do you think this HoloLens application would push you to contact your affections?	5-point Likert scale
	(D3) Do you think this HoloLens application would push you to spend more time visualizing your photo family album?	5-point Likert scale
RP	(C4) Would you use this application to revive memories with a distant affection?	Yes/No question
	(C5) Do you think this application would push you to contact your affections?	Yes/No question
	(D4) Would you use this application to visualize photo family albums of strangers?	5-point Likert scale
	(D5) Nowadays, do you think this application could foster the creation of bonds between strangers?	5-point Likert scale

Table 4.5: Evaluation of HoloLens application usage

Table 4.6: Cronbach's α index and MIIC for the considered constructs.

Construct	Items	α	MIIC
PEEU	A1-A3	0.73	0.46
DLG	B1-B3	0.81	0.58
HLP	D1-D3	0.69	0.43
RP	D4-D5	0.56	0.39
HLP	C1-C3	0.71	0.45

offers an opportunity to bridge geographical gaps, allowing users to experience a sense of presence and connection while revisiting personal memories.

Key Technologies

- **Microsoft HoloLens 2**: A wearable AR device that enables real-time visualization and interaction with digital elements, allowing users to share augmented views of family photo albums.
- **YOLO and IMAGO DL Models**: YOLOv5s aids in detecting and cropping family photos, while the IMAGO-DATING and IMAGO SOCIO-HISTORICAL CLASSIFIER models provide contextual metadata, such as date and socio-historical context, for each image.
- **Live Streaming and Shared View**: Allows remote participants to view the augmented experience on various devices, enhancing the collaborative and immersive aspect of memory sharing.

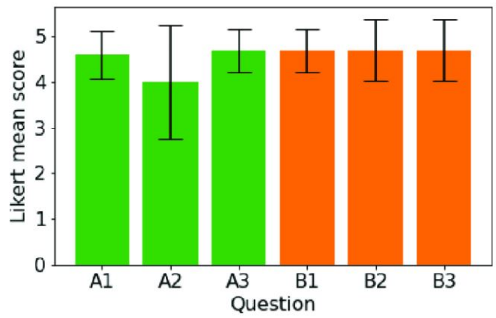


Figure 4.17: Histogram comparison of 5-point Likert questionnaire results related to A-x and B-x items which are relative to the Perceived Ease and Enjoyment of Use (PEEU) and the Deep Learning Gain (DLG). In green and orange we report the mean scores obtained by the PEEU and DLG respectively, along with their standard deviations.

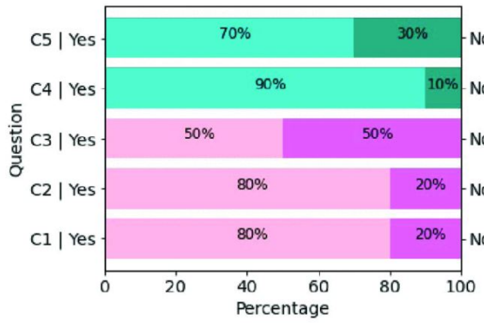


Figure 4.18: Yes/No answer percentages for the C-x items. C-x items are those related to the HoloLens Perspective (HLP) and Remote Perspective (RP), respectively colored in pink and light blue.

Main Findings

- **Enhanced Emotional Engagement**: The AR-based memory-sharing experience significantly increased user emotional connection. Participants reported feeling more immersed and engaged, as the augmented display allowed them to visualize and interact with family photos collaboratively, adding depth to the memory-sharing process.

- **Social Connection and Empathy**: The collaborative aspect of the AR environment promoted empathy and understanding among participants. Users expressed a stronger sense of connection by exploring shared memories, with some participants noting that the experience helped them gain a deeper appreciation for their family history and heritage.

- **User Satisfaction with Interface and Usability**: The study found that participants rated the AR system highly in terms of ease of use and enjoyment. Most users appreciated the interface's intuitive design, which allowed them to focus on the shared experience rather than on learning new technological interactions.

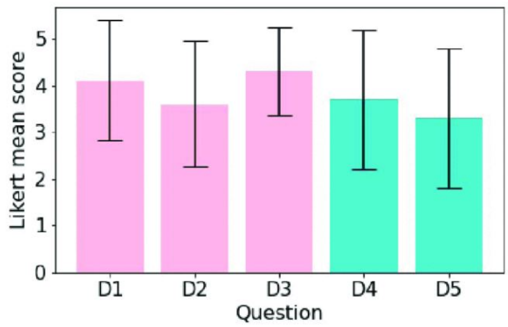


Figure 4.19: Histogram comparison of 5-point Likert questionnaire results related to D-x items which are relative to the HoloLens Perspective (HLP) and Remote Perspective (RP). In pink and light blue we report the mean scores obtained by the HLP and RP respectively, along with their standard deviations.

- **Value of Socio-Historical Metadata**: The automatic tagging of images with socio-historical context and dates, enabled by the YOLO and IMAGO models, provided additional layers of meaning. Participants found this metadata valuable for adding historical insight and enhancing their understanding of family photographs beyond mere visual representation.

- **Interest in Expanding Use Beyond Personal Albums**: Some participants expressed interest in applying this AR system to broader cultural heritage contexts. This feedback suggests that the framework could extend to applications in museums or archives, allowing for public engagement with historical artifacts in an interactive and educational way.

Technical and Usability Limitations

- **Real-Time Synchronization and Latency**: Ensuring that all participants experience synchronized views and interactions in real-time can be challenging, especially in remote settings where connectivity may vary.

To address real-time synchronization and latency challenges, future work should focus on network optimization techniques, such as latency compensation algorithms, predictive synchronization models, and adaptive buffering, to maintain consistency in shared experiences, particularly in remote settings with variable connectivity.

4.3 Discussion and Conclusion

This chapter aimed to answer the research question: *How do cognitive augmentation systems enhance social dynamics, teamwork, and collaborative experiences in shared virtual environments?*

Through the examined case studies, we explored the role of these technologies in facilitating teamwork, communication, and shared virtual interactions.

The Virtual Office for Experiencing Uncertainty case study (N9) highlighted how simulated uncertainty impacts decision-making and communication within collaborative tasks. While the VR environment effectively replicated real-world uncertainties, a primary challenge was maintaining realism in complex scenarios.

The Shared VR for Experiencing Uncertainty case study (N10) demonstrated how XR environments could enhance users' ability to adapt to ambiguous information in shared spaces, promoting resilience in teamwork. However, managing real-time synchronization and latency was critical to preserving social presence, as minor delays often disrupted group cohesion and affected task performance.

The Collaborative Memory Sharing in AR case study (N11) explored the social and emotional dimensions of technology for family memory sharing. AR proved valuable in enhancing empathy and understanding among participants by creating a shared memory space. Challenges included ensuring accurate metadata display and achieving consistent AR synchronization across devices, especially in remote or variable connectivity conditions.

While XR, AI, and sensor technologies offer significant benefits for social and collaborative experiences, challenges remain in latency, real-time synchronization, and usability. Future research should focus on reducing network delays through edge computing, improving AI-driven interaction models, and refining multimodal interfaces to enhance co-presence and communication fluidity. Additionally, advancements in tracking accuracy and adaptive AI responses will be key to ensuring XR-based collaboration remains intuitive, inclusive, and accessible across diverse scenarios.

Together, these findings illustrate how XR, AI, and sensor technologies shape digital collaboration, providing new opportunities for teamwork and social interaction while presenting unique challenges that future research must address to optimize user experience and technological reliability.

Chapter 5

Ethical Challenges

Integrating Extended Reality (XR), Artificial Intelligence (AI), and sensor-based technologies into cognitive augmentation systems offers the potential to revolutionize our interactions with digital environments, which is the primary focus of this thesis. However, with these advancements come complex ethical challenges that require careful consideration. In this section, we will explore key challenges in various contexts, including education, home and personal spaces, and healthcare. We explore these challenges through examples of the case studies investigated in Chapters 3 and 4.

In this chapter we aim to answer this key research question:

- RQ: What ethical considerations arise from the deployment of XR, AI, and sensor-based cognitive augmentation systems in personal, and collaborative environments?

5.1 Educational and Cognitive Challenges

Emerging XR, AI, and sensor technologies hold great promise for transforming education and enhancing cognitive abilities, but their use also raises significant ethical concerns, particularly around ***mental autonomy*** and ***data privacy***.

Virtual environments designed for educational applications, like the Augmented Reality (AR) language tool for dyslexic learners (Case study N1), the Mixed Reality (MR) puzzle-solving assistant (Case study N2), the MR Rubik's Cube notation learning system (Case study N3), and the AR outdoor exercise assistant (Case study N4), provide immersive and adaptive experiences that support personalized learning and cognitive skill-building. However, there is a risk that these systems might inadvertently foster dependency on technological assistance. In the MR puzzle-solving for example, the assistant provides real-time guidance, which, while enhancing task efficiency, may encourage reliance on external help rather than personal strategy formation. AR language tool might limit the development of independent language-learning strategies, while the Rubik's Cube system, though effective in teaching notations, could reduce users' ability to generalize skills to broader contexts. Balancing guidance with opportunities for independent practice is crucial to ensure these tools support autonomy, enabling learners to transfer skills beyond the supported environment. This concern is particularly addressed in the MR puzzle-solving application

(Case study N2), where the user retains control over when to request assistance from the virtual guide. By allowing the user to initiate help only as needed, the design encourages personal problem-solving strategies and reduces the risk of over-reliance on external guidance.

Furthermore, applying these systems raises questions about data ownership and control, as extensive data collection is required to personalize the experience. This concern is amplified in collaborative environments, such as the AR memory-sharing tool (Case study N3), where users contribute personal data to a shared space, raising complex questions about data ownership.

As these technologies reshape education and assisting systems, addressing these ethical issues—particularly in safeguarding data privacy and fostering cognitive independence—becomes essential to ensure that they enhance rather than encroach upon user autonomy and privacy.

5.2 Home and Family Spaces Challenges

As XR technology increasingly permeates personal and family spaces, complex ethical challenges surrounding ***ownership***, ***privacy***, and ***security*** become more pronounced.

Augmented Reality (AR) applications, such as the language-learning app for dyslexic learners (Case study N1) and the family memory-sharing tool (case studies N6 and N11) blur the line between physical and digital realms, raising critical concerns about how personal data and spaces are protected. One primary issue is the ambiguous distinction between private and public boundaries within AR environments, where digital overlays are mapped onto shared or personal spaces, often without clear guidance on who controls or owns these virtual elements. For instance, in an AR-enhanced home users may wonder who holds rights to the virtual content—a question complicated by traditional property laws that do not yet apply to mixed-reality spaces. This blurring of public and private domains leads to potential privacy risks, notably in spatial doxxing, where AR applications unintentionally expose information about a user's location or habits. For example, the language-learning app captures images of users' home environments to recognize objects and concepts, tailoring feedback to the learner's surroundings. Similarly, the AR family memory tool, which involves mapping and sharing personal memories within a shared environment, illustrates how easily sensitive data can be inadvertently disclosed, risking not only the user's privacy but also the security of those within the space.

Moreover, as AR becomes embedded in everyday spaces, the environmental impact of supporting infrastructures, such as data centers and extensive network demands, introduces sustainability concerns. Given the energy-intensive nature of these systems, their widespread adoption may impose significant ecological costs, highlighting the ethical necessity of addressing both the privacy and environmental sustainability of XR technologies as they enter intimate settings.

5.3 Healthcare and Well-being Challenges

As XR technologies advance in well-being and therapeutic settings, they offer transformative potential yet raise significant ethical concerns, especially around ***data privacy***, ***patient safety***, and the ***responsible application*** of immersive tools.

A primary issue is the secure handling of sensitive data, particularly in XR applications that capture biometric information such as physiological or behavioral data. For instance, in the virtual reality (VR) enactment study (Case study N7), an AR assistant provides real-time support to calm users during stressful situations. Although beneficial for anxiety management, the collection and analysis of behavioral data could inadvertently reveal sensitive information about the emotional state of a user, raising concerns about consent and data protection. The "Bimanual Interaction Techniques" VR (Case study N5), designed to assist users with limb loss, highlights key ethical considerations related to privacy and user identity. This system collects detailed health-related data, essential for tailoring VR interactions to meet each user's specific needs. However, securely managing this sensitive information is crucial for safeguarding user identity and privacy while ensuring that accessibility adjustments enhance—rather than compromise—comfort and orientation within the VR environment. Additionally, the studies on user responses to uncertain VR environments (case studies N9 and N10) underscore the need for psychological safety, as exposure to ambiguous virtual cues may exacerbate anxiety, especially in individuals with mental health vulnerabilities.

As XR and AI become integral to well-being applications, establishing ethical standards that safeguard privacy, and prioritize psychological safety is essential for responsibly maximizing their therapeutic value.

5.4 Ethical Frameworks

To address the ethical challenges posed by XR, AI, and sensor technologies, a comprehensive framework must be established, focusing on user privacy, autonomy, safety, and inclusivity.

A primary strategy is **privacy by design**, integrating privacy protections throughout each stage of technology development. This includes data minimization practices, ensuring only essential data—particularly sensitive health-related information—is collected. In therapeutic settings, specialized protocols such as encryption and restricted access are critical for managing biometric and health data securely [830]. Additionally, anonymization techniques, such as differential privacy, and informed consent mechanisms are essential for safeguarding identities [1022]. To enhance user control on their data, systems should provide customizable privacy settings, enabling individuals to determine the type and extent of data they share, including settings specific to health data collection, thereby empowering users to protect their personal and health information [12].

Algorithmic transparency and accountability are also crucial to address concerns about potential manipulation and dependency within immersive environments. In AI-driven systems, implementing Explainable AI (XAI) frameworks allows users to understand AI-driven recommendations and decision-making processes, fostering trust while reducing risks of manipulation [1022]. Transparency measures should also include protocols that prevent AI systems from fostering over-reliance on guidance, ensuring that users retain autonomy and focus on building skills transferable to real-life contexts. Independent audits of algorithms can further verify ethical operation, particularly in applications where user behavior may be influenced [12]. Additionally, incorporating user feedback loops allows for continuous improvement of the system, aligning it with user preferences and ethical standards.

Ensuring psychological safety in XR environments, especially for vulnerable users, is another key aspect. This includes content filters, warnings for potentially distressing material, and user control over exposure to intense immersive elements. In therapeutic contexts, regular system check-ins and adaptive content controls, allowing users to adjust the level of immersion, can help mitigate overstimulation risks [12]. Monitoring for potential psychological impacts and providing tailored content for sensitive populations will further enhance user safety and reduce adverse effects.

Finally, **user safety protocols** are essential, where real-time monitoring of physiological data—such as heart rate or stress levels—can ensure user interactions remain within safe limits [830]. Setting thresholds for safe physiological responses and providing immediate feedback to users if immersive interactions exceed these limits can prevent discomfort and ensure a positive user experience.

Together, these strategies create a multidimensional ethical framework that addresses privacy, psychological safety, and user autonomy at every level of XR, AI, and sensor technology application. This framework fosters responsible development and deployment in diverse settings.

5.5 Discussion and Conclusion

This chapter aimed to answer the research question: *What ethical considerations arise from the deployment of XR, AI, and sensor-based cognitive augmentation systems in personal and collaborative environments?*

Through an exploration of case studies, we analyzed the ethical challenges associated with cognitive augmentation in education, personal spaces, and healthcare. The findings illustrate that while these technologies provide significant benefits, including enhanced learning, social interactions, and accessibility, they also introduce substantial ethical concerns related to privacy, autonomy, security, and psychological well-being.

In educational contexts, XR, AI, and sensor technologies personalize learning experiences, but their integration raises concerns about mental autonomy and data privacy. Similarly, cognitive augmentation tools that collect behavioral and personal data raise critical questions about data ownership and control, particularly in shared environments, where multiple users contribute personal data to a collective digital space. Striking a balance between assistance and cognitive independence is crucial to ensuring that these systems support users without diminishing their autonomy. In personal and home settings, XR technologies create new ethical dilemmas concerning ownership, privacy, and security. Users interacting with AR overlays in home environments may unknowingly expose sensitive information, contributing to risks such as spatial doxxing, where digital applications inadvertently disclose personal details. Additionally, as XR applications become more embedded in daily life, their environmental impact, including data storage and energy consumption, must be addressed to ensure sustainable deployment. Healthcare applications of XR, AI, and sensor-based technologies offer transformative benefits, yet they also present significant risks related to data privacy, patient safety, and responsible implementation. While personalization enhances accessibility and therapeutic potential, it also introduces concerns about data security and consent, particularly when dealing with sensitive health information. Furthermore, immersive virtual environments can introduce psychological challenges, requiring safeguards to mitigate potential distress, cognitive overload, or unintended negative effects on users.

To mitigate these ethical challenges, a structured ethical framework must be developed, prioritizing user privacy, transparency, and psychological safety. Implementing privacy-by-design principles, including data minimization, encryption, and user-controlled privacy settings, can help secure personal and biometric data. Algorithmic transparency and accountability must be reinforced by integrating Explainable AI (XAI) frameworks, enabling users to understand how AI-driven decisions are made and preventing over-reliance on technological assistance. Additionally, ensuring psychological safety through content moderation, adaptive immersion controls, and physiological monitoring will be essential in reducing unintended negative effects on users.

The findings from this chapter emphasize that while XR, AI, and sensor-based cognitive augmentation systems offer immense potential, their ethical implications must be critically assessed to foster responsible and sustainable development. By embedding robust privacy protections, fostering transparency, and maintaining user autonomy, these technologies can be integrated to enhance human cognition while respecting ethical boundaries. Moving forward, future research must continue refining ethical frameworks, ensuring that technological advancements in cognitive augmentation align with fundamental principles of privacy, safety, and user empowerment.

Chapter 6

Discussion, Conclusion, and Future work

This chapter presents a comparative analysis of the case studies, identifying universal design principles and discussing recurring challenges in cognitive augmentation systems. It then discusses key findings concerning the research questions before concluding with a synthesis of insights. Finally, the chapter outlines future research directions, providing pathways for advancing the development and ethical deployment of XR, AI, and sensor-based cognitive augmentation technologies.

6.1 Comparative Analysis of Case Studies

This section examines the fundamental elements that contribute to the effectiveness of CAS, highlighting key similarities and differences to extract universal design principles and best practices for future research and applications in cognitive augmentation. Additionally, it systematically analyzes multiple case studies to identify recurring technical and usability challenges, proposing solutions with the potential to mitigate them.

6.1.1 Universal Design Principles and Best Practices

From the comparative analysis of case studies, several universal design principles emerge:

- **Multi-Modal Engagement for Enhanced Cognitive Load Management:**
  - The use of visual, auditory, and haptic feedback improves knowledge retention, motor skills, and cognitive engagement.
  - Multimodal interfaces ensure that users with different sensory and cognitive needs can interact with the system effectively
  - **Best Practices:** All case studies incorporate multi-modal engagement through visual and auditory modalities, and interactive elements for enhanced accessibility and user experience.

- **Personalization and Inclusive Design for Diverse User Needs:**
  - CAS must adapt to individual differences in cognitive ability, learning style, and physical accessibility.
  - Systems should support dynamic adjustments based on user feedback, physiological monitoring, or behavior tracking
  - **Best Practices:** Several case studies demonstrated the significance of personalization and inclusive design:
    * *Outdoor Augmented Reality Application for Workout Assistance* (Case study N4) validated that sensor-driven personalization (e.g., heart rate monitoring and environmental tracking) enabled real-time adjustment of workout intensity, enhancing user performance and safety.
    * *User Enactment in Virtual Reality Smart Home* (Case study N7) reinforced the importance of user-controlled customization, where individuals could modify AI-driven home automation settings to fit their personal preferences and routines.
    * *Augmented Reality Language Learning for Dyslexia* (Case study N1) demonstrated how inclusive design principles can enhance learning accessibility for students with dyslexia. The system incorporated multimodal interaction strategies, including visual overlays, speech synthesis, and interactive exercises, to support the different cognitive processing styles of this target group.
    * *Bi-Manual VR Interaction for Upper Limb Differences* (Case study N5) highlighted the role of inclusive design by evaluating multiple interface configurations tailored to users with limited motor abilities. The study examined how different interaction techniques could support users with upper limb differences, ensuring that the system was accessible and effective for this range of physical capabilities.
- **Adaptive and Context-Aware Interaction:**
  - Systems should detect and respond to users' real-time cognitive states (e.g., stress levels, attention shifts).
  - Adaptive AI mechanisms should provide tailored feedback that aligns with the user's cognitive and emotional state.
  - **Best Practices:** Several case studies demonstrated the importance of context-aware adaptation:
    * *Augmented Reality Language Learning for Dyslexia* (Case study N1) demonstrated the importance of context-aware adaptation based on a user's language proficiency level. The system provided structured exercises and multimodal support (visual, auditory, interactive elements) adapted to different levels of linguistic competence, ensuring accessibility for students with dyslexia.
    * *Mixed Reality Virtual Assistant in Puzzle-Solving* (Case study N2) provided real-time context-aware (state-aware) guidance based on the user's question about a piece and the current state of the puzzle, ensuring tailored assistance during the problem-solving process.

  * *Rubik's Cube Learning in XR* (Case study N3) offered context-aware guidance based on the state of the cube, dynamically adjusting instructional feedback according to the user's progress in solving different layers, ensuring step-by-step assistance.
  * *Outdoor Augmented Reality Application for Workout Assistance* (Case study N4) utilized real-time sensor data to adjust workout recommendations dynamically based on environmental conditions and user fatigue, ensuring effective and personalized guidance.
  * *Real-Time Environment Feedback in Augmented Reality* (Case study N8) demonstrated how continuous environmental sensing and adaptive feedback mechanisms allowed VR systems to dynamically adjust interface elements based on external conditions, such as temperature and humidity.
  * *Preserving Family Album Photos* (Case studies N6 and N11) showcased context-aware augmentation by overlaying metadata onto physical family photos, allowing users to engage dynamically with historical and contextual information. The system provided adaptive overlays based on image recognition.

- **Scalability and Real-World Integration:**
  - CAS should transition from controlled research environments to real-world applications, such as professional training, education, and collaborative workspaces.
  - Future research should explore how CAS can be deployed at scale while maintaining accessibility and efficiency.
  - **Best Practices:** Several case studies demonstrated the potential for scalable deployment:
    * *Augmented Reality Language Learning for Dyslexia* (Case study N1) showed how AI-driven learning tools could be adapted for a wider range of learning disabilities and languages, extending their applicability in education.
    * Both the *Mixed Reality Virtual Assistant in Puzzle-Solving* and *Rubik's Cube Learning* in XR (Case studies N2 and N3) demonstrated their scalability for a wide range of procedural and assembly tasks.
    * *Outdoor Augmented Reality Application for Workout Assistance* (Case study N4) highlighted the feasibility of AR-driven fitness assistance for broader public use.
    * *Virtual Office Experience for Experiencing Uncertainty* (Case studies N9 and N10) demonstrated that collaborative CAS applications could transition into various professional settings, providing scalable solutions for teamwork and decision-making training.
    * *Bi-Manual VR Interaction for Upper Limb Differences* (Case study N5) emphasized how adaptive VR techniques could be generalized to support a wide range of users with physical impairments, enhancing accessibility.

    * *Collaborative Memory Sharing in Augmented Reality* (Case study N10) demonstrated how AR applications can scale from personal use to shared experiences and broader cultural heritage contexts.

- **User-Centered Design for Cognitive Augmentation:**
  - CAS should be developed using participatory design methodologies, incorporating feedback from target users, including those with disabilities or cognitive differences.
  - The iterative design process should refine interfaces based on usability testing and cognitive load assessments.
  - **Best Practices:** Across case studies, user-centered design played a critical role in ensuring accessibility, adaptability, and engagement:
    * The *Bi-Manual VR Interaction for Upper Limb Differences* (Case study N5) benefited from participatory design approaches, where users influenced interaction techniques to accommodate diverse cognitive and physical abilities.
    * Providing customization options and adaptive controls fostered autonomy, enhancing trust and usability. Several case studies highlight user autonomy, allowing individuals to control and personalize their interactions based on their preferences and needs. The *User Enactment in Virtual Reality Smart Home* (Case study N7) demonstrated how customizable AI-driven interactions enabled users to modify automation settings, increasing trust and system usability. In the *Augmented Reality Language Learning for Dyslexia* (Case study N1), learners could select their language proficiency level, ensuring a tailored experience that best suited their cognitive needs. The *Mixed Reality Virtual Assistant in Puzzle-Solving* (N2) further reinforced user autonomy by allowing users to request assistance on demand, ensuring guidance was provided only when needed. These examples illustrate how user-centered design fosters autonomy, empowering users to tailor their experiences for greater control, adaptability, and engagement.
    * Across all the case studies, multimodal interaction strategies integrate visual, auditory, and interactive elements to support different learning styles and enhance comprehension.
    * Context-aware adaptation mechanisms dynamically adjust interfaces based on user needs and environmental conditions, further enhancing engagement and effectiveness. Several case studies demonstrate context-aware adaptation, dynamically adjusting interfaces based on user needs and environmental conditions. The *Outdoor AR Workout Application* (Case study N4) personalized recommendations using real-time sensor data, while *Preserving Family Album Photos* (Case study N6) enriched interaction by overlaying contextual metadata. *Mixed Reality Puzzle-Solving and Rubik's Cube Learning in XR* (Case study N2 and N5) provided state-aware guidance, adapting instructions based on real-time task progress. These examples highlight

how adaptive systems enhance usability by responding dynamically to users and their environment.

- **Transparency and Explainability in AI-driven Assistance:**
  - AI-driven systems must be explainable to users to foster trust and usability.
  - Users should have control over AI recommendations and be able to override or adjust automated suggestions.
  - **Best Practices:** Several case studies emphasized the importance of AI transparency and user control:
    * *Augmented Reality Language Learning for Dyslexia* (Case study N1) promoted transparency by giving users control over their learning experience, allowing them to set their language proficiency level rather than relying on automated difficulty adjustments.
    * *User Enactment in Virtual Reality Smart Home* (Case study N7) demonstrated that users reported higher trust in AI assistants when they could inspect, modify, or override system-generated recommendations, highlighting the necessity of transparent decision-making.
    * *Preserving Family Album Photos* (Case studies N6 and N11) showcased the importance of clear metadata tagging and retrieval mechanisms, ensuring that users understood how AI was categorizing and presenting information.
- **Ethical Considerations and Data Privacy in Cognitive Augmentation:**
  - User autonomy, data security, and transparency are critical design considerations.
  - Ethical safeguards should be embedded to prevent misuse and ensure responsible deployment of AI-driven and sensor-based cognitive augmentation systems.
  - **Best Practices:** Across various case studies, ethical concerns and strategies for responsible deployment were highlighted. These include the integration of data privacy regulations in AI-driven educational systems, the importance of user consent mechanisms to mitigate risks of biometric data misuse, and the challenges of metadata management in augmented reality applications, emphasizing the need for secure and transparent data processing. Additionally, ensuring user control over data collection emerged as a key factor in maintaining autonomy and trust.

6.1.2 Common Challenges and Potential Solutions

Cognitive Augmentation Systems (CAS) face a range of technical and usability challenges that impact performance, real-time processing, interaction fidelity, and accessibility. Addressing these issues presents promising future research directions for improving stability, adaptability, and user experience in CAS.

1. Technical Challenges

- **System Stability and Reliability**
  - Frequent *crashes, lagging, and freezing* in computationally intensive XR scenarios.
  - **Relevant Case Studies:** N2, N5
  - **Future Research Direction:**
    * *Intelligent load balancing algorithms:* Dynamically distribute computational tasks across system resources to prevent bottlenecks and improve performance.
    * *Cloud-assisted XR architectures:* Offload heavy processing tasks to remote servers, reducing device strain and enhancing XR system efficiency.
- **Real-Time Synchronization**
  - *Network latency and synchronization lags* disrupt XR experiences.
  - **Relevant Case Studies:**N5, N6, and N8
  - **Future Research Direction:**
    * *Edge computing and decentralized synchronization:* Process data closer to the user to reduce latency and enhance real-time responsiveness in XR interactions..
    * *Machine learning-based predictive models:* Anticipate user actions by analyzing interaction patterns, enabling pre-rendering for smoother experiences.
- **Simulator Sickness in High-Movement VR**
  - Users experience *nausea, disorientation, and discomfort* in fast-paced VR interactions.
  - **Relevant Case Studies:** N7
  - **Future Research Direction:**
    * *Biometric sensing (eye-tracking, heart rate monitoring):* Detect early signs of discomfort in XR environments by monitoring physiological responses.
    * *Adaptive frame rate adjustments and predictive locomotion smoothing:* Dynamically modify frame rates and movement transitions to minimize motion sickness.

2. Usability Challenges

- **Balancing Complexity and Intuitiveness in Multimodal Interfaces**
  - Some interfaces are *too complex for new users*, while others *lack advanced functionality.*

  - **Relevant Case Studies:** N5, N4
  - **Future Research Direction:**
    * *Adaptive UI frameworks:* Dynamically modify interface complexity based on user expertise, ensuring a balanced learning curve.
    * *Machine learning-driven personalization:* Gradually introduce features by analyzing user behavior, tailoring the experience to individual needs.

- **Cognitive Overload in Multimodal Interactions**
  - Users experience *cognitive fatigue* from simultaneous multimodal stimuli.
  - **Relevant Case Studies:** N2
  - **Future Research Direction:**
    * *Cognitive load-aware interfaces:* Adjust interface complexity in real-time based on user feedback to prevent cognitive overload.
    * *EEG and eye-tracking:* Monitor brain activity and gaze patterns to dynamically modify interaction modalities for improved user experience.

- **Environmental Adaptation in Outdoor AR Applications**
  - *Sunlight glare and lighting variations* impact AR visibility.
  - **Relevant Case Studies:** N4
  - **Future Research Direction:**
    * *Real-time AR contrast enhancement algorithms:* Automatically adjust contrast in augmented reality displays to improve visibility in varying lighting conditions.
    * *Dynamic brightness control and polarization techniques:* Adapt screen brightness and reduce glare for optimal AR display clarity in different environments.

6.2 Discussion and Reflections on Key Findings

This section revisits the research questions posed in Chapter 1, reflecting on how the findings from the case studies contribute to answering them. By analyzing the integration of Extended Reality (XR), Artificial Intelligence (AI), and sensor technologies, evaluating their impact on cognitive augmentation, and identifying ethical considerations, this thesis offers a structured perspective on the challenges and opportunities in developing Cognitive Augmentation Systems (CAS).

The first research question asked *how XR, AI, and sensor technologies can be effectively integrated to develop and evaluate immersive and adaptive CAS for diverse daily scenarios.* The findings suggest that the effectiveness of this integration relies on the seamless interoperability of these technologies. XR provides immersive experiences that enhance user engagement, while AI enables dynamic adaptation and decision-making by learning from user behavior. Sensors contribute by capturing real-time physiological and environmental data, enabling more responsive and context-aware interactions. Across the case studies, the synergy of these technologies was evident.

The second research question explored *the impact of CAS on cognitive augmentation at both personal and collaborative levels.* The case studies showed that CAS applications significantly influence cognitive processes in both individual and group settings. In personal augmentation, systems such as the AI-powered language learning app for dyslexia demonstrated a notable potential for improvements in skill acquisition, retention, and cognitive efficiency. The use of adaptive AI was particularly effective, ensuring that users received personalized support based on their learning progression. In collaborative settings, studies such as the VR office environment and the AR memory-sharing system revealed that factors like social presence, and real-time feedback play a crucial role in shaping teamwork and communication. The results suggest that environments fostering a strong sense of social presence enhance user engagement and improve collaboration outcomes. The ability to provide real-time, context-aware assistance was shown to be essential in both personal and collaborative cognitive augmentation, reinforcing the importance of adaptive system design in CAS applications.

Finally, the third research question addressed *ethical considerations associated with deploying XR, AI, and sensor-based CAS in personal and collaborative environments.* The findings revealed that privacy, user autonomy, and data security are critical concerns when integrating AI-driven personalization in immersive technologies. Many CAS applications rely on continuous data collection to optimize user experiences, raising concerns about data ownership, transparency, and consent. Another key issue is user autonomy in AI-adaptive systems. While personalization enhances engagement, excessive AI-driven decision-making can reduce user control. This was evident in the collaborative AR memory-sharing study, the absence of explicit control over who could access or modify shared content led to concerns about data governance in multi-user environments. These cases underline the necessity of customizable AI settings, allowing users to actively participate in system adaptation rather than passively receiving AI decisions. Security risks associated with sensor-enabled CAS applications were also evident. Systems that integrate biometric and motion-tracking data, such as the AR workout assistant and bi-manual VR interaction system, raise concerns about data leaks and unauthorized surveillance. The ability of XR devices to capture subtle behavioral patterns could expose users to privacy violations if not properly secured. Implementing encrypted data transmission, local processing, and consent-based tracking can mitigate such risks. Ethical CAS design must prioritize human agency, digital authenticity, and responsible AI augmentation to ensure that XR systems enhance cognitive and social functions without replacing them.

In summary, the research findings indicate that the integration of XR, AI, and sensor technologies in CAS is most effective when these components are interoperable and context-aware. The impact of CAS on cognitive augmentation is significantly influenced by personalization and real-time feedback. Ethical concerns surrounding privacy, transparency, and user autonomy remain critical, underscoring the need for careful design and regulatory considerations in future developments. These insights contribute to the broader discourse on CAS, providing a foundation for designing more adaptive, ethical, and user-centered cognitive augmentation systems.

6.3 Conclusion

From a Human-Computer Interaction (HCI) perspective, this thesis explores the integration of Extended Reality (XR), Artificial Intelligence (AI), and sensor technologies in designing and developing Cognitive Augmentation Systems (CAS) at both personal and collaborative levels, contributing to both theoretical insights and practical applications.

At its core, this study investigated three fundamental questions:

- How can XR, AI, and sensor technologies be effectively integrated to develop and evaluate immersive and adaptive CAS for diverse daily scenarios?
- In what ways do CAS applications, developed through the integration of XR, AI, and sensor technologies, impact cognitive augmentation at both personal and collaborative levels in real-world contexts?
- What ethical considerations arise from the deployment of XR, AI, and sensor-based CAS in personal, and collaborative environments?

From a theoretical standpoint, this study highlights that CAS holds the potential to enhance cognitive performance across diverse scenarios by integrating immersive experiences with multimodal interaction techniques, including adaptive AI-driven assistance, real-time sensor-based feedback, and user-centered interface design. This reinforces the importance of designing intuitive, personalized, and responsive augmentation systems. From a practical standpoint, this research, through case studies, demonstrates the feasibility of implementing CAS for skill acquisition, collaborative tasks, and cognitive support in immersive environments. Additionally, it identifies and discusses each case study's technical and experimental limitations and suggests directions for future studies to address these challenges. Beyond its technological contributions, this thesis also examines the ethical implications of CAS through case studies, highlighting the importance of privacy safeguards, user autonomy, and responsible development.

Overall, this research lays a foundation for future work that seeks to balance technological innovation with ethical accountability, contributing to the responsible advancement of cognitive augmentation technologies.

6.4 Future Research Directions for Cognitive Augmentation Systems

Building on the foundations established in this thesis, future research can expand Cognitive Augmentation Systems (CAS) development in several directions.

First, extending CAS into more diverse real-world settings, such as professional environments or remote education, would provide valuable insights into their scalability and adaptability. Additionally, future work should explore pathways for transforming research findings into practical applications, including commercial products and public services that address real-world challenges. Understanding how CAS can be effectively deployed beyond controlled research environments will be crucial for broader adoption and impact.

Future research should also explore technical innovations in real-time processing, predictive modeling, and AI-driven adaptation. These advancements will enhance CAS functionality by enabling continuous and seamless user interaction, making them more efficient and responsive across a variety of use cases.

Research should also focus on expanding user demographics to understand CAS's impact across different age groups, cognitive abilities, and cultural contexts. This will ensure that cognitive augmentation technologies remain inclusive and adaptable to diverse user needs. Exploring usability improvements in adaptive UI design, accessibility, and multimodal interaction balancing will be crucial for creating more intuitive and inclusive XR experiences. Specifically, understanding how cognitive augmentation strategies differ across younger, middle-aged, and elderly users, as well as users with neurodiverse conditions or cognitive impairments, will help tailor CAS applications to a wider audience. Furthermore, investigating the cultural perception of CAS technologies will help in designing interfaces that accommodate different linguistic and cognitive styles.

Technologically, the development of lightweight, energy-efficient XR devices and more robust AI models can enhance the accessibility and functionality of CAS, enabling continuous and seamless user interaction. Advancements in natural language processing (NLP) and reinforcement learning (RL) also present opportunities to create CAS that provide more personalized and proactive cognitive support. Additionally, further studies should explore the intersection of CAS with neuroadaptive systems, leveraging brain-computer interfaces (BCIs) to develop even more tailored cognitive augmentation experiences.

Future work should also prioritize the ethical and social implications of CAS. This includes integrating real-time monitoring frameworks for data privacy, user autonomy, and ethical usage to safeguard users and promote responsible deployment. Addressing user autonomy and ensuring transparency in AI decision-making will be essential in preventing manipulative or intrusive cognitive augmentation. Furthermore, the development of privacy-aware CAS frameworks should be explored to ensure user data remains protected while maintaining system performance.

Ultimately, interdisciplinary collaborations will be necessary to ensure that cognitive augmentation technologies contribute positively to human capabilities while maintaining ethical and societal responsibility. These advancements will pave the way for seamless human-computer collaboration in augmented and virtual environments, ensuring that CAS remains at the forefront of XR-driven cognitive support.

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