Supporting Dyslexic University Students using Artificial Intelligence and Virtual Reality

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Declaration of Authorship

The undersigned hereby declares that the work entitled "Supporting Dyslexic University Students using Artificial Intelligence and Virtual Reality" is an original creation and has not been submitted, either in whole or in part, to any other university or institution of higher education for other qualifications. Furthermore, to the best of the undersigned's knowledge, this work contains no material authored or published by others, except where proper references, acknowledgments, and citations have been duly provided.

José Manuel Alcalde Llergo, October 2025

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Abstract

Dyslexia is one of the most prevalent specific learning disorders, affecting up to 17% of the population and persisting into adulthood. Although significant efforts have been made in early diagnosis and intervention at the primary and secondary education levels, support for dyslexic students in higher education remains insufficient. This gap often leads to academic dropouts, delayed graduation, and increased psychosocial distress. To address these challenges, this thesis explores the integration of Artificial Intelligence (AI) and Virtual Reality (VR) technologies to provide both personalized academic support and enhanced empathy within university contexts. The research was conducted within the VRAIlexia project, which aims to improve inclusiveness in higher education for students with dyslexia. Two main objectives guided this work: the development of AI-driven methodologies for personalized recommendation of compensatory tools and learning strategies, and the design of immersive VR applications for psychometric assessment and empathy promotion towards dyslexics in higher academic contexts. The AI component involves analyzing data from dyslexic students, optimizing machine learning models for predicting effective learning strategies, and implementing a recommendation system to be integrated into the BESPECIAL platform, designed within the VRAIlexia project context. The VR component includes both data collection from dyslexic students and the creation of two interactive environments, *The Virtual Campus* and *The Magic* Potion, that simulate the cognitive challenges of dyslexia, promoting awareness among peers, educators, and families. Together, these contributions establish an innovative framework that combines AI-based personalization with VR-based experiential learning. The outcomes demonstrate the potential of emerging technologies to foster both cognitive and emotional inclusion, setting the stage for more adaptive and empathetic educational environments in higher education.

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Resumen

La dislexia es uno de los trastornos específicos del aprendizaje más prevalentes, afectando hasta al 17% de la población y persistiendo hasta la edad adulta. Aunque se han realizado esfuerzos significativos en el diagnóstico temprano y la intervención en los niveles de educación primaria y secundaria, el apoyo a los estudiantes con dislexia en la enseñanza superior sigue siendo insuficiente. Esta carencia suele derivar en abandonos académicos, retrasos en la finalización de los estudios, y un aumento del malestar psicosocial. Para abordar estos desafíos, esta tesis explora la integración de tecnologías de Inteligencia Artificial (IA) y Realidad Virtual (RV) con el fin de proporcionar apoyo académico personalizado y fomentar una mayor empatía hacia los estudiantes disléxicos dentro del contexto universitario. La investigación se ha desarrollado dentro del proyecto *VRAIlexia*, cuyo objetivo es mejorar la inclusión en la educación superior para estudiantes con dislexia. Son dos los objetivos principales que guiaron este trabajo: el desarrollo de metodologías basadas en IA para la recomendación personalizada de herramientas compensatorias y estrategias de aprendizaje, y el diseño de aplicaciones inmersivas de RV para la evaluación psicométrica y la promoción de la empatía hacia personas con dislexia en contextos académicos avanzados. El componente de IA incluye el análisis de datos de estudiantes disléxicos, la optimización de modelos de aprendizaje automático para predecir estrategias de aprendizaje eficaces y la implementación de un sistema de recomendación destinado a su integración en la plataforma *BESPECIAL*, desarrollada en el contexto del proyecto. El componente de RV abarca tanto la recogida de datos de estudiantes disléxicos como la creación de dos entornos virtuales interactivos, *The Virtual Campus* y *The Magic Potion*, que simulan los desafíos cognitivos propios de la dislexia, promoviendo así la sensibilización entre compañeros, docentes y familias. En conjunto, estas contribuciones establecen un marco innovador que combina la personalización basada en IA con el aprendizaje mediante experiencias de RV. Los resultados demuestran el potencial de estas dos tecnologías emergentes para promover la inclusión cognitiva y emocional, sentando las bases para entornos educativos superiores más adaptativos.

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Part I

Foundations

This part introduces the problem statement and motivations, and presents the theoretical background and related work on the use of Artificial Intelligence and Virtual Reality in the field of specific learning disorders, with particular attention to dyslexia in higher education.

Chapter 1

Introduction

This chapter introduces the overall context of the thesis. It first outlines the background and motivation for addressing the academic and psychosocial challenges faced by university students with dyslexia, situating the work within current research and within the VRAIlexia project. It then presents the specific objectives that guide the thesis, together with the scope and main contributions arising from the integration of artificial intelligence (AI) and virtual reality (VR) methodologies in the context of supporting university students with dyslexia. Finally, the chapter provides an overview of the document's structure, indicating how the subsequent chapters develop and connect these contributions.

1.1 Background and Motivation

Dyslexia is the most common among specific learning disorders (SLDs). SLDs are a group of neurodevelopmental conditions that hinder the acquisition of key skills such as reading, writing, and arithmetic [1, 2]. Dyslexia is estimated to affect between 5% and 10% of the global population [3], although recent studies suggest that due to frequent underdiagnosis, the actual prevalence could reach up to 17% of the population [2, 4]. Dyslexia manifests in childhood but typically persists into adulthood, with consequences that extend beyond reading and memorization difficulties. Individuals with dyslexia frequently experience social exclusion and neuropsychological issues such as low self-esteem, social anxiety, and depression [5, 6].

While extensive research and resources have been dedicated to early diagnosis and the development of interventions for children at the primary and secondary education levels [7], the support provided in higher education remains insufficient. This disparity creates a barrier, as students with dyslexia continue to face significant academic challenges once they reach university. Recent studies demonstrate that such challenges are not only persistent but often exacerbated in higher education contexts. For instance, data collected by the Italian Ministry of Education (2019) show that while 3.2% of primary and secondary school students are identified with SLDs, this percentage drops to 1.2% at university, highlighting how university can become an insurmountable barrier for them [8]. A case study conducted at the University of Tuscia confirmed the impact of this gap, reporting that dyslexic students accumulated, on average, six fewer European Credit Transfer and Accumulation System (ECTS) credits per year than their non-dyslexic peers, equivalent to approximately one missed examination annually [9]. These results underline a heightened risk of academic delay and dropout, particularly in disciplines such as the humanities, where intensive reading and memorization are unavoidable.

The persistence of these barriers underscores the need for tailored methodologies and digital tools specifically designed for university students with dyslexia. The challenge lies not only in addressing the cognitive difficulties associated with the disorder, such as reading fluency and memorization, but also in mitigating its psychosocial consequences. In this respect, the understanding of schoolmates, teachers, and families plays a crucial role. A lack of awareness often leads to misunderstanding, stigmatization, and insufficient support in academic contexts [10]. Fostering empathy and concern within the broader educational community is, therefore, essential to creating inclusive environments. Against these barriers, this thesis focuses on leveraging AI and VR to support dyslexic students in university settings through scalable, personalized, and engaging interventions that go beyond traditional approaches.

This thesis is framed within the context of the VRAIlexia project (https://vrailexia.eu), an initiative that combines AI and VR-based methodologies to address the academic and psychosocial challenges faced by dyslexic students in higher education. Within this broader context, this thesis pursues a series of objectives that guide the research contributions presented in the following sections.

1.2 Objectives

The objectives of this thesis are defined to address both the academic and psychosocial barriers that dyslexic students encounter in higher education. The work is structured around two main objectives: Artificial Intelligence for Personalized Support and Virtual Reality for Assessment and Empathy. These two objectives are further divided into specific contributions that represent the key outcomes of the research conducted during the thesis.

Artificial Intelligence for Personalized Support

- **Identify and analyze the difficulties** experienced by dyslexic students in higher education using data from surveys, questionnaires, and psychometric assessments.
- **Determine the most useful support tools and learning strategies** reported by students, to guide the design of AI models for personalized recommendations.
- **Design and train machine learning models** capable of predicting the most suitable compensatory tools and learning strategies based on students' profiles.
- **Develop a recommendation system (RS)** enabling personalized delivery of digital tools and adaptive strategies.
- **Develop new AI-based support tools** to extend or adapt current methodologies and explore innovative approaches.

Virtual Reality for Assessment and Empathy

- **Create immersive VR environments** for psychometric assessment, designed to facilitate autonomous data collection without requiring the constant presence of a professional, while increasing user engagement.
- **Develop VR experiences** that replicate the challenges faced by dyslexic students, to foster empathy and awareness among peers, teachers, and families.
- **Evaluate usability and impact** of VR applications in higher education contexts, analyzing both their diagnostic value and their potential to improve inclusiveness.

In summary, this thesis pursues two complementary lines of research to support university students with dyslexia: the use of AI to provide personalized academic support and the use of VR to enhance assessment and promote empathy in educational contexts. Together, these objectives define the methodological foundation of the research and guide the structure of the thesis, which is presented in the following section.

1.3 Thesis Structure

The content of this thesis is structured into four main sections, each further subdivided into individual chapters. The central body of the work is split into two sections that, from different technological perspectives, address the same overarching goal: promoting the inclusion of university students with dyslexia. The first of these focuses on AI-based recommendation systems for personalized academic support, while the second presents VR applications designed to foster assessment and empathy. The sections and their corresponding chapters are summarized below:

I) **Foundations**: present the theoretical background and related work on the use of AI and VR in the field of SLDs, with particular attention to dyslexia in higher education.

- ◇ **Chapter 1** introduces the motivation, problem statement, objectives, and scope of the thesis, and provides an overview of its structure.
- ◇ **Chapter 2** introduces the theoretical background on the main technologies used during this work, and presents the VRAIlexia project as the basis of this thesis.
- ◇ **Chapter 3** reviews the related work in AI and VR for education, and describes the methodological framework adopted in the thesis.

II) **Construction of Recommendation Systems for Dyslexics**: introduce the AI-based contributions, including the analysis of student data, the application of machine learning models, and the design and implementation of a recommendation system for personalized support.

- ◇ **Chapter 4** details and analyzes the main source of data used as the starting point of the implementation of the recommendation system. This chapter also includes a preliminary study about the feasibility of using classical ML algorithms as a recommendation system.
- ◇ **Chapter 5** presents the design and implementation of a recommendation system capable of providing personalized support based on students' individual profiles.

III) **Virtual Reality Applications**: address contributions based on the design, development, and evaluation of a set of VR experiences aimed at fostering empathy towards dyslexic students (In the Shoes of Dyslexic Students).

- ◇ **Chapter 6** presents the *Virtual Campus*, designed as an awareness tool to simulate the daily challenges of dyslexic students in a university environment.
- ◇ **Chapter 7** describes the development of the serious game *Magic Potion*, which simulates how reading difficulties affect even when performing a simple task.

IV) **Conclusions**: present the discussion, final conclusions, and future directions of the thesis.

- ◇ **Chapter 8** discusses the findings obtained in both the AI- and VR-related studies, reflecting on their implications, limitations, and the lessons learned.
- ◇ **Chapter 9** concludes the thesis by summarizing the contributions achieved, highlighting the significance of the results, and outlining avenues for future research and development.

Chapter 2

Background

This chapter provides the conceptual and technical foundations for understanding the research presented in this thesis. The chapter introduces the main principles of AI and VR that will be addressed during the thesis, highlighting their relevance for personalized support, assessment, and training. Finally, the VRAIlexia project and some of the previous work are presented as the starting point for the work developed in this thesis.

2.1 Artificial Intelligence

AI is a field of computer science dedicated to creating systems capable of performing tasks that usually require human intelligence, such as learning, reasoning, and decision-making. Over time, AI has evolved from rule-based approaches to data-driven methodologies, where algorithms learn directly from data and improve their performance as new information becomes available.

Within the scope of this thesis, two branches of AI are particularly relevant. First, machine learning approaches are employed to analyze data collected from dyslexic students, extracting patterns and generating predictions about their difficulties, study behaviors, and potential support tools and learning strategies they could apply. Second, recommendation systems build on these results to provide personalized suggestions for tools and strategies adapted to the needs of each student. These two aspects are presented and explained separately in the following subsections.

2.1.1 Machine Learning Approaches

Several contributions of this thesis are based on data-driven models, specifically on data collected from university students with dyslexia. Among these sources, surveys and psychometric tests were employed to determine the most appropriate study tools and strategies for each student. Machine learning algorithms, particularly supervised ones, are well-suited for this task, as they can learn from existing patterns and improve their predictions as more data becomes available. Next, the different classical machine learning algorithms applied in this thesis will be enumerated and briefly explained to provide a clear understanding of their roles and implementation in Part II of the document.

1. **Logistic Regression** [11]: Logistic regression is a statistical model used for binary classification tasks, where the goal is to predict one of two possible outcomes. It models the relationship between the independent variables (features) and the probability of a specific outcome using a logistic function.

2. **Support Vector Machine (SVM)** [12]: SVM is a powerful supervised learning algorithm primarily used for classification. It works by finding the hyperplane that best separates

the data into two classes, maximizing the margin between the classes.

3. **K-Nearest Neighbors (KNN)** [13]: KNN is a simple, yet effective, algorithm used for classification and regression tasks. It works by assigning a class to a data point based on the majority class among its nearest neighbors in the feature space, using a distance metric such as the Euclidean distance. In this thesis, KNN is also employed as the basis of the recommendation system developed.

4. **Decision Tree** [14]: A decision tree is a flowchart-like structure where each internal node represents a decision based on a feature, and each leaf node represents an outcome. Decision trees are intuitive and interpretable models that are particularly useful for classification tasks.

5. **Random Forest** [15]: Random forest is an ensemble learning method that builds multiple decision trees and combines their predictions to improve accuracy. Each tree is trained on a different subset of the data, and the final prediction is made by averaging the results (for regression) or by majority voting (for classification).

2.1.2 Recommendation Systems

Recommendation systems (RSs) are algorithms designed to suggest relevant items to users based on their preferences, behaviors, or other data sources. These systems have become widespread across various domains, from e-commerce to social media, helping users navigate vast amounts of information and make decisions efficiently. In education, RSs can be used to suggest learning tools, study strategies, or resources that are best suited to each student's individual needs and learning style.
There are two primary types of recommendation systems:

- **Collaborative Filtering (CF)** [16]: The system recommends items based on the preferences or behaviors of other users who are similar to the target user. The system identifies users with similar interaction patterns and suggests items they have liked. For example, suppose a student with a learning profile (including learning difficulties) similar to another student who has benefited from a particular strategy. In that case, the system can recommend that strategy to the target student.

- **Content-based Filtering (CB)** [16]: The system recommends items similar to those the user has preferred in the past, based on the features or attributes of the items. For example, suppose a user has rated the use of conceptual maps as highly effective. In that case, the system can identify and suggest other learning strategies that also involve graphical displays within the same category or type.

In this thesis, a hybrid collaborative recommendation system based on KNN is developed. Its design and application are described in depth in Chapter 5.

2.2 Virtual Reality

VR is a technology that creates immersive environments, allowing users to interact with an artificially generated world as if it were real. This interaction is achieved by different sensory inputs, mainly visual and auditory [17]. In this way, users are able to experience simulations as if they were real-world scenarios. In different contexts, such as medicine or education, VR has been increasingly adopted for training, simulations, and immersive learning [18], as it offers unique opportunities for engaging students and accessing materials not typically available to them. Moreover, recent studies have explored the use of VR as a tool to promote empathy toward disadvantaged social groups [19, 20]. This aspect will be the primary focus of VR applications designed during this thesis, contextualizing them within the experiences of dyslexic students in higher education.

In Part III, the different VR concepts described below will be applied in the design of the *Virtual Campus* and the *Magic Potion* experiences, both of which aim to foster empathy and awareness of the difficulties faced by dyslexic students in higher education.

2.2.1 Development and Deployment

For the development of the VR applications presented in this thesis, the Unity development framework was chosen [21]. Unity is a powerful, real-time engine widely used for both video games and VR development. It provides the necessary tools to create immersive environments, handle user input, and incorporate physical interactions.

The VR applications implemented in this thesis are designed for use on Meta Quest 2 and Meta Quest 3 [22]. These standalone headsets provide high-fidelity, wireless experiences, offering a balance among performance, accessibility, and immersion. The use of these platforms enabled the creation of fully immersive VR experiences without the need for additional hardware, such as external computers or sensors. Moreover, Unity integrates seamlessly with the Meta Quest headsets, enabling efficient development and deployment of VR applications.

2.2.2 Interaction with the Virtual Environment

Within the developed virtual environments, users can engage in various types of interactions, each designed to enhance immersion and provide different ways to navigate and manipulate the virtual space. A key concept in VR development is the degrees of freedom (DoF). When 3DoF are applied, the VR system only tracks rotational movement, allowing the user simply to look around and change their view of the environment. However, Meta Quest 2 and Meta Quest 3 provide 6DoF, allowing users to move freely along all three translational axes (forward/backward, up/down, left/right), as well as rotate along all three rotational axes (pitch, yaw, and roll). This degree of freedom contributes significantly to a more immersive and realistic experience [23].

Interactions with the virtual environment are facilitated by controllers, which are essential for completing tasks and fully experiencing the environment. The main interaction types are described below:

- **Continuous locomotion**: This interaction simulates continuous movement through the virtual environment, allowing users to move freely along the three translational axes and rotate as they explore the space. Continuous locomotion enables precise and uninterrupted navigation, providing a high level of immersion. However, it can induce motion sickness due to a sensory mismatch between visual input and the vestibular system. See Figure 2.1 (a).

- **Teleportation**: Also known as parabolic locomotion, this interaction enables users to instantly jump to a selected point in the virtual environment. By pointing at a destination, users are teleported through a parabolic arc, overcoming the physical space constraints. Teleportation provides an alternative to continuous locomotion, making it especially useful for large virtual environments. While it reduces motion sickness, it can disrupt immersion and hinder the creation of a mental map of the environment. However, this issue is minimized in open spaces, such as *The Virtual Campus*, where the layout and open areas reduce the need for frequent teleportation and help maintain spatial orientation. See Figure 2.1 (b).

- **Button press**: This interaction allows users to activate virtual buttons by bringing the controller close to the corresponding button (or item) in the environment, similar to physically pressing a button. This action involves rotational DoF (via wrist or arm movement), but it may also require some translational movement to accurately position the controller.

- **Grab/release objects**: This interaction enables users to pick up objects within the virtual environment by positioning the controllers over them and pressing the grab button. Both translational and rotational DoF are required to manipulate objects effectively. Releasing an object is accomplished by simply releasing the corresponding button. This method is integral to tasks involving the handling and transportation of objects, enhancing the realism of the virtual experience.

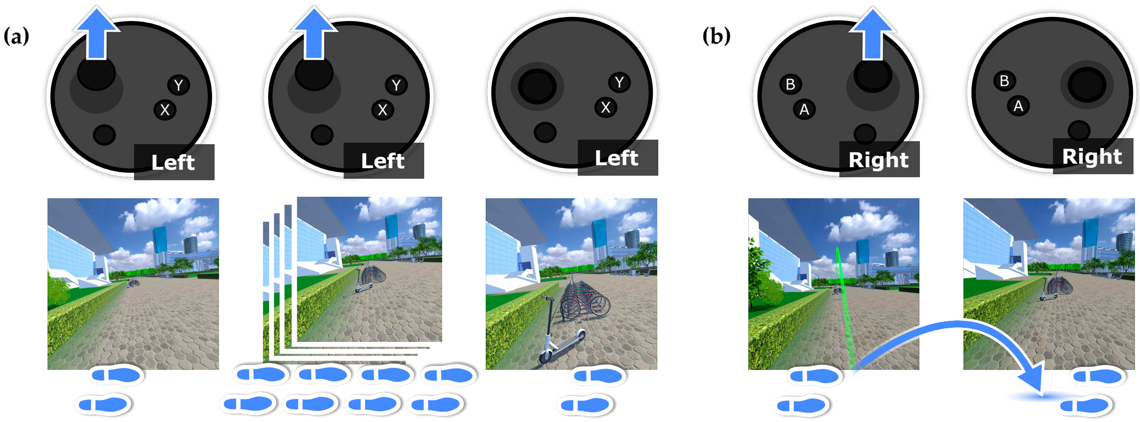

Figure 2.1: **Locomotion modes in *The Virtual Campus* and *The Magic Potion*.** (a) Continuous locomotion using the left controller. (b) Teleportation using the right controller.

2.3 VRAIlexia Project

The VRAIlexia project serves as the foundation of this thesis, providing a comprehensive framework to support dyslexic students at the university level. It has been developed under the Erasmus+ Program as an international initiative to address the specific challenges faced by dyslexic students in higher education by integrating AI and VR technologies. The main contributions of the VRAIlexia project can be summarized as follows:

1. **Out of the Box:** This contribution focuses on the development of the "Out of the Box" VR application, a tool designed to replace traditional dyslexia assessments conducted on-site by educational psychologists [24]. The Out of the Box VR app is used to administer psychometric tests, such as Silent Reading and the Rosenberg Self-Esteem Scale, aiming to facilitate the assessment process for dyslexic students by making it more engaging, less stressful, and eliminating the need for an educational psychologist's physical presence. The psychometric tests implemented in the app were developed in accordance with expert guidelines to ensure the translation of real-world tests into virtual environments remained accurate and effective.

2. **BESPECIAL:** BESPECIAL is a digital platform designed to provide personalized support for dyslexic students based on AI and adaptive learning [9]. It uses data from various sources, including surveys, clinical reports, and psychometric tests, to recommend tailored learning strategies and tools that best suit each student's individual needs. The system uses machine learning algorithms to predict the most appropriate support tools for each student.

3. **VRAIlexia Toolbox:** The Toolbox initiative involves the creation of a set of tools that can be used to support study. These tools were developed in conjunction with the company Tech4All from the University of Tuscia, and were collected in an application named Reasy [25]. Among other things, Reasy allows summarizing texts, extracting keywords, generating conceptual maps, creating flashcards, and creating audiobooks.

4. **ToC & ToT:** The Training of Creativity (ToC) and Training of Trainers (ToT) aims to create a network of experts from various fields to share their knowledge and expertise in Universal Design methodology. The network focuses on promoting creativity in teaching while training educators to support dyslexic students using a student-centered approach effectively. This initiative was reflected in various training sessions at different organizations collaborating on the project.

5. **Memorandum of Understanding:** This initiative promotes the creation of a Memorandum of Understanding (MoU) to foster the adoption of inclusive strategies across European higher education institutions [26]. The MoU promotes collaboration on strategies that support students with dyslexia and foster a more inclusive academic environment.

Building on these foundations laid by the VRAIlexia project, this thesis presents new AI and VR integrations to support dyslexic university students. In Part II, the focus is on new AI methodologies implemented to personalize the support provided to dyslexic students. This part will detail the new recommendation system developed to suggest the most suitable study tools and strategies, enhancing the personalized learning experience within the BESPECIAL platform. In PartIII, the thesis shifts to the VR applications developed as part of the VRAIlexia project. Here, the focus is on creating immersive environments designed to foster empathy and understanding of the challenges that dyslexic students face, providing a novel approach to supporting both students and educators. This part contributes to what was defined in the presented MoU. Together, these two parts build on the core objectives of the VRAIlexia project, offering an innovative, integrated solution to the challenges faced by dyslexic students in higher education.

Chapter 3

Related Works

Although several initiatives have emerged in recent years, technological solutions have yet to fully exploit their potential to support students with dyslexia. The efforts in this direction are progressively increasing, but most remain at an early stage of development. For instance, the studies presented in [27, 28] address the need for an ontology to guide the creation of e-learning tools adapted to the specific requirements of dyslexic learners. However, these works do not provide practical implementations of such support systems. Other approaches, such as the one presented in [29], focus on enhancing the readability of websites for individuals with dyslexia by analyzing interactions with websites among secondary students, both those with dyslexia and those without. A more significant advance is observed in [30], where a computer platform integrating speech synthesis and eye-tracking technologies substantially improved text comprehension among dyslexic participants.

This chapter reviews previous research and technological advances in supporting dyslexic students, with a particular focus on the transition from traditional compensatory methods to data-driven and immersive approaches. Specifically, first, it explores how AI has been applied to the detection and personalized support of dyslexic students, emphasizing its capacity to identify learning profiles and recommend individualized strategies. After that, the chapter analyzes the role of VR as a tool for inclusion and empathy, discussing how immersive environments can replicate dyslexic learners' cognitive and emotional experiences while fostering understanding among educators and peers. Together, these sections provide a comprehensive overview of the current state of research, highlighting the technological foundations upon which the subsequent contributions of this thesis are built.

3.1 AI in the Diagnosis and Support of Dyslexic Students

AI has become an increasingly relevant tool for identifying and addressing the challenges faced by students with dyslexia. Its capacity to process large, multimodal datasets and to learn non-linear patterns has led to new diagnostic and adaptive-support strategies that extend beyond traditional psychometric or clinical approaches.

If dyslexia is not detected at an early stage, the difficulties it causes become harder to mitigate and tend to affect the individual more severely [31]. Classically, the most common method for dyslexia detection relied on psychometric tests, which assessed users' cognitive abilities [32, 33]. In recent years, with the rise of AI, dyslexia detection has also become an active field of study. Several approaches have explored the use of machine learning and neural networks to automatically identify dyslexic patterns from behavioral or physiological data. For instance, [34] proposed an artificial neural network model capable of classifying dyslexic students based on reading performance, while [35] and [36] combined eye-tracking and human–computer interaction features with machine learning algorithms to detect reading impairments in adults. Other authors have employed fuzzy logic and genetic algorithms to refine the diagnostic process and handle data uncertainty [37]. More multimodal frameworks have incorporated neuroimaging information, such as MRI and fMRI scans, together with computational analysis to identify structural or functional brain anomalies characteristic of dyslexia [38].

However, despite the increasing research attention and the improved diagnostic capabilities for dyslexia in recent years, many adults did not receive adequate support during childhood or adolescence. This results in a great number of students still facing significant learning challenges today, particularly in higher education. For this reason, the development and implementation of AI-based compensatory tools have become essential to ensure that dyslexic students can keep pace academically with their peers. Several studies have explored the use of AI to design adaptive and personalized support systems aimed at mitigating reading and writing difficulties. For instance, computer-assisted learning environments have been created to predict and address phonological and spelling errors using Hidden Markov Models and other machine learning techniques, providing tailored exercises that improve literacy skills [39, 40]. Similarly, mobile applications integrating neural networks and SVM have been proposed to dynamically adjust the complexity of reading, writing, and speaking tasks, promoting engagement and gradual skill acquisition [41, 42].

Another promising line of research, which is one of the areas followed during this thesis, focuses on the use of AI-driven RSs to provide personalized support strategies and learning tools to students with dyslexia. Among machine learning algorithms, RSs are a natural candidate for providing a personalized learning experience to students [43], as they are specifically designed to detect user preferences and recommend items accordingly [44]. RSs can be generally categorized in collaborative filtering (CF), in which items are recommended based on the preference of similar users [45], content-based (CB), in which items are suggested to the user based on the description of the item [46], knowledge-based, which focuses on the knowledge of the users' need for a particular item [47], and hybrid system which is a combination of the algorithms described above [48]. In the field of education, several RSs have been proposed to enhance students' learning experience [49]. For instance, in [50] the authors combined a set of RSs with Web 2.0 tools to provide teachers with suggestions on how to design a course and students with guidance on which activities to choose, such as attending seminars, participating in e-courses, reviewing subject matter, and taking online tests. Following this methodology, students achieved better final course results. Another example is found in [51], in which the authors developed a hybrid RS to recommend learning objects to students with similar learning styles. This hybrid recommendation approach increased the relevance of the recommended educational material and improved students' learning.

The literature review reveals a clear evolutionary path in the use of AI for dyslexia, from early diagnostic tools based on physiological data or reading performance, to the design and implementation of compensatory tools focused on literacy skills. However, a significant gap remains in the field of higher education. While general RS have successfully improved student performance by suggesting learning objects or activities, these models do not consider specific neurodivergent profiles that could be present in university students. These systems are designed for "standard" learning styles, without considering the personalized compensatory strategies (such as specific software, exam adaptations, or cognitive methodologies) that are vital for dyslexic adults.

3.2 Role of VR in Supporting Dyslexic Students

The growing application of VR in education has opened new possibilities for addressing learning disorders such as dyslexia. Its distinctive features, such as immersion, interactivity, and multisensory feedback, allow users to experience learning situations in a realistic and emotionally engaging way [52]. These qualities make VR particularly valuable for studying and supporting dyslexia, as it enables both the simulation of cognitive difficulties and the creation of inclusive environments where learners can explore and interact. Through embodied interaction, users can develop deeper emotional understanding and sustained engagement, bridging the gap between abstract awareness and lived experience [53]. This section reviews how VR has been applied to dyslexia and other related educational challenges through two main research directions. The first subsection analyzes early educational uses of VR, focused on serious games and assistive tools to improve reading performance, attention, and motivation in dyslexic children. The second examines the rise of VR for inclusion and empathy, in which immersive technologies began fostering social awareness by recreating the experiences of individuals with disabilities or learning disorders.

3.2.1 Early Educational Uses of VR in Dyslexia

First explorations of VR in dyslexia focused primarily on educational and training purposes, mainly in primary and secondary education settings. The literature demonstrates the capacity of immersive environments to support cognitive and linguistic skills through engaging, multisensory activities. These systems were typically designed for children and teenagers to improve reading, memory, and attention in a controlled yet stimulating context. Studies such as the one conducted in [54] have indicated that VR can have a positive impact on the memory and skills of individuals with dyslexia. In this study, participants completed various assessments in a virtual classroom setting, where they were required to answer tasks posted on a blackboard. While the results did not demonstrate significant enhancements in reading ability, they revealed a notable improvement in participants' attention levels. This heightened attention could potentially lead to long-term improvements in other challenges associated with dyslexia, such as reducing the time required to read low-frequency long words.

Before delving deeper into VR tools, previous digital interventions for dyslexia also explored the use of interactive environments to support diagnosis and training. One of the most representative examples is the Dytective project, first introduced by Rello et al. [55] as a cross-linguistic online game for dyslexia detection and later expanded into DytectiveU [56], a training platform designed to reinforce reading and writing abilities through adaptive exercises. By integrating gamification and data-driven feedback, these systems demonstrated that interactive, play-based learning can enhance user motivation while simultaneously collecting valuable behavioral data for early detection. Their success anticipated many of the advantages later achieved through immersive virtual environments, showing that engagement and emotional involvement are key factors in the design of effective compensatory tools for individuals with dyslexia. The success of these game-based systems also inspired the design of multimodal environments that could combine auditory, visual, and kinesthetic stimuli to reinforce phonological processing. A representative case is Cosmic Sounds [57], a computer-based serious game designed to support phonological awareness in children with dyslexia. The authors demonstrated that integrating auditory cues and responsive visual feedback can enhance user motivation and attention, which are often compromised in traditional reading instruction.

Despite the growing number of digital tools for dyslexia, relatively few studies have explored the potential of VR environments. Among the most notable examples, the European project FORDYSVAR [58] developed a suite of VR and augmented reality applications to improve the reading and writing abilities of children aged 10 to 16. This work's primary objective is to provide a technology-based approach to facilitate the learning process for individuals with dyslexia, with a specific emphasis on leveraging virtual and augmented reality. As part of its contributions, the project team developed supportive software tailored to children with dyslexia. This software, presented in [58], offers an engaging alternative for addressing various learning challenges associated with dyslexia. It takes the form of a VR video game for the Oculus Quest platform, offering an enjoyable, interactive way for dyslexic children to work on alleviating the impact of dyslexia on their learning.

This initial exploration of VR for dyslexia has established a robust foundation by demonstrating how immersive, multisensory environments can significantly enhance engagement and cognitive functions such as attention. However, the existing literature reveals a predominant focus on pediatric and school-age populations, with projects targeting children up to 16 years old. While these interventions successfully address basic literacy and training through gamification, they leave the specific needs of adult students in higher education largely unaddressed. There is a clear gap regarding the transition from pedagogical training to tools that support the complex academic and social navigation required at the university level.

3.2.2 VR for Inclusion and Empathy

VR's capacity to recreate realistic, emotionally engaging environments enables users to face social and physical barriers in ways that traditional devices cannot. In this section, three major categories of VR applications developed in the context of inclusion are analyzed. The first comprises virtual experiences that provide safe and supportive spaces where users can gradually face situations that may cause discomfort or anxiety, fostering adaptation and confidence through controlled exposure. The second encompasses perspective-taking environments that immerse users in the everyday lives and challenges of vulnerable groups, thereby nurturing empathy and social awareness. Finally, a third category involves simulations of sensory or physical barriers, enabling users to directly experience disabilities or constraints that affect others, which has proven effective in reshaping attitudes and promoting understanding.

Firstly, replicating environments where an individual might not feel physically comfortable allows people to adapt to surroundings and events in a simulated and controlled setting before transitioning to reality. The gradual approach to the uncomfortable environment helps them get used to it and build the capacity to face it. An illustrative case study is presented in [59]. This project is a social inclusion initiative that uses VR and spatial augmented reality to create safe spaces for collaborative activities grounded in art therapy techniques and new technologies. The primary goal of the project is to acknowledge and amplify individual distinctions while concurrently encouraging collaboration and ongoing interaction among participants, educators, and experts in cultural heritage and technology. Another application of this kind involves the inclusion of individuals with disabilities in the labor market [60]. In this case, authors leverage immersive environments to enhance employment opportunities for people with disabilities. The system aims to foster workers' inclusion by simulating work-related tasks and facilitating skill development through engaging and interactive experiences. It is worth mentioning that such VR applications can also be extended to specific target groups, such as children with autism. In [61], researchers conducted a case study to explore the effects of *Virtual Reality Social Cognition Training*, aimed at improving the social skills of children diagnosed with autism spectrum disorder (ASD). During the study, the performance of 30 children diagnosed with ASD was assessed across various domains. This assessment involved exposing them to diverse scenarios, such as collaborative classroom projects and ordering food in the school cafeteria. The study's results underscore the potential of employing a VR platform as a promising therapeutic intervention for gaining deeper insights into the social challenges commonly experienced by individuals with ASD. Notably, the study revealed significant improvements in emotion recognition, social attribution, and analogical reasoning.

The second way to make inclusion benefit from VR is to reproduce issues encountered daily by individuals from a disadvantaged social group. Through transporting users to virtual environments, VR enables the exploration of diverse perspectives, cultures, and identities, potentially eliciting empathy. Numerous studies, including the one conducted in [62], have demonstrated the benefits of VR in achieving this objective. In this study, participants were randomly assigned to watch a VR documentary depicting the life of a young girl living in a refugee camp. The findings from this research revealed that VR has the potential to significantly enhance users' empathy, due to the immersive experience it creates. In addition, major companies are investing in the potential of VR to raise societal awareness about the challenges faced by various vulnerable groups. Meta, for instance, created the initiative *VR for Good*, which narrates stories focusing on individuals from underprivileged social groups. Examples of such initiatives include *We Live Here* [20], providing users an insight into the life of a homeless person; *Home After War* [63], depicting the story of a refugee returning to a war-torn homeland facing the fears of an unsafe environment post-war; or *The Hidden* [64], where you can observe the life of an enslaved family, aimed at raising awareness about the persistence of slavery in today's world.

Nevertheless, the potential of VR to cultivate empathy extends beyond these instances. Apart from recreating real scenarios, VR also allows the simulation of various barriers, symptoms, or disabilities experienced by disadvantaged individuals. A case illustrating this potential is found in *Notes on Blindness: Into Darkness* [65], where users engage in an experience that aims to place them in the shoes of someone who is gradually losing vision until becoming completely blind. The experience is narrated through audio recordings by this individual, describing how he visualized the world through sound. Another notable application that replicated the barriers experienced by individuals with disabilities through VR was developed in [19]. The primary aim of this research was to assess the impact of a simulation of the obstacles that students in wheelchairs face in performing everyday tasks. The study's findings demonstrated that this simulation experience effectively transformed participants' attitudes toward individuals with disabilities in the real world, motivating them to become advocates for positive change. This study contributes valuable insights to the growing body of research highlighting the significance of VR simulations in enhancing empathy towards others.

The analyzed research underscores the versatility of VR as an "empathy machine" capable of reshaping attitudes through immersive perspective-taking and the simulation of barriers. However, a thematic imbalance is evident: while physical and sensory impairments—such as visual impairment [65] or motor disabilities [19]—and neurodevelopmental disorders like ASD [61] are well-represented, cognitive conditions like dyslexia remain largely overlooked in the empathy-simulation literature. Most existing social awareness projects focus on broad humanitarian issues or visible disabilities, neglecting the specific, often "invisible" academic barriers faced by dyslexic students. This research addresses this gap by shifting the focus from physical or social marginalization to the cognitive-academic sphere, using VR to make the internal challenges of dyslexia visible to the university community.

This literature review reveals that while VR has been employed to simulate physical, sensory, and social challenges (ranging from visual impairment and motor disabilities to the experiences of refugees), there is a complete lack of research specifically dedicated to simulating the cognitive barriers of dyslexia for promoting empathy. Because current VR research has yet to model these unique academic obstacles, educators and peers often remain unaware of the legitimacy of neurodivergent needs. Without the firsthand perspective provided by simulation, vital support strategies, such as the provision of extended time during examinations, are frequently viewed with skepticism or perceived as a breach of academic rigor, rather than a necessary accommodation to ensure equal opportunity.

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Part II

Personalized Recommendation of Support Methodologies for Dyslexic Students

This part introduces the AI-based contributions, including the analysis of student data, the application of machine learning models, and the design and implementation of a recommendation system for personalised support.

Chapter 4

Data Source and First Steps

This chapter introduces the first AI-based component of the thesis, which aims to recommend suitable study strategies and support tools for university students with dyslexia. The goal is to move from a purely descriptive understanding of dyslexic students' difficulties to a data-driven approach capable of predicting which tools and strategies are likely to be most beneficial for each individual. To this end, we use a structured dataset derived from a dedicated questionnaire that captures both dyslexia-related difficulties and the perceived usefulness of a wide range of compensatory tools and learning strategies. The chapter describes the data source on which all subsequent analyses are based, including its construction, the target population, and the set of variables used as inputs and outputs for the predictive models and, ultimately, for the design of a RS presented in Chapter 5.

4.1 Data Source

The dataset used in this part of the thesis was constructed from a questionnaire aimed at assessing the issues that each dyslexic student has experienced and the learning strategies and study tools they have used and found useful to ameliorate their difficulties. Questions were also asked about the main problems caused by dyslexia. In addition, demographic information is collected in the dataset but used for other purposes, as shown in [66]. The different learning methodologies presented in the questions were selected with the help of experts in SLDs. Here, participants indicate how helpful the supporting tools and strategies presented were for them, by selecting one of the following options: "not at all", "very little", "little", "medium", "much", or "very much". However, to account for the possibility that users never tried or did not know one or more items, two additional answers ("never tried" and "I don't know") were included. These two responses were used to identify tools and strategies that were not well known to users, enabling their promotion to obtain more accurate ratings in future data collections. In order to quantify a qualitative answer and use it profitably for an RS, the different options have been converted into a range of numerical values between 0 and 5, where 0 corresponds to "not at all" and 5 to "very much". Regarding responses labeled as "never tried" and "I don't know", they will be treated and preprocessed as missing values.

This data is represented as a rating matrix, where the rows correspond to individual students and the columns correspond to the support tools and learning strategies that the system may recommend. Figure 4.1 shows an illustrative chart of this representation, including only a small subset of students and support items; in the full dataset, the matrix comprises all participants and all dyslexia-related tools and strategies under consideration.

The questionnaire was created by skilled psychologists, starting with an interview with 20 dyslexic university students about the best tools and strategies they have adopted to overcome those issues. The questionnaire was then administered to another 30 dyslexic students to assess its accessibility and clarity. The final version, comprising 17 support tools and 22 learning

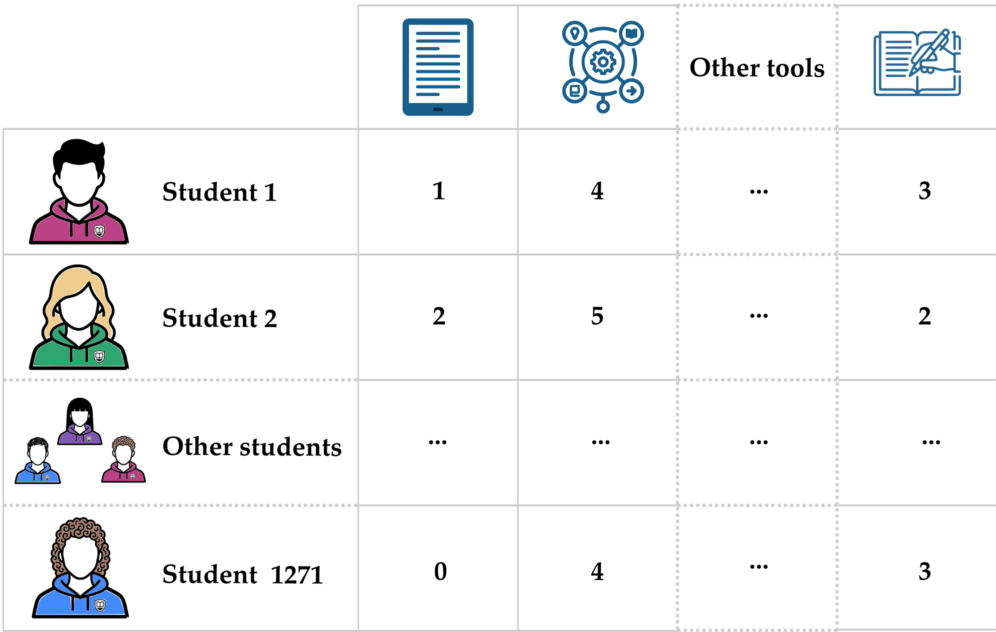


Figure 4.1: **Structure of the rating-matrix representation of the questionnaire data.** Each row corresponds to a student, and each column to a support tool or learning strategy. Only a sample subset of students and items is shown for illustration.

strategies, totaling 39 items, was distributed to 1,237 dyslexic students, in accordance with the following criteria: having a valid diagnosis of dyslexia, being native Italian speakers, being 18 years old or more, and attending university or having finished or abandoned it less than five years before the filling of the questionnaire.

The distribution of participants was nearly even for gender (54% female students vs. 46% male students) and age (an almost uniform distribution across the age range 18-27). In addition, the above-described information collected on the received support, the type of high school attended, the student category (full-time student, worker student, commuter, etc.), and the family context allowed us to verify that all these variables were relatively uniformly distributed. This limits potential biases. On the contrary, an undoubtedly present bias is given by the fact that only Italian-speaking participants took part in the questionnaire, but, as reported previously, limiting the work only to one language is strictly necessary, since dyslexia-related issues are highly dependent on language [67] and, thus, it is opportune to analyze each language by itself. It is worth noting that it was not possible to gather information on variables such as students' socioeconomic status and ethnicity, which may affect the system. However, at least the second one does not pose a significant issue in the considered Italian university context, since it is less ethnically heterogeneous than other European countries, with only a 3% share of non-Italian students. The acquired data have been treated according to Articles 13-14 of the GDPR 2016/679 [68] of the European Union. In particular, they have been processed completely anonymously and used only for research purposes. Table 4.1 presents the questions related to the issues, the tools, and the learning strategies gathered by the questionnaire.

4.1.1 Correlation Analysis

To further characterize the dataset and better understand the internal relationships among the questionnaire items, we conducted a correlation analysis across the three main groups of variables: difficulties (P), support tools (T), and learning strategies (S). The goal of this

Table 4.1: **Questionnaire items grouped by category.** Items are organized into three groups: difficulties (P), tools (T), and strategies (S).

Difficulties (P)			
P1	Reading	P7	Paying attention during online lessons
P2	Writing	P8	Memorizing recently studied concepts
P3	Understanding difficult words	P9	Remembering concepts studied during the exam
P4	Understanding the lessons	P10	Study time management
P5	Concentration	P11	Taking notes
P6	Paying attention during in-presence lessons	P12	Limited time available to prepare a task/question/exam
Tools (T)			
T1	Human voice audio book	T10	Prepared summaries
T2	Robotic voice audio book	T11	E-books
T3	Different color words	T12	Digital tutor
T4	Using the EasyReading font	T13	Images to help understand difficult words
T5	Smart pen/tablet for notes/voice	T14	Images to memorize a concept
T6	Clearer layout of study material	T15	Audio recording of lessons
T7	Keywords highlighted	T16	Video lessons
T8	Prepared concept maps	T17	Supplementing material with Internet research
T9	Prepared schemes		
Strategies (S)			
S1	A person reading for him/her	S12	Online lessons available
S2	Map made by himself/herself	S13	Taking breaks during lessons
S3	Scheme made by himself/herself	S14	Lesson slides available
S4	Summary made by himself/herself	S15	Recording the lesson
S5	Repeat the studied material	S16	Taking notes
S6	Marking keywords	S17	Having the lesson plan in advance
S7	Underlining with colors	S18	Dividing exam/task/question into parts
S8	Having a study group	S19	Only written tests
S9	Having a tutor	S20	Only oral tests
S10	Dyslexic student resource group	S21	Exam alone with the professor
S11	Onsite lessons	S22	Online database with notes from other students

exploratory study is to identify which difficulties tend to co-occur among dyslexic students and how the severity of specific problems relates to the perceived usefulness of the different tools and strategies.

The first step is to examine the correlations among the difficulties reported by the students. The Pearson correlation matrix with the 12 difficulties is shown in Figure 4.2(a). Several meaningful observations arise from this analysis. All pairs of difficulties exhibit positive correlations, indicating that experiencing one difficulty generally increases the likelihood of experiencing others. The weakest correlation is found between P1 (Difficulty in reading) and P6 (Difficulty paying attention during in-presence lessons), with a coefficient of 0.15. In contrast, the strongest relationship is observed between P8 (Difficulty memorizing recently studied concepts) and P9 (Difficulty remembering concepts during exams), with a coefficient of 0.71, which is consistent with the memory-related nature of both difficulties. A notable correlation (0.62) also appears between P2 (Difficulty in writing) and P3 (Difficulty understanding difficult words), suggesting that strengthening one of these abilities may positively influence the other. Furthermore, difficulties related to concentration (P5) show moderate correlations with attention problems in both in-presence (P6) and online (P7) lessons, indicating that concentration may play a central role in students' ability to follow classes.

We then analyzed the correlations between students' difficulties and the perceived usefulness of the study tools. The results, presented in Figure 4.2(b), show that correlations are generally positive but weaker than those observed among the difficulties themselves. The highest coefficient (0.27) appears between P12 (Limited time available to prepare an exam, question, or task) and both T13 (Use of images to understand difficult words) and T14 (Use of images to memorize concepts), suggesting that visual aids might help students optimize their study time. Strong relationships also emerge among some tools. For example, T8 (Prepared concept maps) and T9 (Prepared schemes) exhibit a correlation of 0.9, which is expected given their similar pedagogical purpose. Another meaningful correlation (0.46) links T7 (Highlighted or emphasized keywords) with T14 (Use of images to memorize concepts), indicating that students who benefit from keyword highlighting also tend to benefit from visual memory strategies.

Finally, we investigated the correlations between difficulties and learning strategies, as shown in Figure 4.2(c). Unlike the previous cases, some correlations are slightly negative, although their magnitude is small and close to zero, indicating that such relationships are insignificant. The most negative value is -0.13, observed between P6 (Difficulty paying attention during onsite lessons) and S11 (Attending onsite lessons), a relationship that is reasonable since students who struggle to pay attention in class may find in-person attendance less effective. The highest positive correlation (0.27) occurs between P7 (Difficulty paying attention during online lessons) and S11 (Attending in-presence lessons), reflecting that students who struggle with online formats tend to prefer traditional in-person instruction. As with the tools, stronger correlations are observed among strategies that perform similar functions. The clearest example is the correlation of 0.53 between S12 (Possibility of attending online lessons) and S15 (Availability of lesson recordings), both of which extend flexible access to course content.

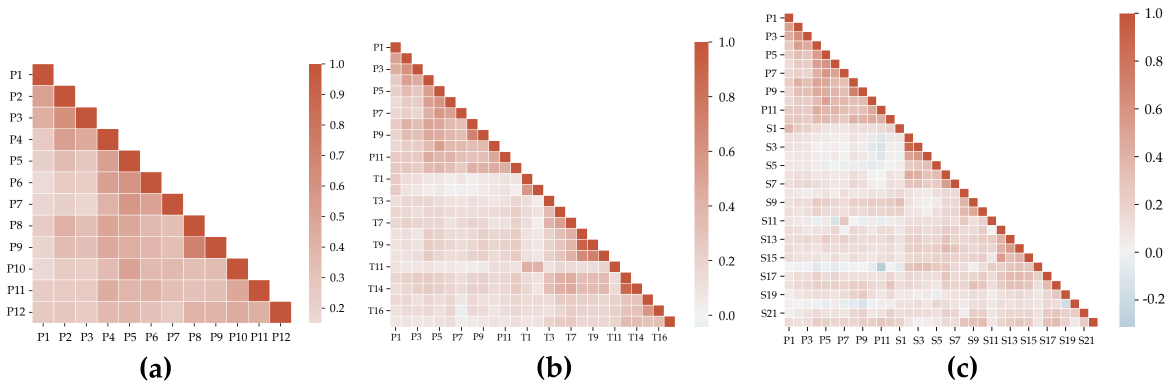


Figure 4.2: **Correlation matrices for questionnaire items.** Panel (a) shows correlations among dyslexia-related difficulties; panel (b) shows correlations between difficulties and support tools; and panel (c) shows correlations between difficulties and learning strategies. To improve legibility, panels (b) and (c) display only the names of a subset of items, ordered as in Table 4.1.

Overall, the correlation patterns provide useful insights into the dataset's structure. Difficulties tend to co-occur in intuitive ways, while tools and strategies that share similar pedagogical objectives naturally exhibit higher correlations. These findings provide valuable context for validating the data's coherence and understanding the behavior of the predictive models. In this way, they support the design of an effective recommendation system for dyslexic students.

4.2 Preprocessing and Experimental Design

In this section, we reproduce the methodology previously adopted in our work [24], which was conducted just before the start of this PhD thesis. In that study, the experiments were conducted on a preliminary version of the dataset, since only the first part of the questionnaire responses were available at the time. Here, we follow the same experimental pipeline but apply it to the complete dataset of 1,217 dyslexic university students collected to date.

The dataset contains, for each student, 12 difficulty items (P1–P12), 17 study tools (T1–T17), and 22 learning strategies (S1–S22), all expressed in a Likert scale from 0 to 5. Higher scores indicate that a difficulty affects the student more strongly or that a tool or strategy is perceived as more useful. Before training any predictive models, a preprocessing phase was performed to handle missing values and remove unreliable attributes. Because some tools and strategies were not yet widely known by the students, several items presented significant rates of missing responses. Following the same criterion adopted in the previous study, we excluded a methodology from the analysis if more than 5% of its values were missing. Consequently, three tools were discarded: T4 (EasyReading font), T5 (smart pen), and T12 (digital tutor). Missing values in the remaining attributes were imputed using the mode, which is appropriate given the ordinal nature of the Likert scale.

This preprocessing resulted in 14 tools and 22 strategies, for a total of 36 support items. Each of these items was treated as an independent prediction task, following the formulation introduced in [24]. For each task, the goal is to predict whether a particular support method is useful or not for a given student based solely on that student's dyslexia-related difficulties. Thus, the 12 difficulty items serve as input features, and the usefulness score of the selected tool or strategy acts as the output label. Since the original responses are on a 0–5 scale, they were binarized by applying a usefulness threshold: scores strictly above this threshold were mapped to the positive class ("useful"), while scores at or below the threshold were mapped to the negative class ("not useful"). In the study, this threshold is global and identical for all students. Still, future stages of the project will integrate personalized thresholds informed by self-esteem measures obtained through the *Out of the Box* application, also presented in [24].

Four classical machine learning algorithms were used to train the models: RF, KNN, SVM, and LR. All implementations were carried out using `scikit-learn` [69]. The evaluation metric is the Correct Classification Ratio (CCR). Finally, as in the original study, all results were estimated using 10-fold cross-validation to ensure a fair and robust comparison across algorithms and configurations.

Additionally, we considered some experimental variants. First, we evaluated whether also binarizing the difficulty items (P1–P12) according to the same threshold improves predictive performance by simplifying the feature space. Second, we analyze the usefulness of applying a consensus method that combines the outputs of the three best-performing classifiers of different types to obtain predictions for the most challenging items. The next section presents the outcomes of these experiments on the full dataset, giving a comprehensive validation of the methodology previously introduced.

4.3 Results

The results obtained confirm the feasibility of predicting the usefulness of support tools and learning strategies from students' difficulty profiles. Tables 4.2 and 4.3 summarize the best-performing models for predicting the usefulness of each item, together with the configuration that led to this performance.

Regarding support tools, CCR values typically exceed 0.90, with several items reaching

Table 4.2: **Best-performing models for support tools.** For each tool, the best classifier and its configuration (Thr, Input, Consensus, CCR) are reported.

ID	Best model	Thr	Input	Consensus	CCR
T1	SVM RBF	4	Numeric	Yes	0.7443
T2	RF, 50 estimators	4	Numeric	No	0.9433
T3	SVM Linear	1	Binary	No	0.9118
T6	KNN K=7	1	Binary	No	0.9397
T7	SVM Linear	1	Binary	No	0.9368
T8	KNN K=1	1	Numeric	No	0.9325
T9	SVM RBF	1	Binary	No	0.9486
T10	SVM RBF	1	Binary	Yes	0.7246
T11	KNN K=7	1	Binary	Yes	0.9100
T13	SVM RBF	1	Binary	Yes	0.9633
T14	SVM RBF	1	Binary	No	0.9463
T15	SVM Linear	1	Binary	No	0.9367
T16	RF 50 estimators	1	Binary	No	0.9100
T17	SVM linear	1	Binary	No	0.9367

particularly strong performance. For example, T13 (images to understand difficult words) and T9 (prepared schemes) achieve CCR values above 0.94, whereas most tools fall within the 0.91–0.94 range. Only a few items, such as T1 (human-voice audio book) or T10 (prepared summaries), are more challenging to classify, with CCR values around 0.72–0.74. This variability reflects differences in how strongly each tool relates to specific difficulty patterns. These findings suggest that tools that rely on visual reinforcement or structural organization are more accurately predicted.

Moving to the learning strategies, they show even higher predictability. Many strategies exceed 0.97 CCR (notably S3, S5, S6, S13, S14 and S16), obtaining almost a perfect performance. These results suggest that behavioral preferences, such as creating self-made summaries, working with clearly organized material, or accessing lesson recordings, are strongly aligned with the self-reported cognitive and attentional difficulties. Only a small subset of strategies, such as S1 (a person reading for the student) or S19 (only written tests), yield more moderate values around 0.80–0.86, likely due to external factors not captured by the difficulty items.

Regarding modeling choices, no single algorithm consistently dominates. Linear and RBF SVMs frequently appear among the best configurations, especially for tools, while Random Forests tend to excel for strategies with very high CCR values. Logistic Regression also performs well across several items, confirming that many difficulty–usefulness relationships are nearly linearly separable. The choice between numeric and binarized difficulty inputs also varies by item: in some cases, preserving the granularity of the Likert scale improves accuracy, whereas for others a simple binary indication of whether the difficulty is present or not leads to better results. Most optimal configurations employ a threshold of 1 to define usefulness, although a stricter threshold of 4 benefits a small number of items. The consensus method is selected only for a few cases, suggesting that for most items, a single well-chosen classifier is sufficient.

Table 4.3: **Best-performing models for study strategies.** For each strategy, the best classifier and its configuration (Thr, Input, Consensus, CCR) are reported.

ID	Best model	Thr	Input	Consensus	CCR
S1	LR	4	Numeric	No	0,7764
S2	RF, 50 estimators	1	Numeric	No	0,9689
S3	SVM Linear	1	Binary	No	0,979
S4	KNN K=5	1	Numeric	No	0,9666
S5	RF, 50 estimators	1	Numeric	No	0,9836
S6	RF, 50 estimators	1	Numeric	No	0,9738
S7	LR	1	Numeric	No	0,9403
S8	SVM RBF	1	Binary	No	0,8902
S9	LR	1	Numeric	No	0,8787
S10	RF, 50 estimators	1	Numeric	Yes	0,9016
S11	RF, 50 estimators	1	Numeric	No	0,9443
S12	LR	1	Numeric	No	0,9636
S13	SVM Linear	1	Binary	No	0,9846
S14	SVM Linear	1	Binary	No	0,9898
S15	SVM Linear	1	Binary	No	0,9603
S16	RF, 50 estimators	1	Numeric	No	0,9725
S17	RF, 50 estimators	1	Numeric	No	0,9551
S18	RF, 50 estimators	1	Numeric	No	0,9698
S19	RF, 50 estimators	1	Numeric	Yes	0,8164
S20	RF, 50 estimators	1	Numeric	No	0,8554
S21	RF, 50 estimators	1	Numeric	No	0,8626
S22	RF, 50 estimators	1	Numeric	No	0,9390

Chapter 5

Collaborative Recommendation System for Dyslexic Students

Building on the previous chapter, which demonstrated that machine learning models can predict the usefulness of individual tools and study strategies from students' difficulty profiles, this chapter presents a complete RS tailored to university students with dyslexia. Instead of evaluating each support item in isolation, collaborative filtering techniques are employed to generate personalized, ranked suggestions of tools and learning methodologies for each student. The chapter describes the design of user-based, item-based, and hybrid RSs, the similarity metrics used to model relationships among students and items, and the experimental protocol adopted to identify the best-performing configuration. Finally, it reports both offline results on historical questionnaire data (presented in Chapter 4) and outcomes from a real educational study, in which the system's recommendations are evaluated in terms of their impact on students' academic performance.

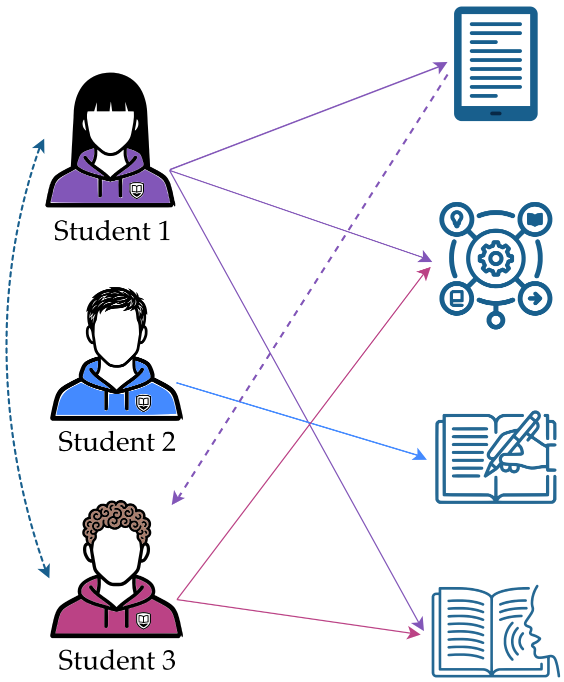
5.1 Designing a Recommendation System

This section introduces the methodology adopted to design and evaluate the proposed RS. Three collaborative filtering RSs are compared in terms of their ability to suggest suitable study tools and learning strategies for university students with dyslexia: a user-based model, an item-based model, and a hybrid model combining both. For each of these systems, three similarity metrics are explored (Euclidean distance, Cosine distance, and Pearson correlation) and, in the hybrid case, different weight configurations are tested to balance user-based and item-based predictions. The optimal configuration is selected by minimizing the mean absolute error, and the resulting model is further assessed using additional evaluation metrics, such as precision and recall at k, before being employed to provide recommendations to students with and without dyslexia.

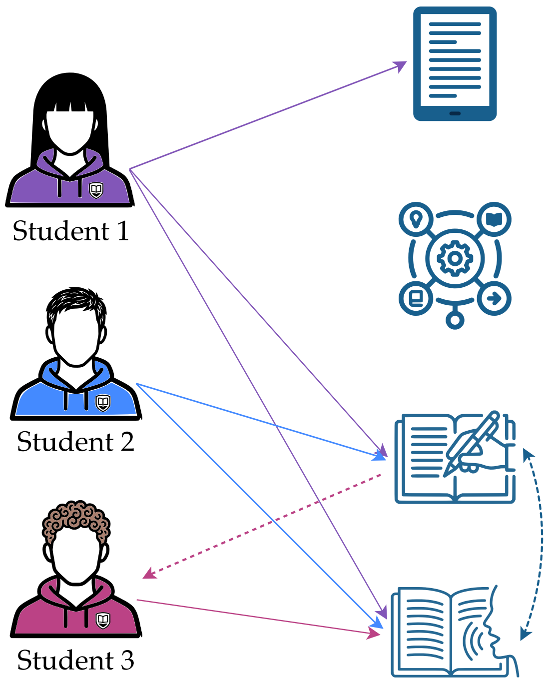
5.1.1 Methodology and Metrics

Within the field of technology-enhanced learning, RSs have become a key tool for tailoring educational resources to individual needs [70, 51]. Among the various techniques employed in this domain, CF and CB approaches stand out as two distinctive methodologies, each with its unique strengths and limitations. CB systems require a large amount of information about items' features, rather than focusing on relationships inferred from user ratings. For this reason, the collaborative systems approach has been considered more appropriate for our data set (presented in Chapter 4).

Data were analyzed using three types of CF as proposed by [71]. The three types of CF systems were: a user-based [72] in which the similarity between users guides the recommendation of the different methodologies, an item-based [73] in which item similarity is analyzed to suggest the most relevant tools and strategies to the users, and a hybrid approach which combines the approaches mentioned above through a weight system. The motivation for using a hybrid model stems from the differences presented between the user-based and item-based approaches. User-based approach makes recommendations based on the similarity between users, meaning the algorithm will recommend items liked by other users similar to the student. On the contrary, in the item-based approach, recommendations are made based on similarities between items, computed from ratings given by different users. The differences between the two approaches are visually depicted in Figure 5.1.



(a) User-based



(b) Item-based

Figure 5.1: **User-based and item-based collaborative filtering.** In the user-based approach (a), Student 1 and Student 3 are considered similar because they have selected similar learning methodologies, so the system recommends (dashed arrow) to Student 3 an item that was useful to Student 1 but that Student 3 has not yet used. In the item-based approach (b), two items receive similar ratings from Students 1 and 2; since Student 3 likes one of them, the system recommends the other to Student 3.

To exploit the complementary strengths of both paradigms, the hybrid approach combines the user-based and item-based methods through a weighted scheme, assigning a specific weight to each of their predicted ratings as defined in the following equation:

$$\widehat{r} = \alpha \widehat{r}_u + (1 - \alpha)\widehat{r}_i \tag{5.1}$$

where α is the weight and $\widehat{r}_u$ is the predicted rating for the user-based approach, whereas $(1 - \alpha)$ is the weight and $\widehat{r}_i$ is the predicted rating for the item-based algorithm.

These weights were used to reduce the error arising from the difference between predicted and actual ratings, as described in [71]. The value of α has to satisfy:

$$\alpha \geq 0 \ and \ \alpha \leq 1 \tag{5.2}$$

To determine the weights assigned to each model (user-based and item-based), a preliminary experiment was conducted. Consistent with the findings reported in [74], the results indicated that higher weights for the item-based method $(1-\alpha)$ led to better performance. Consequently, a range of weight configurations was defined to prioritize larger values for the item-based component, starting with a user-based weight (α) that is twice as large as the item-based weight and ending with item-based weights that are seven times greater than α. All the evaluated configurations are summarized in Table 5.1.

Table 5.1: **Weight configurations for the hybrid RS.** Explored values of the user-based weight α and the item-based weight $(1-\alpha)$ used in the preliminary experiment to select the final combination scheme.

Case	α	$(1-\alpha)$
#1	2/3	1/3
#2	1/2	1/2
#3	1/3	2/3
#4	1/4	3/4
#5	1/5	4/5
#6	1/6	5/6
#7	1/7	6/7
#8	1/8	7/8

It is worth noting that by assigning $\alpha = 1$ or $\alpha = 0$, the fully user-based approach and the fully item-based approach are obtained, respectively. Thus, by properly tuning α, it is possible to include all the analyzed cases within the formula 5.1.

To compute similarities among users or items, three widely used metrics in CF systems were considered and compared: the Pearson correlation coefficient[75], the Euclidean distance, and the Cosine distance [76, 77]. These metrics are used to identify the n most similar users to the target user (in the user-based approach) or the n most similarly rated items according to the target user's ratings (in the item-based approach). The three metrics are defined as follows:

$$\textit{Pearson Correlation} = \frac{\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i-\bar{x})^2}\sqrt{\sum_{i=1}^{N}(y_i-\bar{y})^2}} \tag{5.3}$$

$$\textit{Euclidean distance} = \sqrt{\sum_{i=1}^{N}(x_i-y_i)^2} \tag{5.4}$$

$$\textit{Cosine distance} = 1-\frac{\sum_{i=1}^{N}x_i y_i}{\sqrt{\sum_{i=1}^{N}x_i^2}\sqrt{\sum_{i=1}^{N}y_i^2}} \tag{5.5}$$

where N is the number of users or items; x_i and y_i are the individual ratings; and $\bar{x}$ and $\bar{y}$ are the sample mean.

5.1.2 Algorithms

This subsection describes the procedure and algorithms used to compute similarities among users or items for each of the CF. The Pearson correlation coefficient is applied to directly compute pairwise similarities between all users or items, and the n most similar neighbors are then selected as those with the highest correlation values. In contrast, the Euclidean and Cosine distances are used as distance metrics within a KNN algorithm, from which the n closest neighbors are directly obtained.

The number of nearest neighbors is a key parameter for the similarity computation. After extensive testing with different candidate values, we observed that the best results were obtained for n between 3 and 11. Consequently, the final experiments consider $n \in 3, 5, 7, 11$. Algorithm 1 presents the pseudocode of the similarity computation process for the different metrics. The method returns the *n_neighbors* most similar users or items, sorted by the corresponding similarity measure and stored in *top_similarities*.

Algorithm 1 Compute similarities

function COMPUTESIMILARITIES(*data_similarities*, *similarity*, *n_neighbors*)
  if *similarity* = "pearson" **then**
    correlation_matrix ← correlation matrix computed using pearson coefficient
    test_user_corr ← matrix row corresponding to the *test_user*
    similarities ← sort similar according to *test_user_corr*
    top_similarities ← first *n_neighbors* from similar_users
  else
    knn ← generated k-Nearest Neighbors model using *similarity* as distance metric and considering *n_neighbors* as the number of neighbors
    top_similarities ← nearest neighbors considered by *knn*
  end if
  return *top_similarities*
end function

The objective of the final learning methodologies RS is to predict the ratings of tools and strategies for a particular user. The prediction is made by averaging the ratings of the most similar users in the user-based approach or the ratings of the most similarly scored items in the item-based approach. In the hybrid method, the prediction is obtained by summing the user-based and object-based predictions, each multiplied by its corresponding weight.

The entire process described above is reflected in Algorithms 2 and 3, corresponding to the user-based and item-based RSs, respectively. Both algorithms generate a list of key-value pairs, referred to as *recommendations*, comprising the tools and strategies to be recommended along with their respective ratings assigned by the RS. To achieve this, both algorithms distinguish the data used for similarity computation, *data_similarities*. In the case of user-based, only the training data, *data_train_items*, and the test user's data, *text_user*, for whom the recommendation is to be made, are needed. Conversely, in the case of item-based, it is necessary to consider each test item in *data_test_items* separately to generate its respective rating, without considering the rest, which is treated as unknown to the user. Finally, *recommendations* is completed with the average rating values obtained for the different test items from the *n_neighbors* most similar users or objects.

Algorithm 2 User-based collaborative filtering

function USERBASEDRECSYS(*test_user*, *data_train_items*, *data_test_items*, *similarity*, *n_neighbors*)
  recommendations ← empty key-values map
  data_similarities ← concatenation of *data_train_items* and *test_user* as row
  similarities ← COMPUTESIMILARITIES(*data_similarities*, *similarity*, *n_neighbors*)
  recommendations ← mean of ratings for each item taken from *data_test_items*
  return
end function

To evaluate the accuracy of the proposed methodologies, the MAE between the score

Algorithm 3 Item-based collaborative filtering

```
function ItemBasedRecSys(test_user, data_train_items, data_test_items, similarity, n_neighbors)
    recommendations ← empty key-values map
    for test_item in data_test_items do
        data_similarities ← concatenation of data_train_items and test_user as row
        data_similarities ← concatenation of data_train_items and test_item as column
        similarities ← ComputeSimilarities(data_similarities, similarity, n_neighbors)
        rating ← mean of ratings given to the test item depending on train items
        add (test_item, rating) to recommendations
    end for
    return recommendations
end function
```

predicted by the RS and the user's actual score is computed. The MAE is obtained by averaging the N absolute errors of the rating pairs (p_i, q_i). Since a lower MAE indicates higher accuracy, the weights must be selected to minimize this value:

$$\arg\min(\alpha)\left(\frac{\sum_{i=1}^{N}|p_i(\alpha) - q_i(\alpha)|}{N}\right) \tag{5.6}$$

where N is the total number of tools and strategies considered to be recommended, p_i is the predicted value, and q_i is the actual value.

Finally, one of the main challenges faced by RSs is the cold-start problem, which can occur at either the user or the item level [78]. The user cold-start problem appears when the system must handle new users for whom no prior information is available [79], whereas the item cold-start problem appears when a new item is introduced into the dataset [80]. In the proposed system, the user cold-start issue is mitigated by requesting initial feedback from new users on the system's methodologies for profile generation, which is then compared with the profiles of existing users. Regarding the item cold-start, it is not expected to be critical, as new learning methodologies are introduced only occasionally. The robustness of the system is evaluated by considering both test users and test items in the performance assessment.

5.1.3 Data Split

Of the 39 items in the questionnaire, the T4 support tool (Using the Easy Reading font) was discarded because more than 48% of participants did not know it. Therefore, the actual number of support tools used was 16, to which the 22 learning strategies were added, for a total of 38 items. The data were partitioned, with 75% (947 users) for training and 25% (290 users) for the test set. Subsequently, a 10-fold cross-validation was applied to the training dataset to optimize the model's configuration parameters before validating its performance on the test set. In addition, another separation of the data has been carried out to get some test learning methodologies and use them for the evaluation of the system. This split has been done by randomly selecting 20% of the considered learning methodologies along with different epochs to assess the system's robustness in making predictions for different combinations of unknown items.

5.1.4 Assessment

Finally, to evaluate the algorithm in a real case, the best-performing model is used to assess the efficacy of recommending specific learning tools and strategies to students with or without

Table 5.2: **MAE of the hybrid RS under different configurations.** MAE obtained for each combination of similarity measure, number of neighbors n, and hybrid weight α. Columns correspond to the value of the user-based weight α, ranging from a purely item-based configuration ($\alpha = 0$) to a purely user-based one ($\alpha = 1$). Best performance is highlighted in bold.

		MAE									
		α									
Similarity	n	**0**	**1/8**	**1/7**	**1/6**	**1/5**	**1/4**	**1/3**	**1/2**	**2/3**	**1**
Euclidean	3	1.1832	1.1315	1.1245	1.1152	1.1027	1.0846	1.0563	1.0049	0.9594	0.8920
Euclidean	5	1.1866	1.1347	1.1275	1.1179	1.1050	1.0863	1.0568	1.0015	0.9522	0.8750
Euclidean	7	1.1944	1.1412	1.1342	1.1250	1.1123	1.0939	1.0643	1.0085	0.9562	0.8735
Euclidean	11	1.2193	1.1650	1.1576	1.1479	1.1343	1.1146	1.0829	1.0244	0.9690	0.8782
Cosine	3	1.1839	1.1425	1.1371	1.1301	1.1212	1.1086	1.0895	1.0580	1.0309	0.9876
Cosine	5	1.2505	1.2020	1.1954	1.1867	1.1749	1.1576	1.1301	1.0815	1.0381	0.9647
Cosine	7	1.2754	1.2242	1.2177	1.2091	1.1972	1.1796	1.1511	1.0972	1.0486	0.9636
Cosine	11	1.3106	1.2550	1.2476	1.2380	1.2248	1.2054	1.1737	1.1136	1.0594	0.9659
Pearson	3	0.8217	0.8128	0.8118	0.8107	0.8096	**0.8093**	0.8128	0.8314	0.8648	0.9661
Pearson	5	0.9092	0.8870	0.8843	0.8809	0.8766	0.8708	0.8639	0.8614	0.8735	0.9329
Pearson	7	0.9810	0.9494	0.9452	0.9398	0.9326	0.9227	0.9080	0.8913	0.8889	0.9222
Pearson	11	1.0868	1.0398	1.0336	1.0256	1.0147	0.9992	0.9756	0.9383	0.9160	0.9148

dyslexia. Fifty subjects, 53% male and 47% female, participated in the testing campaign. Among them, 40% are dyslexic, whereas the remaining are not affected by any learning disorders. The subjects are university students or those who have completed university but are still pursuing their academic formation through a master's, a doctorate, or corporate training courses. The test consisted of providing specific textbooks from 3 disciplines (political science, communication, and economics) to students currently enrolled in related PhD or master's degree courses and asking them to study a portion of each book. 50% of the students, equally divided between dyslexics and non-dyslexics, tried the RS that was found to perform best and received personalized suggestions for tools and strategies to help them study. The other 50% received random recommendations, instead of the specific ones output by the RS. Then, all the students were asked to follow the suggested methodologies during the study phase, and the level of knowledge of the studied disciplines was assessed by university professors, on a scale from 0 to 10, with 6 being the minimum sufficient score. A comparison was made between the results of those who benefited from the RS and those who did not. Differences among dyslexic and non-dyslexic students were also examined.

5.2 Results

This section presents the results obtained from the experiments. First, the performance achieved with the different weight configurations used in the hybrid RS is compared. In this initial analysis, the optimal number of neighbors to consider when computing similarities is also determined. Furthermore, this evaluation includes the results derived from the three similarity metrics employed. Finally, a comparative analysis of the three recommendation strategies under study is carried out: user-based, item-based, and hybrid RSs.

Table 5.2 summarizes the MAE obtained for all configurations of the hybrid RS. For each similarity measure (Euclidean, Cosine, and Pearson) and each number of neighbors n, the table reports the MAE achieved for different values of the weighting parameter α, as indicated by the column headers.

Table 5.2 shows that the hybrid model, with an α value of 1/4 and Pearson's correlation with 3 neighbors, yielded the best results among the analyzed cases. The achieved MAE by this model is 0.8093. To have a comparable measure, the relative error was calculated as

$$\varepsilon_r = \frac{1}{N}\sum_{i,j}\left(\frac{|p_{i,j} - q_{i,j}|}{q_{i,j}}\right) \tag{5.7}$$

where i indicates the i-th tool or strategy and j the j-th student tested, N is the total number of evaluations, $p_{i,j}$ is the real score given by the j-th student to the i-th methodology, and $q_{i,j}$ is the real score given by the j-th student to the i-th methodology. The obtained result is 11.93%.

At present, no system has been reported that recommends these types of support tools, study methodologies, or comparable resources, so a direct comparison with alternative approaches is not possible. Even in the absence of baselines, the obtained error supports the feasibility of using the hybrid RS to suggest suitable supporting methodologies for dyslexic students. Indeed, an error of less than one point on the 5-point scale considered in the ratings was obtained. This implies, for instance, that when the RS assigns a rating of 1 (indicating minimal usefulness), the actual rating would fall within the range 0.2 (not useful at all) to 1.8 (somewhat useful), which would still be considered acceptable recommendations. Likewise, if the RS recommends a methodology with a rating of 4 (indicating high usefulness), this would imply that the actual rating would range between 3.2 (useful) and 4.8 (very useful), again providing a reasonably accurate recommendation.

Moreover, the results show that $n = 3$ is the most suitable number of neighbors for the algorithm, yielding an average MAE of 1.1816, while larger values of n generally degrade performance. This behavior can be attributed to the fact that a smaller neighborhood favors the recommendation of less popular items in the overall population, thereby reducing the propagation of misinformative items [81].

An additional noteworthy investigation within the scope of this research involved determining the optimal configurations for each filter weight. To achieve this objective, each of the considered weight variants was subjected to individual analysis, where the optimal configuration and MAE associated with each weight were identified. These results are summarized in Table 5.3.

Table 5.3: **Optimal configurations for each hybrid weight.** For each value of the user-based weight α, the table reports the configuration of the similarity measure and the number of neighbors n that yields the lowest MAE, together with its corresponding error.

α	Best configuration	Best MAE
0	Pearson; n=3	0.8217
1/8	Pearson; n=3	0.8128
1/7	Pearson; n=3	0.8118
1/6	Pearson; n=3	0.8107
1/5	Pearson; n=3	0.8096
1/4	**Pearson; n=3**	**0.8093**
1/3	Pearson; n=3	0.8128
1/2	Pearson; n=3	0.8313
2/3	Pearson; n=3	0.8648
1	Euclidean; n=7	0.8734

Another interesting observation from Table 5.3 is that, in most cases, the best performance is obtained with the Pearson metric. For each value of the weight, the configuration based on Pearson consistently outperforms the others, except for the purely user-based filter, whose optimum is achieved with the Euclidean distance. In this latter case, the optimal number of neighbors is 7 instead of 3, as in the remaining configurations. Nevertheless, the differences across the best results are not substantial, with MAE values ranging from 0.8734 to 0.8093. This gap is further reduced for hybrid models in which the item-based component dominates (i.e., lower α values), with the MAE lying between 0.8093 and 0.8217. Figure 5.2 presents these differences more clearly by showing only a subset of representative weights ($\alpha \in \{0, 1/4, 1/2, 2/3, 1\}$), highlighting that $\alpha = 1/4$ marks the inflection point at which the system achieves its lowest error; moving away from this value leads to a degradation in performance, which becomes more pronounced as α increases.

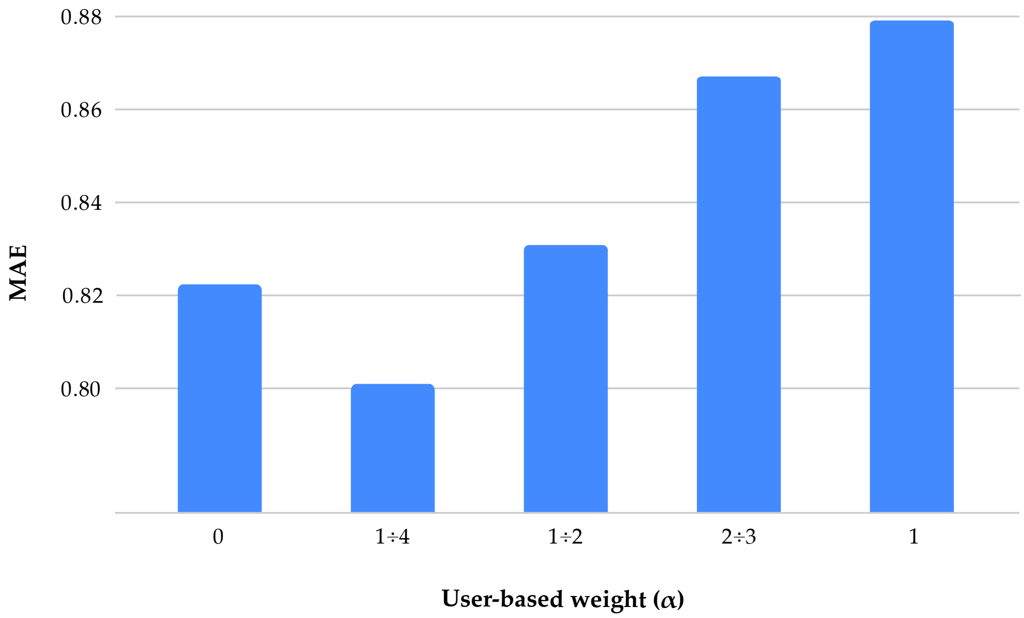


Figure 5.2: **Best MAE across representative hybrid weight configurations.** Bar plot of the minimum MAE achieved by the hybrid RS for representative values of the user-based weight, using the optimal similarity measure and number of neighbors for each case (see Table 5.3).

The distinctions in performance among the different metrics are more evident in Figure 5.3, again selecting only the most representative α values. It shows the results obtained by the different similarity measures for the selected weights, considering the neighbor configuration that achieves the best result. Among the similarity measures, the Cosine distance had the highest average MAE (1.1432) across all experiments, indicating poorer performance. The Euclidean distance yielded results similar to those of the Cosine distance, with an average MAE of 1.0723. Consequently, it may not be a suitable choice for our system. However, as demonstrated earlier, it performs better when applied in a user-based filtering context. Finally, in comparison, Pearson correlation exhibited the lowest MAE, indicating the best performance. It is also interesting to note that as the value of the parameter α increases, both Euclidean and Cosine similarities decrease. In contrast, the Pearson similarity remains relatively stable until it transitions to a fully user-based algorithm, at which point it increases.

Because it achieved the lowest MAE, the hybrid model with $\alpha = 1/4$ and Pearson's correlation, using 3 neighbors to compute similarities, was chosen as optimal for making recommendations on learning strategies and support tools for dyslexic students. To prove the efficacy of the procedure, this optimal RS was also evaluated using precision and recall at k metrics [82]. In this context, a rating scale threshold of 3 was used to determine whether a tool or

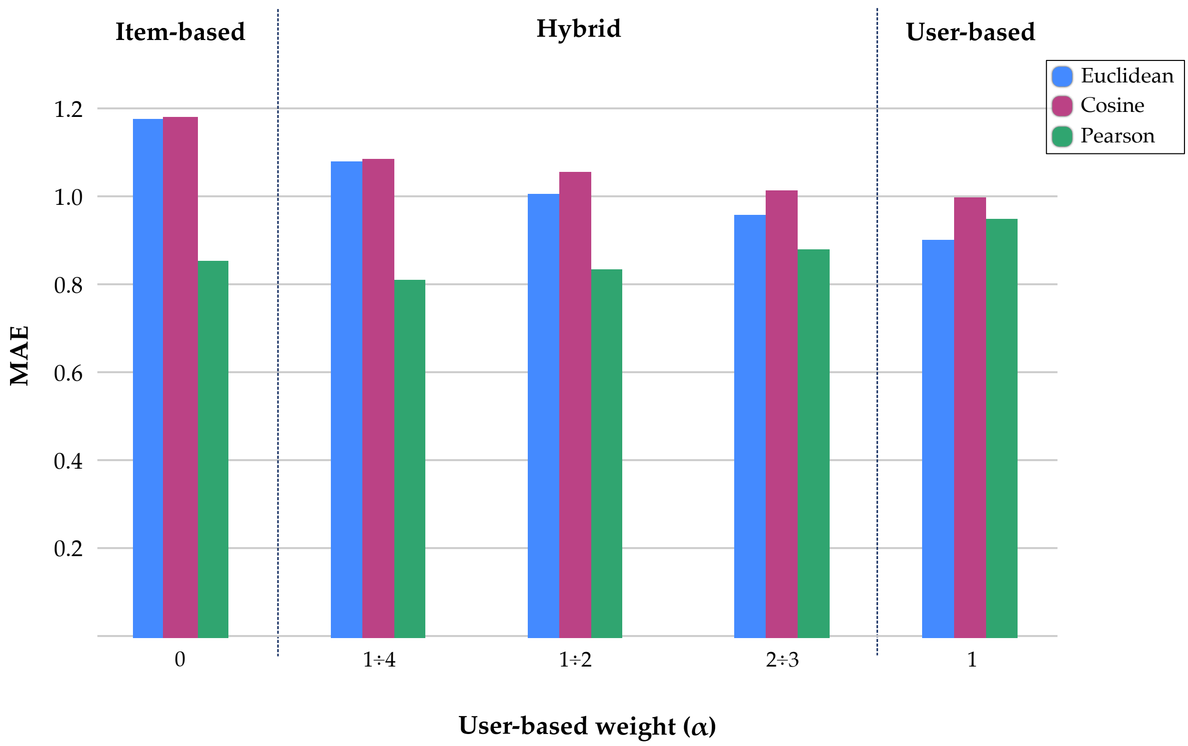


Figure 5.3: **Comparison of similarity measures across item-based, hybrid, and user-based settings.** MAE obtained with Euclidean, Cosine, and Pearson similarities for the most representative values of the user-based weight α.

strategy was relevant. This threshold was established by a panel of experts in methodologies for supporting dyslexic students and simultaneously represents a typical threshold in the literature for Likert-scale ratings in the 0 to 5 range [83]. These metrics can be defined as follows:

- Precision@k: is the proportion of recommended items in the top-k set that are relevant. It can be calculated as:

$$Precision@k = \frac{V@k}{R@k} \tag{5.8}$$

  where $V@k$ is the number of recommended items at k that are relevant for a user and $R@k$ is the total number of recommended items at k.

- Recall@k: is the proportion of relevant items found in the top-k recommendations. It can be obtained through:

$$Recall@k = \frac{V@k}{T} \tag{5.9}$$

  where $V@k$ is the number of recommended items at k that are relevant for a user and T is the total number of relevant items.

As with the MAE calculation, precision@k and recall@k have been computed for the 290 users in the test set. Consequently, the average precision of the proposed hybrid RS is 0.8524, while the average recall is 0.8278. According to precision, this signifies that 85% of the methodologies recommended by the system to a specific student are relevant support tools or strategies for them. Furthermore, with respect to recall, these results indicate that the system's recommended methodologies represent approximately 83% of all tools relevant to that student. These results align with those obtained through MAE, reaffirming the usefulness of the proposed RS.

Once the usefulness of the proposed hybrid recommendation model had been confirmed, its optimal configuration was applied to evaluate the system's effectiveness in improving students' learning experience in a real setting. The experiment described in Section 5.1.4 was conducted, and the resulting data are summarized in Table 5.4. This table reports the average score obtained by four groups: (i) non-dyslexic students who received recommendations from the RS, (ii) non-dyslexic students who did not receive recommendations from the RS, (iii) dyslexic students who received recommendations from the RS, and (iv) dyslexic students who did not receive recommendations from the RS.

Table 5.4: **Course performance with and without RS support for dyslexic and non-dyslexic students.** Average scores obtained by non-dyslexic and dyslexic students depending on whether they received suggestions from the proposed hybrid RS or not.

Group	Received RS suggestions	Not received RS suggestions
Non-dyslexic	8.6	8.2
Dyslexic	8.2	7.1

These results clearly demonstrated that the adoption of the supporting tools and strategies suggested by the implemented RS considerably increases the scores obtained by dyslexic students (more than 1 point), confirming that the proposed procedure can help them in their learning experience. In addition, non-dyslexic students also showed an improvement of their average score (0.4 points), opening up interesting scenarios for future research about the general usefulness of support methodologies suggested by AIs. In our opinion, a very outstanding result is that, thanks to the RS, dyslexic students can achieve the same performance as non-dyslexic students. This represents a step toward the real concept of inclusivity.

5.3 Conclusions

This chapter has presented the design, optimization, and validation of a CF specifically tailored to support university students with dyslexia in selecting effective learning tools and study strategies. Building on the data about item usefulness ratings introduced in the previous chapter, here the focus shifted from assessing individual tools in isolation to generating personalized, ranked sets of recommendations. To this end, three collaborative-filtering paradigms were compared (user-based, item-based, and hybrid), combined with different similarity measures (Euclidean distance, Cosine distance, and Pearson correlation) and neighborhood sizes. The experimental analysis of historical questionnaire data involving 38 support items and more than 1,200 dyslexic students showed that a hybrid configuration can effectively provide flexible and accurate recommendations to students.

The results demonstrated that the best-performing configuration is a hybrid RS with a user-based weight of $\alpha = 1/4$, using Pearson correlation and a neighborhood of 3. This model achieved an MAE of 0.8093 on a 0–5 rating scale, corresponding to a relative error of 11.93%, which indicates that the predicted usefulness of a tool or strategy typically deviates by less than one point from the student's actual rating. Complementary evaluation using precision@k and recall@k confirmed the robustness of this configuration. These findings, together with the analysis of different weight configurations and similarity metrics, highlight the importance of (i) giving more importance to the item-based component while preserving user-based information, (ii) relying on Pearson correlation for similarity modeling, and (iii) using small neighborhoods to avoid popularity bias and reduce the propagation of misleading information.

Finally, the effectiveness of the optimal hybrid RS was assessed in a real educational study involving 50 university students, both dyslexic and non-dyslexic, who were asked to study discipline-specific materials with or without system-generated recommendations. The results indicated that students who followed the RS suggestions achieved higher scores than those receiving random recommendations, with dyslexic students improving by more than one point on a 0–10 scale (from 7.1 to 8.2), and non-dyslexic students also benefited from a smaller but still positive gain (from 8.2 to 8.6). Notably, when supported by the RS, dyslexic students' performance became comparable to that of non-dyslexic peers, illustrating the potential of RSs to promote academic inclusion. Overall, this chapter provides empirical evidence that a carefully designed collaborative RS can act as an effective, scalable, and personalized support mechanism for dyslexic students.

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Part III

Virtual Reality for Empathy

This part addresses contributions based on the design, development, and evaluation of a set of VR experiences aimed at fostering empathy towards dyslexic students.

Chapter 6

The Virtual Campus

After addressing AI-based support tools in previous chapters, the thesis now turns to the use of VR as a complementary line of work. This section presents the first VR-based empathy experience developed in the thesis: *The Virtual Campus*. This experience is designed to immerse non-dyslexic participants in some of the reading, orientation, and support-related barriers commonly faced by university students with dyslexia in their daily lives. Rather than focusing on remediation or training, the experience is constructed as an awareness-raising tool. This chapter details its design and implementation, the main elements of the environment, and the strategies used to simulate dyslexia-related challenges.

6.1 Motivation for Using VR

In the educational field, digital technologies are progressively reshaping how learning differences are understood and supported, yielding increasingly promising outcomes. Among these technologies, VR enables the creation of immersive environments in which users can experience situations that are impossible to reproduce in real life, such as the obstacles faced by individuals with SLDs [84]. As a result, VR is being incorporated across diverse sectors of society, contributing to greater awareness of social issues. Nonetheless, research on the use of VR to foster understanding of SLDs, such as dyslexia, is still at an early stage, particularly when the focus is placed on higher education contexts.

Although previous studies have investigated VR applications in educational contexts [85], few have examined its potential to replicate the lived experiences of individuals with SLDs. Effectively supporting students with dyslexia requires a clear understanding of the challenges they face in their daily lives, particularly within learning environments. The approach proposed in this part of the thesis enables classmates and teachers to directly appreciate the importance of providing adequate support to help students overcome these barriers [10]. Existing research highlights that such understanding is crucial for the development of supportive learning settings. For example, prior work has shown that VR can successfully simulate sensory or physical impairments, yet its use in addressing cognitive and learning difficulties remains comparatively underexplored [86]. Other studies have investigated the role of VR in early education for students with dyslexia, demonstrating its potential to enhance cognitive skills and reading performance [87, 88, 89]. However, research on the use of immersive simulations in higher education remains limited, particularly regarding how these experiences can shape perceptions and promote inclusive learning environments for students with dyslexia. This gap offers an opportunity to investigate how immersive simulations may influence perceptions of, and attitudes toward, students with dyslexia, thereby increasing awareness and supporting inclusive education.

The motivation for this chapter arises from the need to address the limited understanding of how VR can be used to transmit the everyday challenges experienced by university students with dyslexia. To respond to this gap, the chapter focuses on the development of a VR experience, *The Virtual Campus*, that immerses participants in the role of a dyslexic student within a virtual campus.

6.2 *The Virtual Campus*

Within this section, an overview of the overall experience and the sequence of tasks it comprises is first provided. Next, the design of the campus and its core elements is described, detailing how maps, signage, non-playable characters, and guidance mechanisms are organized to balance usability and challenge. Subsequently, specific barriers related to reading, spatial orientation, and perceived lack of support are explained, highlighting how they are simulated in an ethically responsible way to approximate the everyday difficulties faced by dyslexic students. Finally, the gameplay structure is outlined, emphasizing the progression through the different stages and how they collectively support the goal of fostering empathy and awareness in higher education contexts.

6.2.1 Overview

The proposed experience consists of a series of tasks carried out in a virtual environment that simulates a university campus. The campus is extensive and composed of multiple similar buildings, intentionally making navigation via the map more challenging. The objective of the experience is to reproduce some of the barriers that university students with dyslexia encounter in their daily lives. The design guidelines used for the development of this environment are detailed below.

Vitual Campus guidelines

At the beginning of the experience, participants find themselves outside a university campus in front of a sign that shows them how to take their first steps within the virtual environment. Following the provided instructions, the user will go through a brief tutorial on the various available modes of locomotion, which will be very important for navigating the entire campus. After this, the participant must locate a map that will give them a series of directions to ensure they can reach the exam room on time.
To reach their destination, they will need to complete two tasks: collecting the materials needed for the exam and finding the classroom where the exam is being held. However, during these tasks, participants will face significant barriers similar to those that students with dyslexia encounter in their daily lives, such as difficulties with reading, challenges with orientation, and issues with memorization. These barriers will be simulated within the experience using different strategies, such as altering the order of letters in words and providing hard-to-interpret maps, among others.
If the user successfully completes the tasks on time, they will reach the exam room and fulfill their objective on the campus.

In addition, the objective of the virtual campus is not only to raise awareness about dyslexia in university environments but also to serve as a link between other VR experiences that aim to address more specific aspects of dyslexia awareness and other vulnerable groups. These experiences will be incorporated into the campus as they are developed, ultimately aiming to create a comprehensive virtual environment that allows users to understand firsthand the challenges these groups face.

Once the experience is completed, its effectiveness will be evaluated through a survey. The questions were designed based on recommendation models tailored to support dyslexic students [90], integrating elements from the VR aspect of the experience. This evaluation will serve as an initial analysis of the experience's effectiveness, preparing the way for future implementations and the integration of empathy tests into the campus environment. A more detailed analysis will then assess their impact on raising awareness about dyslexia and fostering empathy.

6.2.2 Design

The virtual environment simulates a large-scale university campus composed of multiple interconnected buildings and pathways. This environment includes seven distinct buildings that participants must navigate as they complete the tasks required during the experience. The design prioritizes inclusivity and immersion, leveraging VR to simulate real-world challenges faced by individuals with dyslexia.

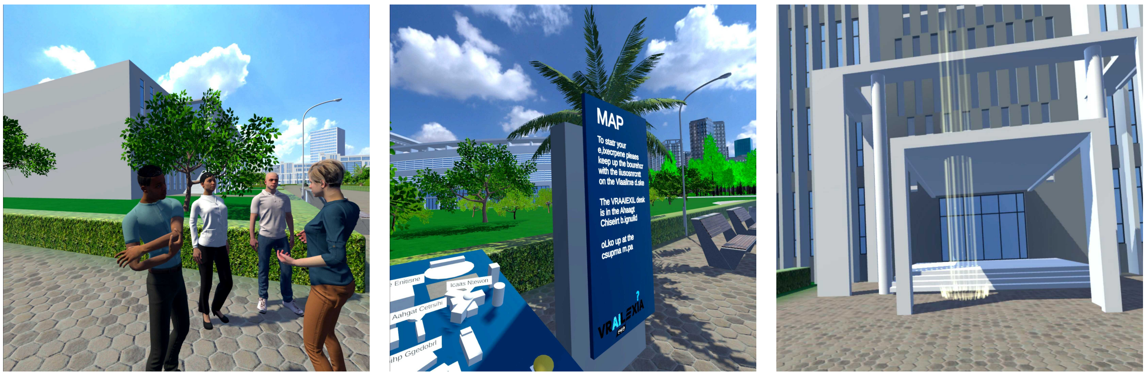
To raise awareness of dyslexia and highlight the contributions of individuals with this SLD, each building on campus is named after famous people with dyslexia. This approach aims to help non-dyslexic users recognize the achievements of individuals who have successfully overcome similar challenges, fostering a deeper connection between the experience and real-world examples of resilience and success. In addition, to enhance the sense of presence and realism, the environment incorporates ambient sounds and common visual elements found in real university settings, such as trees, benches, bike parkings, and avatars representing students. These elements collectively enrich the immersive experience while emphasizing empathy for the barriers encountered by individuals with dyslexia.

Among the virtual campus's core components, the following elements stand out due to their significance in promoting navigation, task progression, and overall engagement:

- **Students**: The campus environment features diverse avatars representing students engaged in common activities, such as group interactions or solitary walks (see Figure 6.1 (a)). These non-playable characters (NPCs) add realism to the experience, simulating the lively nature of a real university setting. However, participants cannot interact with these avatars, nor will the NPCs provide guidance or assistance, further reinforcing the sense of isolation and potential disorientation.

- **Signals**: Informative signage is strategically placed throughout the campus to guide participants in completing challenges and navigating to key locations (see Figure 6.1 (b)). Initially, these signs provide clear instructions (tutorial); however, as the experience progresses, some signs become increasingly difficult to read, simulating the decoding challenges faced by individuals with dyslexia. In addition to directional signs, another set of signs identifies the entrances to campus buildings and displays their respective names to assist with orientation. Some signs are dynamically modified based on the user's behavior. For example, when a participant attempts to enter the wrong building for the current task, the signs at the building entrances will indicate that they are not in the correct building. This dynamic feature helps guide the user and reinforces the navigation challenges inherent to the experience.

- **Beacon**: In order to facilitate task progression and reduce uncertainty, a visual beacon system is employed to highlight critical points within the campus. The beacon appears as a circle of light projected onto the ground, signaling locations such as building entrances, exits, and other significant waypoints (see Figure 6.1(c)). At any given time, the active beacon guides participants sequentially through key stages of the experience. Additionally, there is a challenge beacon, visible from anywhere on campus, that provides a clear indicator of the active 3D map corresponding to the current challenge, guiding the experience. This helps users stay oriented and focused on the specific task at hand.



(a) (b) (c)

Figure 6.1: **Environmental elements for guidance and immersion in the campus.** (a) Students. (b) Signals. (c) Light-based beacon.

- **Maps**: To facilitate navigation within the campus, two types of maps are provided to participants:
  - ◇ **Vertical Map:** This simplified map highlights only the user's current location and the target destination, enabling a focused and streamlined experience (see Figure 6.2 (a)).
  - ◇ **Interactive 3D Map:** Offering a comprehensive, overhead 3D view of the campus, this map displays the names and positions of all buildings along with the user's location. Users can interact with this map to receive real-time navigation assistance toward specific destinations by pressing a designated button. See Figure 6.2 (b).

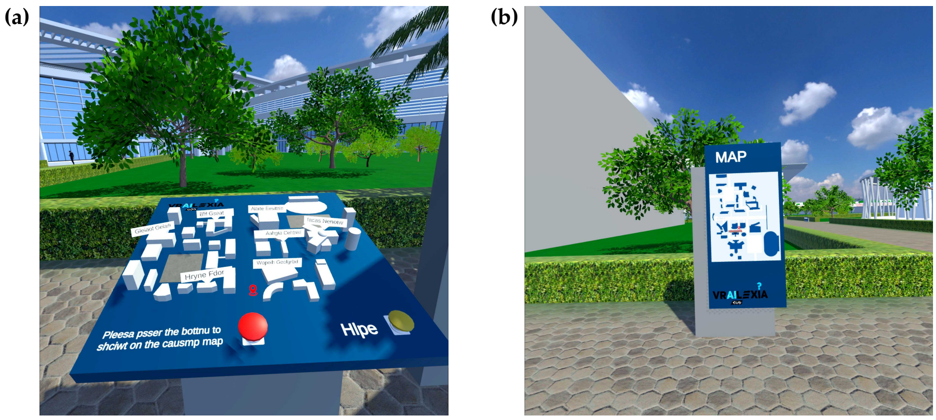


Figure 6.2: **Maps for campus navigation.** Different maps provided to support participants in finding their way through the virtual campus: (a) Vertical map, and (b) Interactive 3D map.

6.2.3 Simulating University Barriers for Dyslexics

The main objective of the experience is to raise participants' awareness of the barriers that students with dyslexia encounter during their higher education years. To achieve this, different simulated barriers have been designed and integrated into the virtual environment to reflect similar challenges. It is important to emphasize that these barriers are not intended to replicate dyslexia itself but to mimic the difficulties it can cause, such as slower reading, disorientation, and feelings of isolation or lack of support.

One of the primary challenges associated with dyslexia is difficulty in reading and comprehending text. To simulate this challenge, two distinct strategies have been employed: letter movement and word substitution.

- **Letter movement:** This barrier involves dynamically and randomly rearranging the letters, except for the first letter of the word, within individual words, as illustrated in Figure 6.3 (a). In this example, the letters of the word "exam" change their order, forming nonexistent words like "exma". This effect is applied to the full text of informative signs that describe tasks on the campus and also in the names of the buildings that are reflected in the maps, making the text harder to read and increasing the time needed for comprehension.

- **Word swapping:** This barrier involves replacing some words in the text with other existing words that have similar sounds, which is one of the primary issues associated with surface dyslexia [91]. In this way, during the experience, words in task instructions are continuously swapped, forcing the user to pause and consider what the actual instructions are. This is illustrated in Figure 6.3 (b), where the word "stairs" is replaced with "stare".

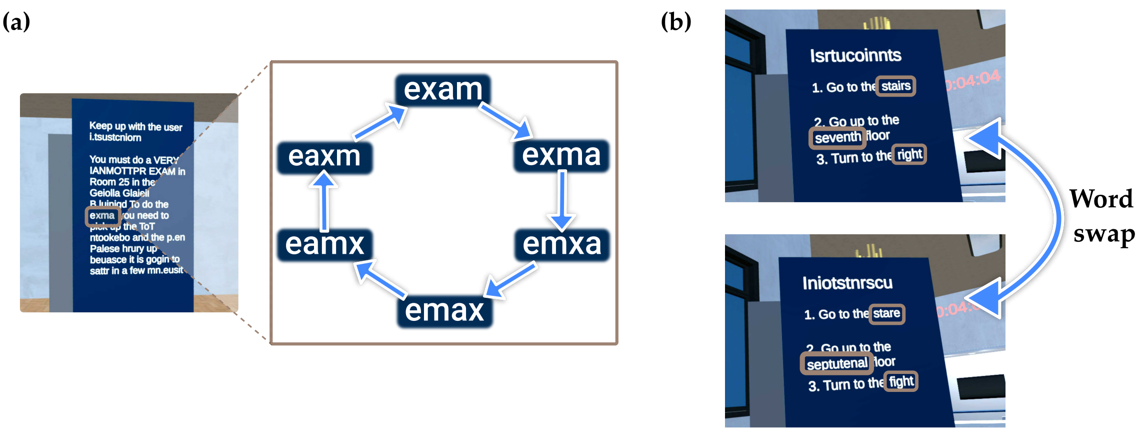


Figure 6.3: **Reading barriers simulated through letter movement and word swapping.** (a) Letter-movement effect. (b) Word-swapping effect.

Another significant challenge faced by university students with dyslexia is orientation within large environments [92]. These environments are often vast, with similar-looking buildings and limited signage to guide navigation between locations. To replicate this challenge, the virtual campus was designed as a large-scale map featuring similar paths and structures. The scaled dimensions of the buildings and streets within the modeled campus are depicted in Figure 6.4 (a). Furthermore, the 3D maps represent the shapes of buildings in a manner that does not fully correspond to their actual structures within the virtual environment. Similarly, vertical maps omit the names of the main buildings, further complicating navigation. This design requires users to rely on both types of maps to orient themselves and reach their destination effectively.

Additionally, a help button was incorporated into the 3D maps, enabling participants to display guiding arrows on the ground, as illustrated in Figure 6.4 (b), to assist them in navigating to their destination. However, to ensure that this feature does not entirely mitigate the orientation challenge, the arrows are deliberately designed to point in the wrong direction 25% of the time, introducing an additional layer of disorientation. This design emulates some of the barriers encountered by individuals with dyslexia, particularly difficulties with left-right or up-down orientation. By occasionally providing incorrect directions, this feature simulates the disorientation and navigational challenges that individuals with dyslexia may face in spatial environments.

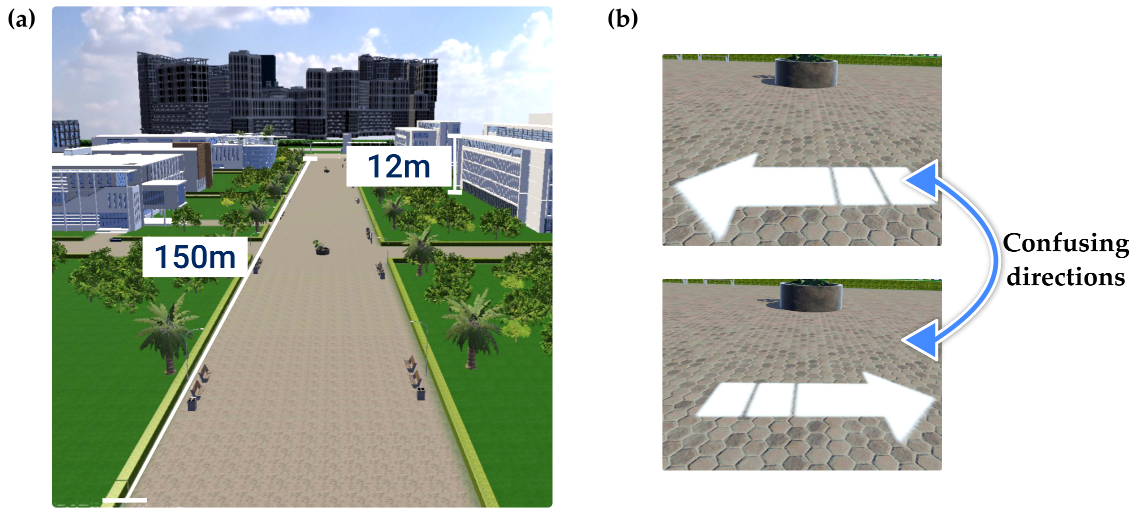


Figure 6.4: **Orientation challenges in the virtual campus.** (a) Large-scale layout. (b) Confusing help directions.

Another significant barrier faced by students with dyslexia is the lack of support from peers and teachers [10]. This sense of isolation and frustration often exacerbates the difficulties of their academic journey and can, in some cases, result in the abandonment of their studies. To replicate this experience, participants are placed in a campus environment populated with NPCs representing students and peers, but interaction with them for assistance is not possible. Furthermore, the support provided through the virtual experience itself is intentionally limited and, at times, deliberately misleading. This design choice seeks to heighten the user's sense of frustration, transforming seemingly straightforward tasks into complex challenges and effectively simulating the emotional and practical difficulties experienced by students with dyslexia.

6.2.4 Gameplay

The experience is designed to visit multiple locations across the campus and is structured into distinct stages or levels. This section provides a detailed analysis of each phase of the experience, including the specific tasks participants are required to complete at each stage.

Figure 6.5 illustrates the layout of these levels, mapping the progression from the user's entry into the virtual environment to the conclusion of the experience. Each stage, along with the corresponding tasks, is classified into three main categories, which are outlined below:

- **Start–End Stages**: These stages indicate the beginning and conclusion of the experience. They include the introductory tutorial at the beginning and the final exam, where the experience ends.
- **Main Building Task**: These stages involve specific challenges within certain campus buildings, where participants face dyslexia-related barriers, particularly those related to reading and text comprehension.
- **Navigation Stage**: These stages require participants to locate specific points on the campus to progress to the next phase. While the start and end points of these stages are predefined, as shown in Figure 6.5, the path taken by the player is not fixed and is influenced by the user's navigation choices.

Figure 6.5: **Structure and stages of the VRAIlexia experience.** (a) Campus render indicating the locations of the main stages of the experience. (b) Flow of experience stages. (c) Legend representing the different types of levels.

The user progresses through a series of stages, each designed to represent a distinct type of interaction and challenge within the virtual campus. The following breakdown categorizes the levels by their specific tasks and explains their relationship to the previously described phase types: Start–End Stages, Main Building Tasks, and Navigation Stages.

1. **Tutorial Stage (Start–End Stage):** The experience begins with a tutorial stage located at the campus entrance. The primary objective of this stage is to familiarize users with the controls and basic navigation mechanics of the virtual environment. Informative signs provide guidance on operating the controllers and selecting between different locomotion options to navigate to the first 3D interactive map. Upon reaching the map, users receive instructions on interacting with elements such as virtual buttons. Successfully pressing the button transitions the experience into the next phase, marking the formal commencement of the user's task-based journey.

2. **Journey 1 (Navigation Stage):** Following the tutorial, the user encounters their first navigation challenge. A sign displaying instructions directs them to their next destination, utilizing the "Letters Movement" barrier to simulate the difficulties individuals with dyslexia may experience when interpreting text (see Section 6.2.3). The instructions indicate that the user must proceed to the Agatha Christie building to collect materials required for an exam. This navigation task requires the user to interpret signs displaying building names and follow them to reach the designated location, thereby testing their ability to navigate the campus under conditions analogous to those faced by individuals with dyslexia.

3. **Agatha Christie (Main Building Task):** Upon entering the Agatha Christie building, the user encounters another barrier: a sign displaying text altered by the "Letters Movement" effect. The task requires the user to locate a notebook and pen within the building, collect them, and place them in their virtual backpack before proceeding to the exam room. Upon completing this task, the user is informed that the exam room is located in the Galileo Galilei building. This challenge not only simulates the difficulties associated with reading impairments but also underscores the importance of time management, as the user must complete the task within a limited time frame.

4. **Journey 2 (Navigation Stage):** After exiting the Agatha Christie building, the user must navigate to the Galileo Galilei building using the newly provided instructions. This stage introduces a new 3D map to assist the user in locating the building. The map includes an interactive help function, which offers additional guidance when required. The user is tasked with traversing the campus to reach the Galileo Galilei building, marking a key milestone in this phase of the experience.

5. **Galileo Galilei (Main Building Task):** Upon entering the Galileo Galilei building, the user encounters a room featuring a staircase, a countdown timer, and two hallways. A new sign appears, using the "Swapping Words" barrier to simulate another challenge faced by individuals with dyslexia, the difficulty with word recognition. This sign provides instructions specifying the floor and hallway the user must follow to locate the exam room. The countdown timer introduces a time-sensitive element, replicating the stress and pressure that students may experience during exams.

6. **Exam Classroom (Start–End Stage):** Finally, the user reaches the exam room, where they receive instructions to begin the exam. These instructions, while seemingly straightforward, contain "swapped" words that resemble real words but are, in fact, nonsensical (e.g., "Go to your zona" instead of "Go to your zone"). This final task simulates the challenges of reading comprehension and word recognition difficulties commonly experienced by individuals with dyslexia in academic settings. Upon completing this task, the experience concludes.

A gameplay example and the download links for *The Virtual Campus* are available online. The corresponding URLs are listed in the Contributions section at the end of this document.

6.3 Evaluation of the Experience

This section details the methodological framework used to evaluate the effectiveness of the proposed VR experience in fostering empathy and raising awareness about dyslexia. The assessment is structured into three key aspects: the features of the participants involved in the study, the methods employed for data collection and analysis, and the instruments used to measure the impact of the experience.

6.3.1 Participants

To assess the effectiveness of the proposed method as a VR experience aimed at raising awareness about dyslexia, an initial evaluation was conducted with 32 participants from the higher education sector. These participants were selected from volunteers who expressed interest in the experience during a project's dissemination campaign carried out at the University of Córdoba (Spain). Socio-demographic data were collected during the participant selection process to assess the methodology's applicability across different demographic groups, with a primary focus on gender, age, and participants' academic or professional roles within the higher education context. Table 6.1 contains information on these characteristics for the 32 participants selected for this study. During the selection process, efforts were made to maintain a balance in the gender of participants, ultimately resulting in a slightly higher participation of male participants, comprising approximately 59% of the total sample.

Regarding profiles, the majority of the experience was conducted with university students who shared classes with dyslexic students, representing the largest group (53.17%). Nonetheless, a significant number of teachers of students with dyslexia also showed interest in the experience (21.88%), as well as other individuals who, despite not being educationally connected to someone with dyslexia, had a relative with dyslexia. Concerning age, as previously mentioned, the tool was primarily used by students, making the predominant age range between 18 and 26 years, with over 60% of participants falling within this range.

Table 6.1: **Socio-demographic profile of the study participants.** Distribution of the 32 participants according to gender, age group, and role within the higher education context.

Feature	Subgroup	#	Percentage
Gender	Female	13	59.38
	Male	19	40.62
	Other	0	0.00
Age	[18, 26)	20	62.50
	[26, 50]	10	31.25
	>50	2	6.25
Profile	Dyslexic relative	6	18.75
	Higher education student	17	53.12
	Higher education professor	7	21.88
	None	2	6.25

6.3.2 Methods

The evaluation was conducted through a controlled study with a structured data collection process, ensuring the validity and reliability of the findings. The primary aim was to determine how the VR experience influences users' understanding of dyslexia-related challenges. To this end, a selected group of participants engaged in the VR experience under supervised conditions, after which they were asked to complete a structured questionnaire that will be defined later.

The theoretical framework guiding the immersive learning experience is based on constructivist and experiential learning theories. Constructivist and experiential learning theories emphasize active, learner-centered engagement, where participants acquire knowledge through meaningful interactions with their environment. In this context, the VR experience was designed to provide an immersive simulation that exposes users to the barriers faced by dyslexic individuals, encouraging a deeper understanding through direct experience and reflection [93]. Additionally, the cognitive theory of multimedia learning informed the integration of visual and interactive elements to enhance engagement and retention. By simulating real-world scenarios and embedding dyslexia-related challenges, the experience aligns with these pedagogical principles, ensuring that learners are actively involved with the presented difficulties, rather than passively receiving information.

All participants provided informed consent before engaging in the study, ensuring they were fully aware of the research objectives and the handling of their data. The study complied with all ethical guidelines, including Organic Law 3/2018 on Personal Data Protection and the ethical principles outlined in the Declaration of Helsinki [94, 95]. Ethical approval for the study was granted by the institutional ethics committee (approval number 367). In addition, to ensure data privacy, all information obtained was treated with strict confidentiality. The questionnaire was designed to be anonymous, including an introductory section explaining the study's objectives, followed by an informed consent form.

6.3.3 Instruments

To evaluate the quality of the experience and its effectiveness as a tool for raising awareness about dyslexia, a questionnaire-based evaluation methodology was developed. The questionnaire consists of 15 questions to be completed after participating in the experience, divided into three categories: socio-demographic data, VR experience quality, and dyslexia awareness. Finally, a general evaluation question regarding the overall experience is also included. Table 6.2 presents the list of questions organized by category. All items are answered using a 5-point Likert scale, except for socio-demographic questions.

The collected data provided quantitative insights into how users perceived the VR experience and whether it effectively enhanced their understanding of dyslexia-related challenges. The next section presents and discusses the results obtained from the evaluation.

Table 6.2: **Post-experience questionnaire for evaluating *The Virtual Campus* experience.** Set of socio-demographic and evaluation items administered after the VR experience.

Category	**Question**
Socio-demographic information	Gender Age Relationship to a dyslexic student*
VR experience quality	VR prior experience Motion sickness Visual immersion Interaction within the environment
Barriers simulation	Navigation among buildings Finding the exam class Use of the help option
Dyslexia awareness	Awareness of dyslexia Experience with empathy applications Effectiveness of the virtual campus in promoting dyslexia awareness
Overall	Overall rating of the experience

* The following types of relationships with a dyslexic student have been considered: 1) Classmate, 2) Teacher, 3) Relative, 4) Other, 5) None.

6.4 Results

This section presents and discusses the results of the study, focusing on the effectiveness of the empathy experience both as a VR application and as a tool for raising awareness about dyslexia. The results are structured into two main aspects: the assessment of the VR application in terms of usability and immersion, and the evaluation of its effectiveness in simulating barriers and raising awareness about dyslexia.

6.4.1 VR Application

In order to assess the quality of the proposed tool, it is critical to evaluate not only its effectiveness in achieving its primary objective, raising awareness about dyslexia, but also its ability to effectively utilize the unique features of VR. Therefore, the first evaluation aspect focused on assessing the quality of the VR experience in terms of immersion, interaction, and user comfort. Figure 6.6 illustrates the responses to four key questions regarding prior VR experience, motion sickness, visual immersion, and interaction within the virtual environment.

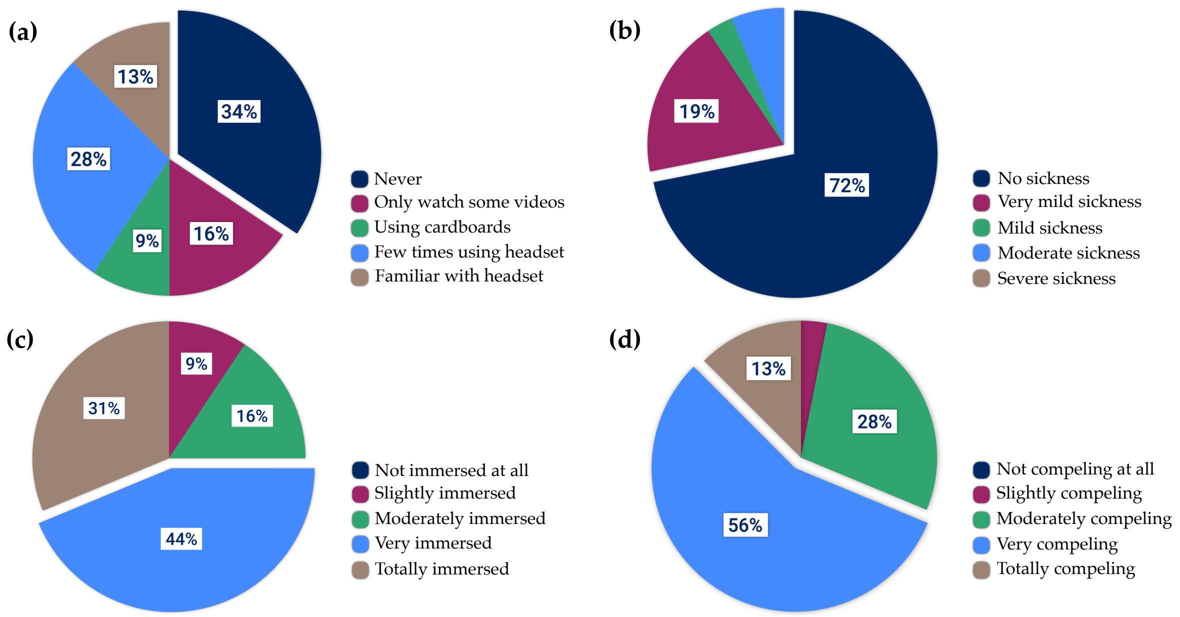


Figure 6.6: **Responses to the questions measuring the quality of the VR application**. (a) Have you ever tried VR before the experience? (b) Did you experience nausea, loss of balance, or discomfort during the experience? (c) How much did the visual aspects of the environment engage you? (d) How compelling was your sense of moving around and interacting within the virtual environment?

The questionnaire results revealed that a significant proportion of participants had no prior experience with VR, making this their first encounter with a complete setup involving a headset and controllers. Conversely, 28% of participants reported familiarity with VR equipment, providing valuable feedback based on their previous exposure to other VR applications or games. Regarding discomfort or motion sickness, the findings were predominantly positive. The majority of participants reported no sickness, with only one individual experiencing moderate symptoms and none reporting severe discomfort.

Regarding immersion, participants generally expressed favorable opinions. Specifically, 44% indicated feeling "Very immersed", and 16% reported being "Totally immersed" in the virtual environment. Among the remaining participants, the most commonly cited issue was that the use of controllers for locomotion, particularly teleportation, diminished their sense of immersion. Finally, most participants expressed high satisfaction with the interaction mechanics and locomotion options within the virtual environment. However, the primary criticism is centered on the limited physical space available, which restricts freer physical movement.

6.4.2 Barrier Simulation and Dyslexia Awareness

The objective of this study is to raise awareness about the challenges faced by dyslexic students in higher education. To evaluate the effectiveness of the proposed tool in achieving this goal, the evaluation questions were divided into two categories: the simulation of barriers and awareness of dyslexia. The first category focused on assessing the extent to which the simulated barriers hinder task completion during the VR experience. The second category aimed to evaluate participants' prior knowledge of dyslexia as an SLD and how their perceptions of dyslexic students are influenced after participating in the experience.

Regarding the barriers, Figure 6.7 illustrates the responses obtained when participants were asked about the difficulties encountered while performing the two main tasks of the experience.

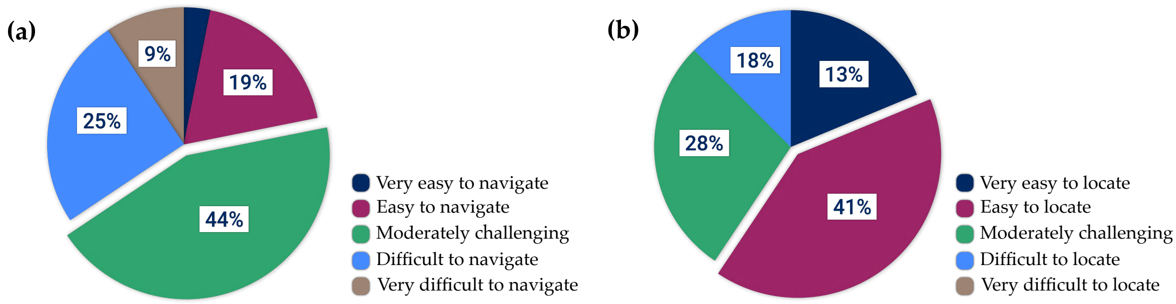


Figure 6.7: **Responses to the questions measuring the effectiveness of the application in simulating barriers.** (a) How challenging did you find navigating among the buildings? (b) How challenging did you find locating the classroom for the exam?

The first task required participants to navigate between various campus buildings (see Figure 6.7 (a)). During this task, participants encountered barriers related to orientation in a monotonous, large-scale environment, as well as difficulties reading the instructions on signs due to the implemented "Letter movement" strategy. To address these challenges, the experience included mitigation measures, such as the availability of various maps and a help option that displayed guiding arrows on the ground to guide participants between buildings. Despite these aids, only 12 out of 32 participants utilized the help function, as most preferred to complete the task without additional assistance. Participants generally identified this task as the most challenging, citing their main difficulty as transferring the information from the provided maps, particularly the 3D interactive maps, to the virtual campus space.

The second task involved finding the exam classroom within the building where the final exam takes place (see Figure 6.7 (b)). Upon entering the building, participants are presented with confusing instructions generated using the "Word swapping" strategy. This challenge is further intensified by the monotonous design of the building's floors, which makes it difficult for participants to easily distinguish between them. Despite these barriers, participants generally found this task to be straightforward, noting that the allotted time was more than sufficient. While some participants needed to review the instructions multiple times to fully understand them, the overall simplicity and limited number of steps contributed to the task being perceived as easy.

On the other hand, the responses to the questions regarding the awareness of dyslexia are shown in Figure 6.8.

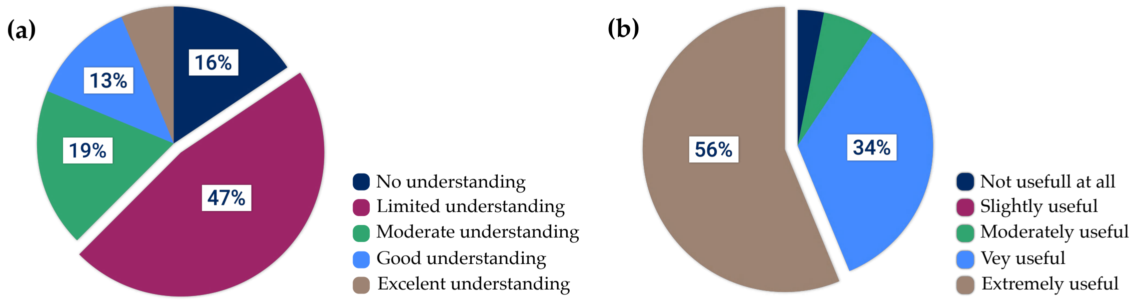


Figure 6.8: **Responses to the questions about participants' dyslexia awareness.** (a) How would you rate your understanding of dyslexia? (b) How useful do you consider the VR experience in raising awareness about dyslexia?

The first notable finding is the general lack of knowledge about dyslexia, with more than 60% of participants either being unaware of what this learning disorder is or having only heard about it (see Figure 6.8 (a)). In contrast, more than 90% of participants indicated that the campus experience is "Very useful" or "Extremely useful" in raising awareness about dyslexia (see Figure 6.8 (b)). Participants frequently noted that they had not previously considered how the challenges associated with this learning disorder could result in significant difficulties when performing seemingly simple tasks. Only one participant reported finding the tool not useful for raising awareness about dyslexia. This individual stated that he did not fully understand the connection between the tasks and challenges presented during the experience or the definition of dyslexia difficulties.

6.4.3 Impact, Theoretical Implications, and Limitations

The findings of this study highlight the potential of VR as an effective tool for raising awareness about dyslexia by immersing participants in the challenges faced by dyslexic students. These results align with previous research demonstrating that VR can enhance empathy for individuals with disabilities [96]. Compared to traditional awareness methods such as text-based or video interventions, the interactive and embodied nature of VR provides a more engaging and impressive experience [97].

Beyond its practical contributions, the study supports key theoretical frameworks. The results align with embodied cognition theory, which suggests that active engagement enhances learning and understanding [98]. Situating these findings within the broader research landscape, this study contributes to the emerging field of VR-based disability awareness [19, 99]. While VR has been extensively explored for cognitive training, including in the dyslexia field [55], its application in fostering social awareness remains underdeveloped. The results presented suggest that VR can effectively complement existing educational interventions by providing an experiential understanding of dyslexia.

Despite its promising results, the study faced limitations. The sample size was relatively small, and it focused on higher education participants. Additionally, another important limitation of the proposal was that, despite the software being freely available to users, a Meta headset was required to participate in the experience. This requirement represents a significant barrier, as the cost of such headsets may make them inaccessible to many potential users.

6.5 Conclusions

Overall, the results obtained with *The Virtual Campus* indicate that VR can be effectively used as an empathy-oriented tool to raise awareness about dyslexia in higher education. Despite most participants having little or no prior experience with VR, the application was rated as highly immersive and comfortable to use, and more than 90% of participants considered it very or extremely useful for understanding the everyday challenges faced by dyslexic students. The simulated barriers related to reading, orientation, and perceived lack of support were generally perceived as meaningful and demanding, successfully transforming seemingly simple daily tasks into situations that require some effort from dyslexic students to be completed.

At the same time, several limitations should be analyzed. The study relied on a relatively small and localized sample. In addition, the evaluation was based on self-reported perceptions collected immediately after the experience, without long-term follow-up or comparison with a control condition using more traditional awareness-raising methods. Finally, although the software is freely available, the requirement of a commercial VR headset constitutes an economic barrier for many institutions and people.

Taken together, these findings indicate that *The Virtual Campus* is a successful first step in exploring how VR can be used to demonstrate the difficulties caused by dyslexia in real university scenarios, while also revealing the need for more targeted interventions and evaluations for dyslexic students. Building on this foundation, the next application presented in the thesis, *The Magic Potion*, shifts the focus from a broad simulation of campus life to a more specific dyslexia-related task, specifically targeting phonological dyslexia.

Chapter 7
The Magic Potion

Building on the previous chapter, where *The Virtual Campus* was used to simulate a broad set of barriers related to navigation, reading, and perceived lack of support in authentic university scenarios, this chapter narrows the focus to a specific dyslexia profile: phonological dyslexia. The aim is to move from a general depiction of everyday difficulties to a more fine-grained modeling of phonological decoding problems, particularly the effort required to read unfamiliar words and pseudo-words under time pressure. First, the main cognitive and academic implications of phonological dyslexia are outlined, with an emphasis on higher education contexts. The chapter then introduces *The Magic Potion*, a VR game in which progress depends on interpreting simulated unfamiliar items and non-words, supported by progressive compensatory tools that mirror real educational aids that can be applied in university settings. Finally, the design choices and empirical evaluation of this experience are presented, extending the VR-based empathy framework established in the previous chapter toward a more targeted understanding of phonological difficulties.

7.1 Phonological Dyslexia

Research on dyslexia has progressively refined its conceptualization [100, 101] and characterized it into distinct profiles, which helps explain the heterogeneity of the problems that cause reading difficulties. Among these profiles, phonological dyslexia is characterized by difficulty in reading both unfamiliar words (words not previously known by the reader) and pseudo-words (pronounceable but not real words), while maintaining a relatively strong effect with familiar words [102, 103]. Individuals with this profile often struggle to map graphemes to phonemes, leading to slow, error-prone reading of novel items and pseudo-words. These difficulties are especially evident in contexts where new vocabulary, technical terminology, or morphologically complex words are frequent [104], as is the case in many higher education programs.

From an academic perspective, phonological dyslexia can therefore affect not only reading speed and accuracy, but also access to course content, participation in class, and performance in written examinations. Neurocognitive studies suggest that these difficulties are associated with atypical functioning in regions involved in phonological processing and language decoding [105]. Nevertheless, targeted interventions and appropriate accommodations can substantially improve reading efficiency and comprehension, mitigating the impact on academic trajectories [106]. In parallel with these direct language-based interventions, promoting understanding of phonological difficulties among peers and teachers has been highlighted as a complementary strategy that can reduce stigma and support more inclusive practices.

Within this chapter, phonological dyslexia is addressed not only at a conceptual level but also through an immersive, experience-based approach. While the VR application presented in the previous chapter, *The Virtual Campus*, focused on a broad set of barriers (navigation, reading, and lack of support) in authentic university scenarios, the second application presented here, *The Magic Potion*, narrows the focus to the phonological dimension of dyslexia. The game mechanics are designed so that progress in the experience depends on interpreting a simulation of unfamiliar words and non-words under time pressure and uncertainty, thereby mirroring the core decoding challenges experienced by individuals with phonological dyslexia.

7.2 Modeling Phonological Dyslexia in VR

This section details how the core characteristics of phonological dyslexia are introduced within a VR experience. The modeling process involves: (i) the construction of a fantasy but emotionally grounded context, including the spatial layout of the castle and its rooms; (ii) the simulation of decoding difficulties through the use of unfamiliar words and dyslexia-inspired typography; and (iii) the design of interactive elements and compensatory tools that mirror real academic support methodologies.

7.2.1 Overview

The proposed experience consists of a game set in a virtual magic castle, where participants must brew a potion by following written instructions under time pressure. Progress in the game depends on reading and interpreting unfamiliar words written in a special font (described in the following section), matching them with the corresponding ingredients, and respecting both order and quantity. The design guidelines that structure this experience are summarized below.

The Magic Potion guidelines

At the beginning of the experience, participants enter a dark magic castle and receive a brief introduction to phonological dyslexia and to the basic controls of the VR environment. They are then informed that their friend Sam is in danger and can only be helped by correctly preparing a magic potion.
To brew the potion, participants must read a recipe book and identify the required ingredients among multiple labeled flasks placed on the shelves of the potions laboratory. Both the recipe and the labels are written in Britton's font and include unfamiliar words, forcing participants to work hard to decipher rather than relying on visual familiarity.
The task is structured into several timed levels. In the initial level, participants must complete the recipe with very limited time and no additional support, experiencing the difficulty of decoding long, complex words under pressure. In subsequent levels, compensatory tools inspired by real educational accommodations are progressively introduced, such as extended time, word simplification, and an audio guide that reads the words aloud when touched.
If the participant succeeds in preparing the potion within the allowed time, Sam recovers and celebrates. If they fail, Sam's condition gets worse, and the teacher reprimands them.

The virtual environment is characterized by a dark and dim atmosphere, intentionally crafted to evoke feelings of desolation, fear, and helplessness [107, 5] in the face of the impending challenge. Within the virtual castle, participants will be granted admittance to three distinct rooms, organized as shown in Figure 7.1. The initial of these enclosures is the starting point of the exploration, where players can familiarize themselves with the operational features of the controller buttons (Figure 7.1 (a)). In addition, they will find a brief explanation about the effects of phonological dyslexia. The second room is Sam's room. It is an empty room where players can see their friend and his current state as shown in Figure 7.1 (b). Finally, the third room is where the game takes place. It is a potions laboratory where players can find their teacher, the table where the potion instruction book is placed and all the ingredients needed to brew the potion to help Sam, which are laid out on shelves. A first view of the lab is shown in Figure 7.1 (c).

(a) Starting corridor (b) Sam's room (c) Potions laboratory

Figure 7.1: **Chambers from the virtual castle**. (a) Corridor to access the lab. (b) Sam's room. (c) Potions laboratory.

7.2.2 Simulating Reading Difficulties

The methodology proposed in this study involves immersing participants, including teachers and peers of dyslexic students, into a virtual world to execute a specific task. This task entails reading a recipe book and accurately combining the ingredients in the specified sequence and amount, with an additional reading challenge designed to evoke the core difficulties of phonological dyslexia. To hinder fluent decoding and increase the cognitive load associated with reading, the text in the book and on the ingredient labels is presented in Britton's Dyslexia font [108]. This font was created by removing parts of the letters, thereby making words harder to recognize even for non-dyslexic readers. It is important to note that this visual distortion does not claim to reproduce how people with dyslexia literally "see" text, but rather serves as an artificial mechanism to approximate the effortful, slow, and error-prone nature of their reading experience. Figure 7.2 shows how the word "Dyslexia" is written using this font.

Figure 7.2: **Example of text rendered with Britton's font.** Visualization of the word "Dyslexia" using Britton's font.

7.2.3 Main Characters and Items

Throughout the VR experience, participants are required to interact with a diverse range of items and characters that have been specifically designed to guide and enhance their level of immersion within the simulated environment. A list of these characters and objects is exposed below, and their representation in the virtual world is shown in Figure 7.3.

- **Teacher**: This non-player character (NPC) has the role of potions teacher. The avatar explains to the players the rules of the game and what they have to do to create the correct potion and win the game. In addition, this NPC takes on the role of a strict teacher who yells at the students when they fail in their tasks. In this way, the player put himself in the place of dyslexic students when they are not valued for their effort by those teachers [7, 10], who only keep performance in mind.

- **Sam**: Represents the player's friend in the game. The player must prepare a potion correctly and within a limited time frame in order to save this NPC. The player's results will be directly reflected in Sam's conditions. If the correct potion is created, Sam will be happy and will celebrate, but if users fail during the different levels, they will see Sam suffer.

- **Ingredients and shelves**: Around the potions laboratory, the player finds several shelves with different ingredients to make potions. These ingredients are carefully arranged in a particular order on each shelf and stored within flasks of varying shapes and colors, each labeled with the corresponding ingredient's name. Notably, the labeling is composed using Britton's font, trying to replicate the reading difficulties experienced by a dyslexic person.

- **Table**: In the center of the potion laboratory lies an irregularly-shaped table designed to promote different modes of locomotion in VR (teleportation-based and controller-based). Over the table, there are different key objects for the game, including the hourglass, the recipe book, and the pot, which players may interact with as part of their gameplay experience. Furthermore, the table serves as a practical space for players to place some of the potion ingredients.

- **Hourglass**: Is the item used to start the game. Next to it, there is a digital clock with the time available to complete the level. Upon starting the game, the assigned time begins to decrement, with the level concluding once the timer reaches zero. The design of this item, which constantly displays the remaining time, was created to be overwhelming for the player, in a manner similar to how the deadline of an exam can be stressful.

- **Pot**: Container in which the potion has to be brewed. Players must pour the correct ingredients into the pot in the correct order to pass the game. The pot will release a heart if the poured ingredient is correct and a purple smoke if it is not, serving as feedback to guide the player towards successful completion of the game.

- **Recipe book**: It is a big book containing the recipe for the potion to be brewed by the player. It denotes the specific type and quantity of each ingredient required and specifies the correct order in which they must be added to the container, in order to ensure the successful completion of the potion. Consistent with the font utilized for ingredient labeling, the recipe book also employs Britton's font.

(a) Ingredients. (b) Irregular table. (c) Hourglass.

(d) Pot. (e) Recipe book. (f) Beacon.

Figure 7.3: **Main items in *The Magic Potion*.** Key objects that structure the gameplay and support the simulation of dyslexia-related challenges during the VR experience.

- **Beacon**: A light beam that guides the player throughout the virtual environment. It indicates specific points within the potions laboratory where the player must be situated to initiate teacher conversations or start the next level.

7.3 Gameplay Design

This section presents a detailed overview of the game design. First, the compensatory methodologies considered are introduced. After this, the different stages of the game are differentiated. Then, the flow of the game is illustrated, encompassing the player's journey from the initial entry into the virtual environment to the culmination of the experience. Finally, a detailed exposition of the various levels of difficulty under consideration is presented.

7.3.1 Compensatory Tools

The development of the game has required the translation of various compensatory methodologies for dyslexic students into the virtual environment. These tools have been inspired by real-world methodologies [66] and adapted for the tasks to be performed during the game. Three support tools have been considered:

- **Time extension:** Each time users fail an attempt in the game, they are granted additional time to complete the task. Initially, the available time is set at three minutes, which, upon failing, increases first to five minutes and ultimately, in the game's final phase, to ten minutes. This system simulates the compensatory educational tool of allotting extra time for a student to complete an exam.

- **Word abbreviation:** After failing the first level, some of the ingredient names, both in the recipe book and the potion labels, are simplified to make them easier for the player to recognize and memorize. An example of simplification can be observed in Figure 7.4, where the term "Testudinidae" is replaced with "Turtle". This tool simulates the practice of employing simple and familiar language both in explaining lessons and in formulating exam questions for dyslexics to facilitate recognition and reduce cognitive load.

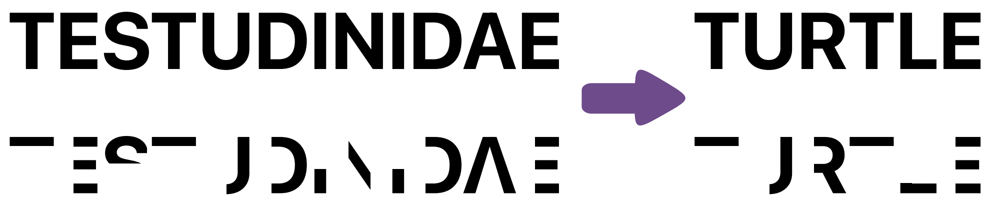


Figure 7.4: **Ingredient simplification through word abbreviation.** The term "TESTUDINIDAE" is replaced by the simpler and more familiar word "TURTLE".

- **Audio guide:** Upon failing the second level, an auditory aid will be unlocked, so that each time the player touches a word in the recipe book or an ingredient, the system will read the word aloud. This way, players will be able to accurately match the recipe with the different jars of required ingredients. This simulates the use of a real-life audio guide to facilitate the comprehension of complex texts for students with dyslexia, leveraging auditory support to enhance textual understanding.

7.3.2 Game Levels

The game comprises four distinct phases. The phase zero, or tutorial phase, serves as an introductory stage, providing users with a concise overview of phonological dyslexia and an opportunity to familiarize themselves with the game controls. Subsequent to this initial phase, the primary game flow begins, where players are tasked with the preparation of the potion. The primary flow is structured into three levels, each corresponding to a distinct phase of the gameplay experience.

In the first level, the primary objective is to immerse the player in the experience of empathizing with a person challenged by dyslexia. With a limited time of 3 minutes, the player will face the challenge of handling lengthy, intricate words written in a font that is difficult to read during the potion-brewing process. Furthermore, to convey a sense of frustration at the end of this phase, the teacher reprimands the player for failing to accomplish what might be perceived as a straightforward task. Moreover, the timer increases feelings of anxiety, causing players to experience this problem as well.

In the second phase, the player is provided with two compensatory tools similar to those that might be provided to a university student with dyslexia when taking an exam. Firstly, an extended time allowance grants the player 5 minutes to craft the potion. Secondly, the simplification of the terms that describe the ingredients facilitates their identification. In the case of failure, the teacher once more reproves the player, aiming to convey the frustration and sense of incomprehension experienced by a dyslexic student despite earnest efforts to complete any task.

In the concluding phase, the player is once again presented with two additional compensatory tools. Firstly, an extended time limit of up to 10 minutes is provided. Secondly, an audio aid feature is introduced, enabling the narration of recipe instructions and ingredient labels upon the player's interaction within the virtual environment. Users can repeat this final phase as many times as needed since, with the use of the compensatory tools provided, they can successfully overcome the experience. There is still negative feedback from the teacher in these cases; however, upon successful completion, they receive positive feedback, highlighting the benefits for individuals with dyslexia stemming from the aids provided during the game.

The depiction of the game's progression throughout the task across the various levels has been presented in Figure 7.5, which is divided into three subfigures: (a) displays a view of the potions laboratory within the virtual environment, highlighting key interaction areas labeled as A (Level start point), B (Potion shelves), C (Pot), and D (Timer); (b) shows the flow diagram guiding the logic progression of the game; and (c) summarizes the three levels and their associated compensatory tools.

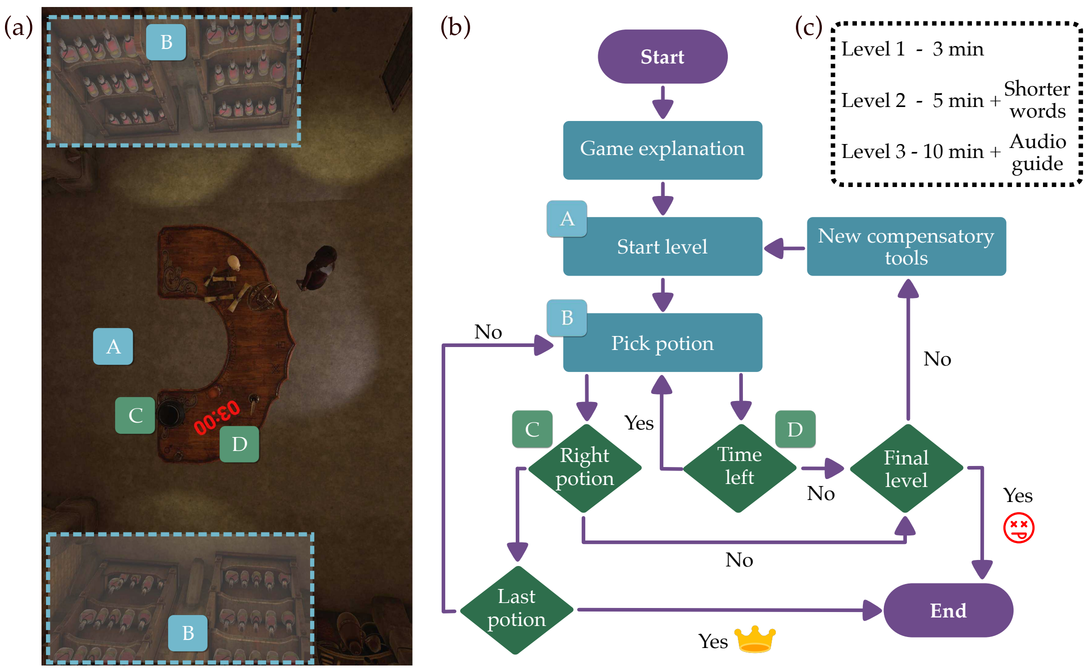


Figure 7.5: **Overview of *The Magic Potion*.** (a) Main scenario of the game. (b) Flow diagram of the game. (c) Compensatory tools included at each level.

A gameplay example and the download links for *The Magic Potion* are available online. The corresponding URLs are listed in the Contributions section at the end of this document.

7.3.3 Difficulty Levels

During the game's development, another scale of difficulty has been considered. Two levels of hardness involve all three previously mentioned levels of the game. At the easiest level, there will be only one container per ingredient, and the ingredient's dose is not considered, since just one container per ingredient must be poured into the pot. This simplifies the task by eliminating the need to consider quantities in the recipe. Conversely, in the hardest mode, there will be multiple labeled flasks per ingredient, increasing the probability of confusion between visually similar words and amplifying the decoding demands, thereby simulating the bigger reading challenges that individuals with dyslexia often face in more challenging scenarios. With the inclusion of these two different difficulty levels, the aim is to enable non-dyslexic individuals to observe how dyslexia impacts the performance of tasks of varying complexities [104].

7.4 Evaluation Methodology

This section describes the methodology used to evaluate the effectiveness of the proposed VR experience, both in terms of its impact on empathy and its usability. It includes details on participants, procedure, measurement instruments, and a preliminary testing of the application prior to the final analysis.

7.4.1 Participants

A total of 101 non-dyslexic people participated in the full VR experience and answered a series of questionnaires. Among the participants, there were mostly students and professors from the universities of Córdoba (Spain) and Tuscia (Italy), as well as relatives of university students with dyslexia. Moreover, individuals completely unrelated to the environment of dyslexic university students were also allowed to participate. These participants tested the game during different sessions held during the second semester of the 2022-2023 academic year. The average duration participants needed to finalize the complete experience was approximately 20 minutes. Complete information collected about participants is shown in Table 7.1.

Table 7.1: **Demographic and experiential profile of the participants.** Summary of the main characteristics of the 101 non-dyslexic participants who completed the experience.

Feature	Subgroup	#	Percentage
Age	< 18	8	7.92
	[18, 30]	71	70.30
	> 30	22	21.78
Gender	Female	57	56.44
	Male	44	43.56
	Other	0	0.00
Participant profile	Dyslexic relative	12	11.88
	University student	47	46.53
	University professor	22	21.78
	Other	10	9.90
Experience with VR applications	None	52	51.49
	Only videos	8	7.92
	Yes, but without headset	3	2.97
	Yes, using a headset	27	26.73
	Very familiar with VR	11	10.89
Experience with empathy applications	None	67	66.33
	Know some empathy application	18	17.82
	Watch some videos	1	0.99
	Try one empathy application	5	4.95
	Try several empathy applications	2	1.98

Given that the study was conducted in a university setting, about 70% of the participants are between the ages of 18 and 30. It is also worth noting that the gender participation was quite balanced, with 43.56% male participation compared to 56.54% female participation. Regarding VR experience, most participants had never tried it before or had only done so in the context of a specific VR experience at a technology event. Finally, the participants' experience with empathy applications was even more limited, with over 65% of them not being familiar with any such application.

7.4.2 Measures

One of the main objectives of this study is to assess the developed VR experience both as a VR application and as a tool for promoting empathy. To achieve this, a concise set of questions was developed to collect the necessary data for evaluating the user experience and the change in empathy towards dyslexic students. To this end, the methodology defined in [109] was adapted to collect a suitable set of questionnaires for evaluating the effectiveness of a VR application. The chosen questionnaires were selected from previous studies in the literature and were specifically prepared and validated to measure the main factors relevant to the VR game: empathy improvement [110], sickness [111], and presence [112].

Regarding the measure of how experience affects user empathy, the Toronto Empathy Questionnaire (TEQ) [110] will be used. The TEQ was preferred over longer instruments such as the Empathy Quotient [113] due to its brevity and its demonstrated reliability and construct validity in prior studies [114, 115], making it more suitable for the experience assessment. However, questions from the original TEQ are formulated to measure empathy without focusing on any specific study group. Therefore, for this work, these questions have been reformulated to target students with dyslexia and make them more suitable for this study. The responses to all the questions are on a 5-point Likert scale, where: Never = 0; Rarely = 1; Sometimes = 2; Often = 3; Always = 4. It should also be noted that questions 2, 4, 7, 10, 11, 12, 14, and 15 are negative, and the order of the given values must be reversed for calculating the questionnaire score. The final TEQ score is calculated by summing individual scores, which range from 0 to 64. The TEQ was administered to the same group of participants before and after the VR experience. The second administration was conducted four months later to evaluate the persistence of any changes in empathy. Additionally, to capture the participants' immediate impressions, qualitative feedback and behavioral observations were also collected directly after the session, as reported in Section 7.6.1.

Another important point is to ensure that the VR experience will not have adverse effects on the participants' health, such as dizziness, nausea, or disorientation. To achieve this, during an initial assessment phase of the application, the participants were subjected to the VRSQ [111] (see Section7.4.3), a questionnaire based on the SSQ designed by Kennedy et al. [116] and adapted for modern VR experiences and tools. This questionnaire simplifies the measurement of sickness in virtual environments into just 9 questions classified into two components: oculomotor and disorientation. All items are measured on a 4-point Likert scale, where: Not at all = 0, Slightly = 1, Moderately = 2, and Very much = 3. The final result of this metric is given by the average of the results obtained for each of the considered components, yielding a final result in the range between 0 and 3.

Additionally, in any virtual environment, it is important to evaluate the level of presence the user feels within that environment. Presence is defined as the experience of being in one place or environment without depending on whether you are physically there or not [117]. To calculate the relative impact of the developed virtual environment, the participants were subjected to the Slater-Usoh-Steed (SUS) questionnaire [112], one of the most accepted tools in the literature for this task. This questionnaire is composed of 6 items. Each question is answered on a 7-point Likert scale, where 7 represents the highest level of presence. The final SUS score is determined by counting the number of questions rated 6 or 7, but the average of all the ratings can also be considered as a measure of the presence.

Finally, additional questions were included to collect sociodemographic information and to better understand the profile of the users. Then, after distributing the questionnaires, each of them and their responses will be individually analyzed to assess the effectiveness of the experience based on the different factors considered. The various measures of factors to be collected by the questions and the main characteristics of the chosen questionnaires are summarized in Table 7.2.

Table 7.2: **Questionnaires used to assess the effectiveness of the VR experience.** Summary of the main measures collected to evaluate *The Magic Potion*, including user characteristics, sickness, presence, and empathy improvement.

Measures	**Definition**	**Adapted from**	**Questionnaire features**
Features of users	Different features of the participants, including: Gender, Age and number of previous VR experiences	–	3 items. Multiple-choice questions
Sickness	Side effects caused by the application that may affect the experience	VR Sickness Questionnaire (VRSQ) [111]	9 items. 4-point Likert scale (from *Not at all* = 0 to *Very much* = 3)
Presence	Comprises assessing the extent to which users perceive themselves to be genuinely immersed within the virtual environment	Slater-Usoh-Steed (SUS) questionnaire [112]	6 items. 7-point Likert scale (from *Not at all* = 1 to *Very much* = 7)
Empathy improvement	Self-reported considered improvement in empathy towards dyslexic students	Toronto Empathy Questionnaire (TEQ) [110]	16 items. 5-point Likert scale (from *Never* = 0 to *Always* = 4)

The evaluation was conducted in two stages. First, a preliminary test with 32 non-dyslexic participants was performed using an early version of the game to assess its usability and detect potential adverse effects, measured via the VRSQ (see Section 7.4.3). Based on the results, the experience was refined and validated for broader use.

In the final study, 101 participants completed the TEQ empathy questionnaire before using the application. After a four-month interval, they played the VR experience and answered the TEQ again to assess long-term changes. Additionally, the SUS and VRSQ were administered immediately after the session, and qualitative feedback was gathered to complement the quantitative results.

7.4.3 Preliminary Testing and Prototype Evaluation

A first version of the game, available only in hard mode and in English, was tested by 32 non-dyslexic participants. The majority were unable to complete the task unassisted, with only 10 managing to finish the entire game. These individuals also reported experiencing frustration due to the inability to read the words correctly, noting that this frustration tended to decrease as compensatory tools were incorporated. Figure 7.6 shows two of the main questions presented to the participants after playing the game, the first referring to the difficulty of performing the proposed task and the second to the growth of their empathy towards people with dyslexia, both on a 5-point Likert scale. From this, it can be concluded that awareness towards phonological dyslexia and towards the importance of support tools increased, thus fulfilling the main objective of the experience. However, due to the absence of rigorous validation of the game's utility and the need to address certain errors identified during this initial phase, a more comprehensive data collection and analysis were required.

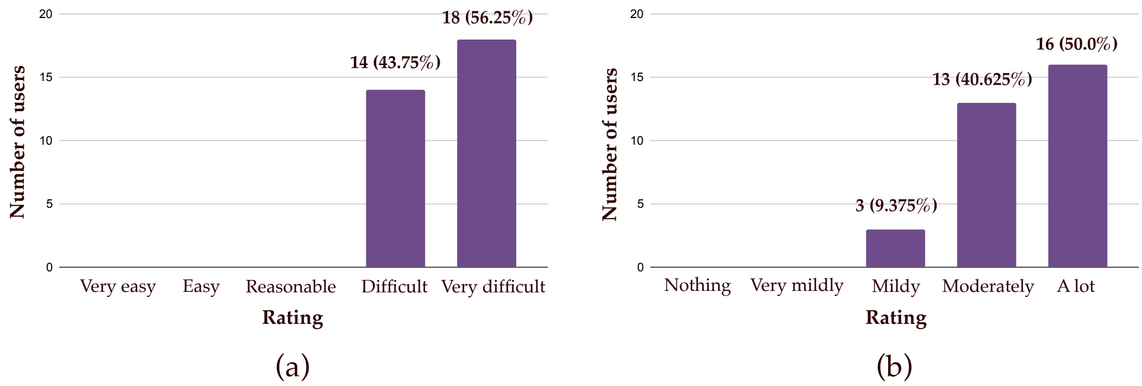


Figure 7.6: **Perceived task difficulty and empathy growth in the first prototype of *The Magic Potion*.** Responses of the 32 non-dyslexic participants who tested the initial hard-mode English version of the game.

In addition, this preliminary study was used to assess the feasibility of the application's use with regard to potential symptoms that exposure to a virtual environment might produce during the experience. For this purpose, the participants were subjected to the VRSQ. The results showed an average score of 0.24 for the oculomotor component and 0.41 for disorientation (on a scale from 0 to 3), which is sufficiently low to ensure the viability of using the application to foster empathy without being adversely affected by other side effects typical of VR.

7.5 Quantitative Results

This section describes the quantitative evaluation of *The Magic Potion* using the questionnaires introduced in the previous section to assess key aspects addressed by the game, such as improvements in empathy and sense of presence. The results are then analyzed and discussed to evaluate the effectiveness of the experience.

7.5.1 Measuring presence

To assess the relative impact of the developed virtual environment, participants completed the SUS questionnaire [112]. After participating in the experience, the participants were asked to answer its six questions, each rated on a 7-point Likert scale. The obtained results align with those reported in previous studies using the SUS questionnaire. For instance, [112] and [18] reported mean SUS scores of 3.8 and 4.4, respectively, in other VR simulations. In our study, participants scored a mean of 3.65 ± 0.95, and an interquartile range (IQR) of [2.96–4.42] (compared to [3.8–5.5] in [18], where the sense of presence and realism played a more central role). Additionally, the average number of responses rated 6 or 7 on the scale (SUS Count) was 1.25 ± 0.91, which is comparable to the 1.0 ± 1.7 reported for virtual training in [112]. These slightly lower scores are expected, as the environment was intentionally designed to prioritize usability and comfort over photorealism, ensuring participants could carry out the task effectively while remaining engaged and immersed.

7.5.2 Empathy Improvement

Since the objective is to calculate the empathy enhancement with the use of the proposed VR serious game, the TEQ was first performed globally on 112 non-dyslexic university students and professors who had not experienced the developed VR serious game. From them, an average TEQ score of 39.45 was obtained. Four months later, TEQ was also administered to the 101 users who actually participated in the serious game. From them, the average TEQ score obtained was 58.77. Figure 7.7 shows a boxplot comparing TEQ scores before and after the game. Before the experience, scores show a wider spread, with a substantial number of participants showing low empathy levels. However, after participating in the game, the distribution becomes narrower and shifts upward, with most scores concentrated near the upper side of the scale. This indicates that after participating in the VR experience, a more homogeneous and higher empathetic response among participants was obtained.

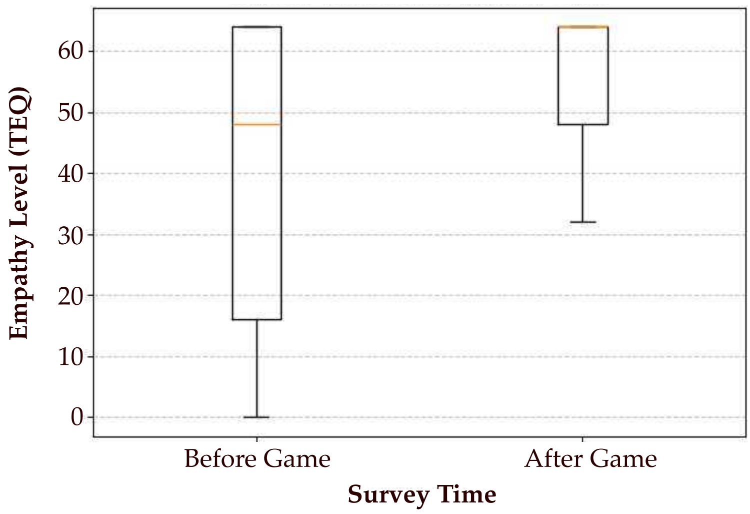


Figure 7.7: **Change in empathy levels before and after the VR experience.** Boxplot of TEQ scores measured in two groups: people before experiencing the VR game (Before Game), and four months after completing the experience (After Game).

The score obtained for people who had not participated in the experience is a little lower than that normally obtained in other empathy studies, suggesting limited baseline awareness regarding students with dyslexia.

Although there are no established benchmarks specifically for empathy toward individuals with dyslexia, several general empathy studies using the TEQ in adult populations can be useful as reference values. In previous works using the TEQ, average scores above 45 are generally considered indicative of good empathy levels in adult populations. For example, [118] reported a mean TEQ score of 46.84 evaluating 347 medical students; [119] obtained an average score of 42.31 for 941 Saudi people, also medical students; and [120] found an average of 38.37 assessing the empathy of 698 Turkish university students. Compared to this literature, the baseline score in our study (39.45) reflects lower-than-average empathy towards dyslexics, while the post-experience score (58.77) clearly exceeds the expected threshold.

Finally, it can be determined that the increase in empathy in terms of the TEQ is 19.32 points, representing approximately a 20% increase compared to the empathy calculated for these people in the university community before experiencing “The Magic Potion” four months earlier. A Wilcoxon signed-rank test was conducted to assess whether the observed increase in TEQ scores was statistically significant. The results confirmed a significant difference between pre- and post-experience TEQ scores ($W = 32.0$, $p < 0.001$), supporting the effectiveness of the VR experience in enhancing empathy.

7.6 Qualitative Results

Once a quantitative analysis based on different metrics and questionnaires from the literature has been performed, it is also important to consider other aspects and observations that cannot be measured in this way. For this purpose, in this section, the opinions given by the participants after completing the experience of *The Magic Potion* are analyzed, as well as the most common behaviors identified by external observers. Additionally, the game is compared with other applications designed to support students with dyslexia, highlighting the innovations it offers. Similarly, during the comparison, the main limitations found in this type of VR tool, and more specifically in *The Magic Potion*, are also indicated.

7.6.1 Participants' Feedback and Common Behaviors

Participants provided qualitative feedback and exhibited common behavioral patterns throughout the experience. The most interesting and recurring observations included:

- **Difficulty in adapting to the game's movement and controls:** This was particularly indicated by some users who did not progress beyond the first level because they were unable to adapt to the mobility within the virtual environment. In contrast, those who completed the game praised the utility of the various locomotion systems implemented.
- **Issues using the audio guide:** Several users reported being unable to properly activate the audio guide function during the third phase (touching the name of the ingredients is the way to do it). These users were typically the same individuals who experienced difficulties in adapting to movement within the virtual environment, likely due to their lack of familiarity with such systems. However, overall, the audio guide was deemed the most useful tool for completing the task.
- **Discomfort feeling during the experience:** Three-quarters of the participants reported feelings of fear, loneliness, dejection, and helplessness due to the features of the challenge and the environment. The teacher's reprimands, as well as Sam's deteriorating condition, also created feelings of frustration and powerlessness for such users. This effectively fulfilled the intended role of these NPCs within the game.
- **Significant challenge for the players:** Players emphasized the considerable difficulty of the challenge, especially during the first two levels of the game before obtaining the audio guide. In this way, it is demonstrated that the game achieves its objective of illustrating the necessity of compensatory tools for individuals with dyslexia.
- **Increase in awareness towards phonological dyslexia:** The majority of participants affirmed that they had never imagined that reading difficulties could have such an impact on a simple task, indicating an increase in empathy towards individuals with dyslexia.
- **Shift in perspective regarding compensatory tools:** A minority of users thought before playing the game that giving compensatory tools was unfair with respect to their non-dyslexic classmates. However, after completing the experience, all of them indicated a better understanding of the importance of these tools in facilitating the educational journey of individuals with dyslexia, thereby fulfilling the objectives of this work.

Concerning common behaviors, the following ones have been deemed noteworthy:

- The majority of users adhered to the implicit game sequence, initiating the timer before starting the task. However, a small number of them, specifically 12 over 101, took advantage of available information before starting the first level. They searched for some of the necessary ingredients and arranged them on the table before activating the timer, a strategy aimed at saving time for task completion.
- Due to the human need to avoid obstacles and disadvantageous situations, a significant portion of the users requested the possibility to switch the text to the "normal" alphabet after five minutes of the experience, but upon being informed that it was not possible, they attempted to continue with the challenge.
- The hard game mode was attempted and successfully completed in the third stage by only 10 of the users who reached this stage in the easy mode, granting them a ten-minute break. The rest of the users declined the proposal due to fatigue and the difficulty they had encountered, even with the easy mode.

Much of the information gathered about these opinions and behaviors aligns with the anticipated outcomes of the experience design. This includes the sentiment of frustration, leading some participants to disengage, and the increase in empathy towards individuals with phonological dyslexia. Additionally, encountered issues, such as the difficulty of adapting to the controls and movement within the game, will be considered for resolution in future experiences.

7.6.2 Overview of Existing Dyslexia Applications

To provide context and illustrate the positioning of our work, a comparative review of existing applications focused on dyslexia has been conducted. The applications for comparison are: *The Magic Potion*, *The Virtual Campus* (see Chapter 6), *Out of the Box* [24], *Dytective* [55], *Cosmic Sounds* [57], and *FORDYS-VAR* [121]. Comparison is summarized in Table 7.3, and has been conducted on the basis of the following elements:

- **Reinforce reading (Reading):** The application provides a form of reinforcement to enhance reading for users with dyslexia.
- **Dyslexia detection (Detection):** The application aims to predict if the user has any type and degree of dyslexia.
- **Mobile:** Indicates whether the application can be used on mobile devices or requires any special device.
- **Kids:** The application is intended for children under 16 years old. Meta Quest 2 devices are not recommended for children under 13 years old. Therefore, if they wish to try applications deployed on these devices, they should do so under adult supervision.
- **Adults:** The application is intended for an adult audience.
- **Dizziness:** The application may cause dizziness in sensitive users.
- **Empathy**: The application aims to increase awareness and empathy towards individuals with dyslexia.

This comparison clearly indicates that, although all reviewed applications are designed as support tools for individuals with dyslexia, they pursue very different objectives. Most of them focus on enhancing reading skills in school-aged children, whereas only *Out of the Box*

Table 7.3: **Qualitative comparison of dyslexia-focused applications.** Overview of key characteristics of several representative tools designed to support individuals with dyslexia.

Application	Reading	Detection	Mobile	Kids	Adults	Dizziness	Empathy
The Magic Potion	–	–	–	✓	✓	✓	✓
The Virtual Campus	–	–	–	✓	✓	✓	✓
Out of the Box	–	✓	✓	✓	✓	✓	–
Dytective	✓	✓	✓	✓	–	–	–
Cosmic Sounds	✓	–	✓	✓	–	–	–
FordynVAR	✓	–	–	✓	–	✓	–

and our proposal are intended for adult users. In contrast to training tools, our application, *The Magic Potion* (and also *The Virtual Campus*), addresses dyslexia from a different perspective: by promoting empathy among individuals in the educational environment, particularly in university and higher education settings. This underexplored focus highlights the originality and relevance of the presented approach, offering a complementary and awareness-raising tool rather than a direct intervention.

7.7 Discussion and Limitations

The results obtained through the TEQ demonstrate a significant increase in empathy levels following the VR experience *The Magic Potion*. Participants showed an average gain of 19.32 points (approximately a 20% increase), confirming a consistent trend across users. This indicates that VR activity can effectively foster greater empathetic understanding toward individuals with dyslexia. Qualitative feedback collected after the sessions supports these quantitative findings. Many participants reported increased awareness of the frustration and confusion dyslexic individuals may experience in academic contexts. The emotional impact of the experience was frequently highlighted, with several users suggesting the usefulness of such tools in teacher training programs or inclusion workshops.

On the other hand, in the broader landscape of applications related to dyslexia, most applications focus on skill development or diagnostic support for children. Very few target adult users or seek to influence their perceptions of dyslexia. In contrast, "The Magic Potion" contributes a novel approach; instead of aiming to improve reading abilities, it aims to promote empathy towards dyslexics within the university context. This distinction positions our application as an awareness-oriented tool, adding relevance to current efforts in inclusive education.

However, several limitations must be considered. From a technological point of view, the use of VR comes with accessibility challenges. Devices like the Meta Quest 2 & 3, while offering the level of realism needed for this type of immersive simulation, are not as widely available or affordable as mobile or web-based alternatives. Moreover, some users, particularly older individuals or those unfamiliar with video games, may experience discomfort or dizziness [122].

In addition to these general barriers associated with VR, other specific limitations of our deployment were observed. One of the main issues was the time required to complete the full experience, which lasted approximately twenty minutes. This made it difficult for many participants to try the experience during short sessions, and some chose to leave due to time constraints. Another constraint was related to physical space. Users enjoyed the experience more in wide, open areas, especially those unfamiliar with movement via controllers. Since Meta Quest 2 & 3 headsets require indoor usage conditions for optimal performance and maintenance [22], securing large indoor spaces for extended sessions posed logistical challenges.

7.8 Conclusion

The work presented in this chapter shows that it is possible to model core aspects of phonological dyslexia within an immersive VR experience and to use this model as a vehicle for promoting empathy in higher education contexts. While the previous chapter introduced *The Virtual Campus* as a broad simulation of everyday barriers related to navigation, reading and perceived lack of support, *The Magic Potion* narrows the focus to the phonological dimension of dyslexia.

The collected results from more than 100 people support the effectiveness of this design. Quantitatively, participants reported a substantial and statistically significant increase in empathy scores after engaging with the experience, while presence remained within acceptable ranges and sickness scores were low enough to guarantee safe use. Qualitatively, participants described feelings of frustration, helplessness and anxiety when facing the reading challenge, as well as an increased appreciation of the role of compensatory tools and a shift in their attitudes toward their fairness. These convergent findings indicate that the combination of carefully designed game mechanics can foster a more nuanced understanding of phonological difficulties among non-dyslexic users.

In summary, this chapter reinforces the potential of VR as a complementary tool for promoting empathy toward students with dyslexia. Rather than replacing direct language-based interventions or structural support measures, VR experiences such as *The Virtual Campus* and *The Magic Potion* provide a first-person, embodied perspective that is difficult to achieve through traditional awareness activities. By allowing teachers, peers, and relatives to "be in the shoes" of situations that approximate the cognitive and emotional load associated with dyslexia, these applications can help reduce stigma, raise awareness about the relevance of support methodologies, and promote more inclusive practices in university settings.

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Part IV

Conclusions

This part presents the discussion, final conclusions, and future directions of the thesis.

Chapter 8

Discussion

In this chapter, the main contributions of the thesis are summarized, examining them from a broader perspective and considering their most relevant implications. Rather than revisiting the results in detail, the discussion focuses on what these findings reveal about the challenges and opportunities involved in supporting university students with dyslexia through AI and VR. By analyzing both strengths and limitations and exploring the synergies between the AI- and VR-based approaches developed during this research, this chapter provides an overview of the role these technologies can play in fostering more inclusive higher-education environments for dyslexics.

8.1 Personalized Recommendation of Support Methodologies for Dyslexic Students

The development of the recommendation models presented in this thesis builds on work that precedes the doctoral project, specifically the study introduced in [24] as part of the author's master's thesis. That contribution established the basis for modeling how dyslexic students evaluate support tools and learning strategies, and it provided the first evidence that these methodological preferences follow stable, learnable patterns that could be useful for making customized recommendations to different students. During the PhD, this research line has been substantially extended by completing this preliminary work to incorporate it in the BESPECIAL platform [9], where it served as a first step toward creating intelligent systems capable of guiding students with SLDs.

Within this broader context, the two recommendation models developed in the thesis approach the problem from complementary perspectives. The first, presented in Chapter 4, focuses on predicting the usefulness of each tool and strategy based solely on students' historical ratings. The resulting models achieve high CCRs, above 0.90 for most tools and exceeding 0.97 for many strategies, demonstrating that students' evaluations of support methodologies follow predictable patterns even without considering detailed difficulty profiles.

The second recommendation model, presented in Chapter 5, shifts the focus from predicting useful methodologies based on the specific user dyslexia-related problems to direct personalized recommendations based on the ratings given by other students' profiles. The CF system exploits similarities in students' rating behavior, enabling it to estimate which methodologies a user is likely to find helpful even when they have never rated them. In this context, three classical variants of cF were explored. The user-based approach identifies students with similar rating patterns and recommends the tools and strategies that these peers found useful. The item-based approach, in contrast, focuses on identifying relationships between the methodologies themselves, recommending those that tend to be rated similarly across the population. Finally, the hybrid model combines both perspectives, weighting the predictions from user-based and item-based components to capture complementary sources of information. This combined strategy proved particularly effective for the dataset used in this thesis. Finally, the hybrid system configuration proved to be the most effective. Specifically, the model using Pearson correlation with three neighbors and a weight parameter $\alpha = 1/4$ achieved the lowest mean absolute error of 0.8093. These values ensure that the recommended items fall within ranges that preserve their practical meaning.

The main outcome of this effort is the empirical confirmation that the use of support methodologies has a significant, quantifiable influence on the academic performance of dyslexic university students. The real-world experiment conducted with 50 participants demonstrates the educational impact of effectively selecting such methodologies. Dyslexic students who followed personalized recommendations improved their performance by more than one point compared to those who received random suggestions, ultimately achieving results comparable to their non-dyslexic peers. This finding underscores that personalization is not merely beneficial but essential for fostering inclusion in higher education.

In addition, the thesis also explored the feasibility of building a content-based recommendation system. However, the experiments revealed that this approach is not feasible with the current dataset. Since the questionnaire collected ratings but did not provide or require students any descriptive information about the content of each tool or strategy, neither the students nor the system had access to the semantic characteristics required to model item similarity. Without such metadata, the content-based approach produces unstable and unreliable recommendations. This limitation highlights the importance of collecting detailed item descriptors in future data campaigns, especially when the goal is to compare collaborative and content-based approaches on equal terms.

8.2 Virtual Reality Applications

The VR contributions of this thesis add a distinct yet equally significant dimension to the goal of supporting university students with dyslexia. While the AI recommendation models previously described focus on identifying which support methodologies are most effective for each student, the VR experiences developed in Chapters 6 and 7 address a different aspect of inclusion: the need to foster awareness, empathy, and understanding among peers, educators, and the wider academic community. Dyslexia is not only an academic difficulty; it is accompanied by emotional, social, and perceptual challenges that often remain invisible to non-dyslexic individuals. The two VR applications developed in this thesis address this gap by enabling users to experience firsthand the barriers that dyslexic students face in their daily lives.

First, *The Virtual Campus* experience demonstrates how immersive environments can be used to replicate real-world academic obstacles in a controlled and pedagogically meaningful way. Its design simulates reading difficulties, disorientation, misleading guidance, and the absence of peer support, mirroring the cognitive and emotional load experienced by dyslexic students in everyday university settings. The evaluation results confirm the tool's capacity to raise awareness, with over 90% of participants evaluating the experience as "very useful" or "extremely useful' in understanding dyslexia-related barriers, and qualitative feedback highlighted increased recognition of how some barriers that could seem to have no importance can hinder a lot the daily life of dyslexic students. Importantly, this work fills a notable gap in the literature, as VR empathy applications for dyslexia, particularly in higher education and empathy contexts, remain almost unexplored.

The second VR experience, *The Magic Potion*, builds upon this foundation by shifting the focus from general academic barriers to a more specific manifestation of dyslexia: the challenges associated with phonological processing. By immersing the user in a fantasy world, the experience consists of performing a very simple task but introducing reading difficulties through Britton's font, time pressure, confusion, and disapproval. However, in the meantime, if the participant fails the task, the experience provides them with different progressive compensatory tools to make the task easier. In this way, the participant can understand the importance of these kinds of tools for dyslexic students. The results obtained with over 100 participants provide strong evidence of the tool's effectiveness. The TEQ empathy score increased by an average of 19.32 points (approximately 20%). This improvement was measured via a post-experience TEQ that was administered four months after the initial baseline measurement, indicating that the empathy gains were sustained over time. Additionally, the SUS and VRSQ results further demonstrate that the experience provided acceptable levels of presence and comfort, supporting the feasibility of using VR for prolonged educational interventions.

Taken together, these two experiences show that VR is a powerful way for addressing the lack of empathy that is often seen towards dyslexic students, especially in a university setting. Another important point to consider is that both applications demonstrate that simulating cognitive barriers requires careful balancing. The environment must be challenging enough to evoke emotional and cognitive responses, while remaining accessible and not overwhelming for users unfamiliar with VR. Feedback from both studies highlighted issues related to locomotion and interaction with the virtual environment, which informed refinements in design and highlighted the importance of usability when simulating cognitive impairments. Moreover, the need for Meta Quest headsets introduces accessibility constraints that must be considered for future large-scale deployment.

8.3 Approaching AI and VR

The AI and VR components of this thesis were developed to address different, yet deeply interconnected, facets of supporting university students with dyslexia. On the one hand, the AI models provide mechanisms for identifying which study tools and learning strategies are most beneficial for each student, thereby enabling personalized academic support at scale. On the other hand, VR applications focus on the experiential, affective, and social dimensions of dyslexia by allowing non-dyslexic users to experience the challenges faced by dyslexic students and to understand the importance of support methodologies. Although these threads were explored in separate chapters and periods of the PhD, their combined value is greater than only the sum of their parts.

From a conceptual perspective, AI and VR address two complementary questions within inclusive higher education. AI responds to the question *"What does this specific student need in order to learn effectively?"*, offering evidence-based recommendations tailored to individual profiles. On the other hand, VR responds to the question *"Why does this support matter, and how does dyslexia affect real academic experiences?"*, enabling peers and educators to understand and appreciate the barriers that require such support. The integration of these two approaches, therefore, provides not only personalized assistance for dyslexic students but also the institutional and social awareness required for this assistance to be accepted and understood.

In practical terms, the technologies developed during this thesis naturally converge within the broader VRAIlexia project and BESPECIAL platform [9]. A unified pipeline becomes possible, beginning with students first completing questionnaires that capture their methodological preferences, which AI models then process to generate personalized recommendations. These recommendations can be further contextualized through VR experiences, which help non-dyslexic students, educators, and university staff recognize the importance of the suggested methodologies. Conversely, VR itself can serve as an additional source of behavioral data, offering richer, ecologically valid signals that complement traditional questionnaire-based inputs. For example, the information collected via the psychometric tests using the VR experience Out of the Box [24].

An example that illustrates this synergy is the work described in [123], in which the author also collaborated as part of his PhD period. In that study, VR behavioral data extracted from the Out of the Box application were used to predict the presence or absence of dyslexia in Italian and Spanish university students, achieving classification accuracies of 87.5% for Italian participants, 66.6% for Spanish participants, and 75.0% for the mixed dataset. These results show how VR interactions can capture behavioral signatures measured by face-to-face psychometric tests related to reading speed and comprehension, and self-esteem processing. This complementary work demonstrates the feasibility of combining immersive VR environments with supervised ML models to explore diagnostic or pre-screening applications, thus reinforcing the idea that VR can generate novel and highly informative data streams that enrich AI-driven educational support.

Overall, the contributions of AI and VR within this thesis advance the state of the art in two ways. First, they introduce novel and validated VR tools specifically designed to raise awareness and empathy for dyslexia in higher education, a topic that has received very limited attention. Second, they demonstrate that VR can meaningfully complement AI-based personalized support, addressing the social and emotional aspects of inclusion that data-driven methods cannot directly capture. By providing users with first-hand experiences of dyslexia-related challenges, the developed tools contribute to a more global understanding of inclusion, supporting not only dyslexic students directly but also the teachers and peers who interact with them in their academic environments.

8.4 Limitations of the Proposed Approaches

Although the results obtained throughout this thesis demonstrate the potential of AI and VR to support university students with dyslexia, some limitations must be acknowledged when interpreting these findings.

A first limitation concerns the nature of the dataset used for the AI models. The questionnaire was designed to capture students' perceived usefulness of tools and strategies, yet it did not include detailed semantic descriptions of the support items themselves. This omission directly limited the development of content-based recommendation approaches, as the system lacked the descriptive features needed to measure item similarity. Additionally, the population is also geographically and institutionally constrained, raising concerns about representativeness and the degree to which the findings can be generalized to students from other academic contexts or cultural backgrounds.

Regarding the real-world validation study conducted for the CF system, although the observed improvement in academic performance among dyslexic students who received personalized recommendations is encouraging, the sample size remained modest, and the evaluation was limited to a single academic context and short-term outcomes. The study did not examine long-term adoption of the recommended methodologies, nor did it explore whether the recommendations remain effective across different courses, disciplines, or types of academic activities.

On the VR side, limitations are likewise present. Both the *Virtual Campus* and *The Magic Potion* experiences require access to standalone VR headsets, which may pose logistical challenges for large-scale deployment in universities. The simulations also involve design choices that intentionally introduce cognitive difficulty, yet these choices must be carefully calibrated to avoid excessive frustration or sickness. Although the VRSQ results indicated acceptable comfort, some participants reported discomfort related to locomotion mechanics, reading difficulty, or time pressure. These reactions highlight the difficulty of authentically simulating dyslexia without compromising the user experience. In addition, the empathy gains measured via the TEQ were assessed four months after the initial baseline, but the durability of these effects beyond this time frame remains unknown.

A further limitation concerns the integration of AI and VR within the broader VRAIlexia project's vision. While this thesis demonstrates conceptual and practical synergies between both technologies, their combination has not yet been fully implemented in an operational platform. VR data were not used to refine AI recommendations in this thesis, and AI-generated suggestions were not embedded into VR experiences to provide personalized or adaptive scenarios. Such integration requires not only technical development but also ethical considerations related to data privacy, informed consent, and the management of sensitive behavioral information gathered in the VR environments.

Taken together, these limitations do not undermine the thesis's contributions, but they highlight areas where future research is needed. Addressing these challenges by expanding datasets, refining VR designs, integrating AI and VR more deeply, and validating systems across broader, more diverse populations will be essential to translating these technologies into sustainable, widely applicable tools for inclusive higher education.

Chapter 9

Conclusions and Future Work

This chapter summarizes the main findings of the thesis, outlines future lines of research and highlights both the formal contributions of the thesis and additional achievements developed in parallel to its core objectives. The work presented here demonstrates the potential of combining AI and VR to support dyslexic students in higher education.

9.1 Conclusions

The contributions presented in this PhD have successfully achieved their primary objectives, advancing the state of the art in the use of AI and VR to support university students with dyslexia. Through empirical studies, innovative methodological developments, and the integration of different AI and VR-based approaches, this work has addressed key academic and psychosocial challenges faced by dyslexic students and proposed effective, scalable solutions. Below, we summarize the main achievements of this research:

- **Analyze the difficulties experienced by dyslexic students.** Achieved through the study of survey and questionnaire data, revealing meaningful patterns in students' difficulties, study habits, and methodological preferences.
- **Design and train machine learning models to predict suitable compensatory tools and strategies.** Accomplished by developing multiple classical machine learning models with high predictive accuracy, demonstrating that students' preferences can be reliably estimated.
- **Develop a recommendation system for personalized delivery of support methodologies.** Completed through a hybrid collaborative filtering system with strong performance, experimentally validated in a real educational setting where dyslexic students significantly improved their academic performance.
- **Create immersive VR environments for psychometric assessment.** Completed through the integration of Silent Reading and self-esteem tests in VR, enabling autonomous data collection and yielding high-quality behavioral metrics.
- **Develop VR experiences to simulate dyslexic challenges and foster empathy.** Achieved with the design of the *Virtual Campus* and *The Magic Potion*, both validated with different participants and shown to significantly improve awareness and empathy.
- **Evaluate usability and impact of VR applications in higher education.** Achieved by designing an evaluation methodology grounded in the literature on inclusive and empathy-oriented VR systems, and applying it through SUS and VRSQ usability analyses together with TEQ-based empathy assessments, which demonstrated high usability and emotional impact.

9.2 Future Work

Several avenues for future research emerge naturally from the limitations discussed in Chapter 8, as well as from opportunities revealed during the development of the thesis:

- **Expand datasets and integrate richer item descriptors.** Future development design of RS will benefit from collecting semantic descriptions of tools and strategies, enabling the possibility of constructing content-based models.
- **Deeper integration between AI and VR.** VR environments could produce behavioral indicators to refine AI models, while AI could adaptively adjust difficulty and provide personalized guidance directly within VR tasks.
- **New VR experience on types of dyslexia.** A promising line of work is the development of a VR serious game that illustrates the differences between surface, deep, and mixed dyslexia. Such an experience could help teachers, families, and even students understand the linguistic and cognitive distinctions across dyslexia subtypes.
- **Incorporation of physiological sensors.** In addition, we are studying the possibility of including new types of sensors, such as heart-rate monitors, to enrich the amount of information obtained during virtual reality experiences and enable more comprehensive behavioral and emotional analysis.

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Contributions

These pages summarize the scientific contributions achieved during the PhD period. It includes both outputs directly derived from the core line of the thesis, supporting dyslexic students in higher education through Artificial Intelligence and Virtual Reality, and additional contributions stemming from parallel research collaborations. For clarity, the main scientific and technical advances in the thesis research line are first synthesized, and then the resulting publications and software created are enumerated.

Summary of Scientific Contributions

The work conducted in this thesis can be broadly grouped into two complementary domains: AI for Personalized Support and VR for Assessment and Empathy. The main contributions in each domain are summarized below.

- **AI for Personalized Support:**
  - ◇ Collection and analysis of data on dyslexic students' difficulties and study strategies through surveys, questionnaires, and psychometric assessments [24, 123].
  - ◇ Optimization of machine learning models for predicting the most suitable compensatory tools and strategies for individual students based on their difficulties [24].
  - ◇ Implementation of a RS capable of delivering personalized study aids based on different dyslexic students' profiles [90].
- **VR for Assessment and Empathy:**
  - ◇ Design and implementation of immersive VR environments for psychometric assessment, enabling autonomous data collection and enhanced user engagement [24].
  - ◇ Development and evaluation of VR serious games that replicate the challenges faced by dyslexic students in university settings, with a specific focus on usability, educational impact, and the capacity to foster empathy among peers, teachers, and families [124, 125].
  - ◇ Integration of VR-based tasks with AI methods to explore the potential of cross-linguistic, VR-driven screening approaches for dyslexia [123].

Together, these contributions define the methodological and technological foundation of the thesis and are distributed across the different chapters of this document.

Thesis Contributions

The core research developed in this thesis has produced several scientific publications directly linked to its main objectives and methodological developments. These works constitute the primary outputs associated with the thesis and reflect its progression across the AI and VR domains. In total, they comprise four journal articles, one indexed conference paper, and two publicly released VR applications.

Journal Publications

Authors: Morciano, Gianluca and Alcalde-Llergo, José M. and Zingoni, Andrea and Yeguas-Bolívar, Enrique J. and Tanborri, Juri, and Calabrò, Giussepe.
Title: Use of recommendation models to provide support to dyslexic students.
Journal: Expert Systems with Applications
Year: 2024
Volume: 249
DOI: 110.1016/j.eswa.2024.123738

Authors: Alcalde-Llergo, José M.; Aparicio-Martínez, Pilar; Zingoni, Andrea; Pinzi, Sara; and Yeguas-Bolívar, Enrique
Contribution: Fostering Inclusion: A Virtual Reality Experience to Raise Awareness of Dyslexia-Related Barriers in University Settings
Journal: Electronics
Year: 2025
Volume: 14
DOI: 10.3390/electronics14050829

Authors: Alcalde-Llergo, José M.; Zingoni, Andrea; Aparicio-Martínez, Pilar; Pinzi, Sara; and Yeguas-Bolívar, Enrique
Contribution: Design and Evaluation of a Serious Game in Virtual Reality to Increase Empathy Towards Students with Phonological Dyslexia
Journal: Multimedia Systems
Year: 2025
Volume: 31
DOI: 10.1007/s00530-025-01953-9

Authors: Materazzini, Michele; Morciano, Gianluca; Alcalde-Llergo, José M.; Yeguas-Bolívar, Enrique; Zingoni, Andrea; Calabrò, Giussepe; and Taborri, Juri
Contribution: Combine Virtual Reality and Machine-Learning to Identify the Presence of Dyslexia: A Cross-Linguistic Approach
Journal: Information
Year: 2025
Volume: 16
DOI: 10.3390/info16090719

Indexed Conferences

Authors: Alcalde-Llergo, José M.; Yeguas-Bolívar, Enrique; Aparicio-Martínez, Pilar; Zingoni, Andrea; Taborri, Juri; and Pinzi, Sara
Contribution: A VR Serious Game to Increase Empathy towards Students with Phonological Dyslexia.
Proceedings: 2023 IEEE International Conference on Metrology for Extended Reality
Year: 2023
DOI: 10.1109/MetroXRAINE58569.2023.10405809

VR Applications

Contribution: In the Shoes of Dyslexic Students: The Virtual Campus
Download link: `https://sidequestvr.com/app/37775`
Gameplay: `https://www.youtube.com/watch?v=j0hBD1j5bgc`
Number of downloads: 165

Contribution: In the Shoes of Dyslexic Students: The Magic Potion
Download link: `https://sidequestvr.com/app/37611`
Gameplay: `https://www.youtube.com/watch?v=02QqEEKxmC8`
Number of downloads: 296

Contribution: In the Shoes of Dyslexic Students: Explode the Bomb
Download link: `https://sidequestvr.com/app/37705`
Gameplay: `https://www.youtube.com/watch?v=lbsJhtA9TKI&t`
Number of downloads: 286

Note: The number of downloads was last updated on November 18, 2025.

Contributions Not Directly Related to the Thesis

During the PhD period, the author has also contributed to several research projects beyond the central line of this thesis. These collaborations have resulted in additional scientific publications that form part of the scholarly output generated during the PhD. In total, they comprise two journal articles, five indexed conference papers, and two book chapters.

Journal Publications

Authors: Alcalde-Llergo, José M.; Ruiz-Mezcua, Aurora; Ávila-Ramírez, Rocío; Zingoni, Andrea; Taborri, Juri; Yeguas-Bolívar, Enrique
Contribution: Automatic Identification and Description of Jewelry Through Computer Vision and Neural Networks for Translators and Interpreters
Journal: Applied Sciences
Year: 2025
Volume: 15
DOI: 10.3390/app15105538

Authors: Alcalde-Llergo, José M.; Fernández, Mariana Buenestado-Fernández; George-Reyes, Carlos E.; Zingoni, Andrea; Yeguas-Bolívar, Enrique
Contribution: Leveraging Machine Learning Techniques to Investigate Media and Information Literacy Competence in Tackling Disinformation
Journal: Information
Year: 2025
Volume: 16
DOI: 10.3390/info16110929

Indexed Conferences

Authors: Alcalde-Llergo, José M.; Yeguas-Bolívar, E.; Zingoni, Andrea; and Fuerte-Jurado, Alejandro
Contribution: Jewelry Recognition via Encoder-Decoder Models
Journal/Conference: 2023 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE)
Year: 2023
Location: Milano, Italy
Pages: 116–121
DOI: 10.1109/MetroXRAINE58569.2023.10405609

Authors: Zingoni, Andrea; Alcalde-Llergo, José M.; Morciano, Gianluca; Melloni, Daniele; Yeguas-Bolívar, Enrique; Fantasia, Nicola; and Sperandio, Matteo
Contribution: Real-time Detection of Criminal Actions in Everyday Life from Camera-Equipped Streetlamps
Journal/Conference: 2024 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE)
Year: 2024
DOI: 10.1109/MetroXRAINE62247.2024.10795879

Authors: Ruko, Sediola; Alcalde-Llergo, José M.; Yeguas-Bolívar, Enrique; and Zingoni, Andrea
Contribution: Enhancing Tourist Experience via Automatic Personalized Route Suggestions
Journal/Conference: 2024 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE)
Year: 2024
DOI: 10.1109/MetroXRAINE62247.2024.10796573

Authors: García-Ruíz, Pablo; Alcalde-Llergo, José M.; Zingoni, Andrea; Aparicio-Martínez, Pilar; and Yeguas-Bolívar, Enrique
Contribution: A Vision-Based Fiducial Object Input Device for Intuitive Interaction
Journal/Conference: Extended Reality (XR Salento 2025), Lecture Notes in Computer Science
Year: 2025
DOI: 10.1007/978-3-031-97763-3_22

Authors: Zingoni, Andrea; Alcalde-Llergo, José M.; Melloni, Daniele; Nervini, Ricardo; Fantasia, Nicola; Sperandio, Matteo; and Yeguas-Bolívar, Enrique
Contribution: The Viterbo2025-1.0 Dataset for Training and Testing AI Algorithms for Criminal Actions Detection and Recognition
Journal/Conference: 2025 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE)
Year: 2025
Status: Proceedings pending

Book Chapters

Authors: Alcalde-Llergo, José M.; and Yeguas-Bolívar, Enrique
Chapter Title: Dynamic route generation for people with disabilities in the city of Córdoba based on Artificial Intelligence
Book Title: Improving Urban Accessibility for Inclusive Cities
Publisher: FrancoAngeli Series
Publication Place: Italy
Year: 2024
Pages: 10
ISBN: 9788835169192

Authors: Alcalde-Llergo, José M. and Aparicio-Martínez, Pilar.
Chapter Title: Inteligencia Artificial, Salud y Género.
Book Title: Desafíos de la Inteligencia Artificial: ¿Una herramienta al servicio de la igualdad?
Publisher: Tirant lo Blanch
Publication Place: España
Year: 2025
Pages: 8
ISBN: 978-84-1081-494-3

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Appendix A

Glossary and Abbreviations

This appendix notes the glossary of terms and abbreviations used in this doctoral dissertation.

Appendix A
Glossary and Abbreviations

A.1 Glossary

Dyslexia A neurodevelopmental learning disorder that primarily affects accurate and/or fluent word recognition, spelling, and decoding. Its difficulties can persist into adulthood, especially in reading- and writing-intensive contexts such as higher education.

Learning strategy A deliberate, often self-regulated way of organizing, studying, or engaging with learning materials. Strategies include, for instance, creating personal summaries or conceptual maps, taking breaks during lessons, or revisiting recorded lectures to reinforce understanding.

Phonological dyslexia A dyslexia profile characterized by marked difficulties in reading unfamiliar words and pseudo-words, while relatively preserving the reading of familiar words. It is associated with impairments in mapping graphemes to phonemes and in phonological decoding, often leading to slow and effortful reading of novel or complex terms in academic settings.

Presence The subjective feeling of "being there" inside a virtual environment, as if the user were physically located in the simulated world. High presence is often associated with stronger engagement and more impactful experiential learning in VR.

Recommendation system An AI-based system that analyzes user data (e.g., profiles, behaviors, and preferences) to suggest items that are likely to be useful for that user.

Serious game A game designed primarily for educational, training, or awareness purposes, rather than pure entertainment. *The Virtual Campus* and *The Magic Potion* are serious games that leverage VR to raise awareness of dyslexia-related barriers and promote empathy toward dyslexic students.

Specific Learning Disorder A group of neurodevelopmental conditions that affect the acquisition of key academic skills such as reading, writing, and mathematics. In this thesis, the focus is on Specific Learning Disorder with impairment in reading, commonly referred to as dyslexia.

Support tool Any technological or educational resource designed to compensate for learning difficulties. Examples include audio books, clearer layouts of study material, or video lessons that help students access content more effectively.

Virtual reality sickness A form of motion sickness that can occur in VR environments, typically characterized by symptoms such as nausea, dizziness, or eye strain.

A.2 Abbreviations

AI Artificial Intelligence, a field of computer science dedicated to creating systems capable of performing tasks that usually require human intelligence.

CB Content-based Filtering, a kind of RS that recommends items similar to those the user has preferred in the past, based on the features or attributes of the items.

CF Collaborative Filtering, a kind of RS based on the preferences or behaviors of other users who are similar to the target user.

KNN K-Nearest Neighbor, an algorithm used for classification and regression tasks. It works by assigning a class to a data point based on the majority class among its nearest neighbors in the feature space

RS Recommendation System, an algorithm designed to suggest relevant items to users based on their preferences, behaviors, or other data sources

SLD Specific Learning Disorder, group of neurodevelopmental conditions that hinder the acquisition of key skills such as reading, writing, and arithmetic.

SVM Support Vector Machines, a supervised learning algorithm that works by finding the hyperplane that best separates the data into different classes.

SUS System Usability Scale, a standardized ten-item questionnaire that provides a global measure of perceived usability.

TEQ Toronto Empathy Questionnaire, a self-report instrument designed to measure trait empathy as a single, global construct. It consists of 16 items rated on a 5-point Likert scale (from Never to Always), and provides a total score that reflects an individual's general tendency to experience empathic responses in everyday life.

VRSQ Virtual Reality Sickness Questionnaire, a questionnaire designed to assess the severity of VR-induced discomfort, including symptoms such as nausea and disorientation.

VR Virtual Reality, technology that creates immersive environments, allowing users to interact with an artificially generated world as if it were real.

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Bibliography

[1] R. Butterfuss and P. Kendeou, "The role of executive functions in reading comprehension," *Educational Psychology Review*, vol. 30, pp. 1–26, Sep. 2018.

[2] R. Farah, S. Ionta, and T. Horowitz-Kraus, "Neuro-behavioral correlates of executive dysfunctions in dyslexia over development from childhood to adulthood," *Frontiers in Psychology*, vol. 12, Aug. 2021.

[3] A. Costantini, A. Ceschi, and R. Sartori, "Psychosocial Interventions for the Enhancement of Psychological Resources among Dyslexic Adults: A Systematic Review," *Sustainability*, Sep. 2020.

[4] J. Gabrieli, "Dyslexia: A new synergy between education and cognitive neuroscience," *Science*, vol. 325, pp. 280–3, Aug. 2009.

[5] E. Livingston, L. Siegel, and U. Ribary, "Developmental dyslexia: emotional impact and consequences," *Australian Journal of Learning Difficulties*, vol. 23, pp. 1–29, Jun. 2018.

[6] M. E. Christopher, A. Miyake, J. M. Keenan, B. Pennington, J. C. DeFries, S. J. Wadsworth, E. Willcutt, and R. K. Olson, "Predicting word reading and comprehension with executive function and speed measures across development: A latent variable analysis." *Journal of Experimental Psychology: General*, vol. 141, no. 3, pp. 470–488, Aug. 2012.

[7] T. Nevill and M. Forsey, "The social impact of schooling on students with dyslexia: A systematic review of the qualitative research on the primary and secondary education of dyslexic students," *Educational Research Review*, vol. 38, p. 100507, Dec. 2022.

[8] MIUR, "Pubblicati i dati sugli alunni con disturbi specifici dell'apprendimento," 2019, Ministero dell'Istruzione, Università e Ricerca. Accessed: 2025-09-23. [Online]. Available: https://www.miur.gov.it/web/guest/-/scuola-pubblicati-i-dati-sugli-alunni-con-disturbi-specifici-dell-apprendimento

[9] A. Zingoni, J. Taborri, V. Panetti, S. Bonechi, P. Aparicio-Martínez, S. Pinzi, and G. Calabrò, "Investigating Issues and Needs of Dyslexic Students at University: Proof of Concept of an Artificial Intelligence and Virtual Reality-Based Supporting Platform and Preliminary Results," *Applied Sciences*, vol. 11, no. 10, p. 4624, May 2021.

[10] O. Rohmer, N. Doignon-Camus, J. Audusseau, S. Trautmann, A.-C. Chaillou, and M. Popa-Roch, "Removing the academic framing in student evaluations improves achievement in children with dyslexia: The mediating role of self-judgement of competence," *Dyslexia*, vol. 28, no. 3, pp. 309–324, May 2022.

[11] H.-F. Yu, F.-L. Huang, and C.-J. Lin, "Dual coordinate descent methods for logistic regression and maximum entropy models," *Machine Learning*, vol. 85, pp. 41–75, Oct. 2011.

[12] C. Cortes and V. Vapnik, “Support-vector networks,” *Machine Learning*, vol. 20, no. 3, pp. 273–297, 1995.

[13] N. Altman, “An introduction to kernel and nearest-neighbor nonparametric regression,” *The American Statistician*, vol. 46, no. 3, pp. 175–185, 1992.

[14] J. R. Quinlan, “Induction of decision trees,” *Machine Learning*, vol. 1, no. 1, p. 81–106, Mar. 1986.

[15] L. Breiman, “Random forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[16] F. Ricci, L. Rokach, B. Shapira, and P. B. Kantor, *Recommender Systems Handbook*, Springer, Ed. Springer US, 2011.

[17] M. J. Park, D. J. Kim, U. Lee, E. J. Na, and H. J. Jeon, “A literature overview of virtual reality (vr) in treatment of psychiatric disorders: recent advances and limitations,” *Frontiers in psychiatry*, vol. 10, p. 505, 2019.

[18] T. Birrenbach, R. Wespi, W. E. Hautz, J. Berger, P. R. Schwab, G. Papagiannakis, A. K. Exadaktylos, and T. C. Sauter, “Development and usability testing of a fully immersive vr simulation for reboa training,” *International Journal of Emergency Medicine*, vol. 16, no. 1, Oct. 2023.

[19] E. Hoter and I. Nagar, “The effects of a wheelchair simulation in a virtual world,” *Virtual Reality*, vol. 27, Feb. 2022.

[20] Meta, “We Live Here,” 2020, Accessed: 2025-06-20. [Online]. Available: https://about.meta.com/es/community/vr-for-good/we-live-here/

[21] J. K. Haas, “A history of the unity game engine,” 2014. [Online]. Available: https://api.semanticscholar.org/CorpusID:86824974

[22] Meta, “Meta Quest,” 2020, Accessed: 2025-06-20. [Online]. Available: https://www.meta.com/en/quest/

[23] S. Rossi, I. Viola, L. Toni, and P. Cesar, “Extending 3-dof metrics to model user behaviour similarity in 6-dof immersive applications,” in *Proceedings of the 14th ACM Multimedia Systems Conference*, ser. MMSys ’23. New York, NY, USA: Association for Computing Machinery, 2023, p. 39–50.

[24] E. Yeguas-Bolívar, J. M. Alcalde-Llergo, P. Aparicio-Martínez, J. Taborri, A. Zingoni, and S. Pinzi, “Determining the Difficulties of Students With Dyslexia via Virtual Reality and Artificial Intelligence: An Exploratory Analysis,” in *2022 IEEE International Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE)*, 2022, pp. 585–590.

[25] Tech4All, “Reasy,” https://www.reasyedu.com, 2022, Accessed: 2025-10-02.

[26] V. Project, “Memorandum of understanding (mou),” https://vrailexia.eu/wp-content/uploads/2023/10/vrailexia-mou_nosignature.pdf, 2022, Accessed: 2025-06-20.

[27] R. Wang, L. Chen, I. Solheim, T. Schulz, and A. Ayesh, “Conceptual motivation modeling for students with dyslexia for enhanced assistive learning,” in *Proceedings of the 2017 ACM Workshop on Intelligent Interfaces for Ubiquitous and Smart Learning*, ser. SmartLearn ’17. New York, NY, USA: Association for Computing Machinery, 2017, p. 11–18.

[28] A. Y. Alsobhi, N. Khan, and H. Rahanu, "Personalised learning materials based on dyslexia types: Ontological approach," *Procedia Computer Science*, vol. 60, pp. 113–121, Sep. 2015.

[29] L. Pang and C. C. Jen, "Inclusive dyslexia-friendly collaborative online learning environment: Malaysia case study," *Education and Information Technologies*, vol. 23, no. 3, p. 1023–1042, Sep. 2017.

[30] G. Schiavo, N. Mana, O. Mich, M. Zancanaro, and R. Job, "Attention-driven read-aloud technology increases reading comprehension in children with reading disabilities," *Journal of Computer Assisted Learning*, vol. 37, no. 3, p. 875–886, Feb. 2021.

[31] L. Battistutta, E. Commissaire, and G. Steffgen, "Impact of the time of diagnosis on the perceived competence of adolescents with dyslexia," *Learning Disability Quarterly*, vol. 41, no. 3, pp. 170–178, 2018.

[32] G. Schulte-Körne, "The prevention, diagnosis, and treatment of dyslexia," *Deutsches Ärzteblatt International*, vol. 107, no. 41, p. 718, 2010.

[33] D. Wechsler, *WISC-V: Technical and interpretive manual*. NCS Pearson, Incorporated, 2014.

[34] K. Maitrei and T. V. Prasad, "Identifying dyslexic students by using artificial neural networks," in *World Congress on Engineering (WCE 2010)*, London, UK, 2010.

[35] L. Rello and M. Ballesteros, "Detecting readers with dyslexia using machine learning with eye tracking measures." New York, NY, USA: Association for Computing Machinery, 2015.

[36] L. Rello, E. Romero, M. Rauschenberger, A. Ali, K. Williams, J. P. Bigham, and N. C. White, "Screening dyslexia for english using hci measures and machine learning." New York, NY, USA: Association for Computing Machinery, 2018.

[37] A. Palacios, L. Sánchez, I. Couso, and S. Destercke, "An extension of the furia classification algorithm to low quality data through fuzzy rankings and its application to the early diagnosis of dyslexia," *Neurocomputing*, vol. 176, pp. 60–71, 2016.

[38] A. Elnakib, M. F. Casanova, G. Gimelrfarb, A. E. Switala, and A. El-Baz, "Dyslexia diagnostics by 3-d shape analysis of the corpus callosum," *IEEE Transactions on Information Technology in Biomedicine*, vol. 16, no. 4, pp. 700–708, 2012.

[39] S. S. A. Hamid, N. Admodisastro, and A. A. A. Ghani, "Computer-based learning model to improve learning of the malay language amongst dyslexic primary school students." New York, NY, USA: Association for Computing Machinery, 2015.

[40] D. Mpia Ndombo, S. Ojo, and I. O. Osunmakinde, "An intelligent integrative assistive system for dyslexic learners," *Journal of Assistive Technologies*, vol. 7, no. 3, pp. 172–187, 2013.

[41] S. Rajapakse, D. Polwattage, U. Guruge, I. Jayathilaka, T. Edirisinghe, and S. Thelijjagoda, "Alexza: A mobile application for dyslexics utilizing artificial intelligence and machine learning concepts," in *2018 3rd International Conference on Information Technology Research (ICITR)*, 2018, pp. 1–6.

[42] S. Thelijjagoda, M. Chandrasiri, D. Hewathudalla, P. Ranasinghe, and I. Wickramanayake, "The hope: An interactive mobile solution to overcome the writing, reading and speaking weaknesses of dyslexia," in *2019 14th International Conference on Computer Science & Education (ICCSE)*, 2019, pp. 808–813.

[43] S. U. Masruroh, D. Rosyada, Zulkifli, Sururin, and N. A. Rizqy Vitalaya, "Adaptive recommendation system in education data mining using knowledge discovery for academic predictive analysis: Systematic literature review," in *2021 9th International Conference on Cyber and IT Service Management (CITSM)*, 2021, pp. 1–6.

[44] A. Khalid, K. Lundqvist, and A. Yates, "A literature review of implemented recommendation techniques used in massive open online courses," *Expert Systems with Applications*, vol. 187, p. 115926, 2022.

[45] J. L. Herlocker, J. A. Konstan, L. G. Terveen, and J. T. Riedl, "Evaluating collaborative filtering recommender systems," *ACM Transactions on Information Systems (TOIS)*, vol. 22, no. 1, pp. 5–53, 2004.

[46] F. T. Marana, R. da Silva Fernandes, J. L. B. Guzmán, A. C. P. de Leon Ferreira, M. Cúri *et al.*, "What rating they will probably give: A cognitive diagnosis approach for recommending items based on polytomous responses and latent attributes," *Expert Systems with Applications*, p. 122981, 2023.

[47] W. Carrer-Neto, M. L. Hernández-Alcaraz, R. Valencia-García, and F. García-Sánchez, "Social knowledge-based recommender system. application to the movies domain," *Expert Systems with applications*, vol. 39, no. 12, pp. 10 990–11 000, 2012.

[48] R. Burke, "Hybrid recommender systems: Survey and experiments," *User modeling and user-adapted interaction*, vol. 12, no. 4, pp. 331–370, 2002.

[49] A. H. Nabizadeh, J. P. Leal, H. N. Rafsanjani, and R. R. Shah, "Learning path personalization and recommendation methods: A survey of the state-of-the-art," *Expert Systems with Applications*, vol. 159, p. 113596, 2020.

[50] N. Hoic-Bozic, M. H. Dlab, and V. Mornar, "Recommender system and web 2.0 tools to enhance a blended learning model," *IEEE Transactions on education*, vol. 59, no. 1, pp. 39–44, 2015.

[51] P. A. Rodríguez, D. A. Ovalle, and N. D. Duque, "A student-centered hybrid recommender system to provide relevant learning objects from repositories," in *International Conference on Learning and Collaboration Technologies*. Springer, 2015, pp. 291–300.

[52] D. Banakou, A. Beacco, S. Neyret, M. Blasco-Oliver, S. Seinfeld, and M. Slater, "Virtual body ownership and its consequences for implicit racial bias are dependent on social context," *Royal Society Open Science*, vol. 7, no. 12, p. 201848, Dec. 2020.

[53] F. Herrera, J. Bailenson, E. Weisz, E. Ogle, and J. Zaki, "Building long-term empathy: A large-scale comparison of traditional and virtual reality perspective-taking," *PLOS ONE*, vol. 13, no. 10, p. e0204494, Oct. 2018.

[54] E. Pedroli, P. Padula, A. Guala, M. T. Meardi, G. Riva, and G. Albani, "A psychometric tool for a virtual reality rehabilitation approach for dyslexia," *Computational and mathematical methods in medicine*, vol. 2017, 2017, publisher: Hindawi.

[55] L. Rello, K. Williams, A. Ali, N. C. White, and J. P. Bigham, "Dytective: Towards detecting dyslexia across languages using an online game," in *Proceedings of the 13th International Web for All Conference*, ser. W4A '16. New York, NY, USA: Association for Computing Machinery, 2016.

[56] L. Rello, A. Macias, M. Herrera, C. de Ros, E. Romero, and J. P. Bigham, "Dytectiveu: A game to train the difficulties and the strengths of children with dyslexia," in *Proceedings of the 19th International ACM SIGACCESS Conference on Computers and Accessibility*, ser. ASSETS '17. New York, NY, USA: Association for Computing Machinery, 2017, p. 319–320.

[57] A. Brennan, T. McDonagh, M. Dempsey, and J. McAvoy, "Cosmic sounds: A game to support phonological awareness skills for children with dyslexia," *IEEE Transactions on Learning Technologies*, vol. 15, no. 3, pp. 301–310, 2022.

[58] S. Rodríguez-Cano, V. Delgado-Benito, V. Ausín-Villaverde, and L. M. Martín, "Design of a virtual reality software to promote the learning of students with dyslexia," *Sustainability*, vol. 13, no. 15, p. 8425, 2021.

[59] V. De Luca, C. Gatto, S. Liaci, L. Corchia, S. Chiarello, F. Faggiano, G. Sumerano, and L. T. De Paolis, "Virtual reality and spatial augmented reality for social inclusion: The includiamoci project," *Information*, vol. 14, no. 1, 2023.

[60] S. D. Piovesan, R. Wagner, R. D. Medina, and L. M. Passerino, "Virtual Reality system to the inclusion of people with disabilities in the work market," in *2013 12th International Conference on Information Technology Based Higher Education and Training (ITHET)*, 2013, pp. 1–7.

[61] N. Didehbani, T. Allen, M. Kandalaft, D. Krawczyk, and S. Chapman, "Virtual Reality Social Cognition Training for children with high functioning autism," *Computers in Human Behavior*, vol. 62, pp. 703–711, 2016.

[62] E. Stilinović, "Facilitating empathy through virtual reality," *Motivation and Emotion*, vol. 41, Dec. 2017.

[63] NowHere, "Home after war," 2018, Accessed: 2025-06-20. [Online]. Available: https://about.meta.com/es/community/vr-for-good/home-after-war/

[64] Within, "The Hidden," 2018, Accessed: 2025-06-20. [Online]. Available: https://about.meta.com/es/community/vr-for-good/the-hidden/

[65] ARTE, "Notes on Blindness: Into Darkness," 2016, Accessed: 2025-06-20. [Online]. Available: https://www.arte.tv/digitalproductions/en/notes-on-blindness/

[66] I. Benedetti, B. Marcella, V. Panetti, J. Taborri, T. Urbani, A. Zingoni, and G. Calabrò, "Clustering analysis of factors affecting academic career of university students with dyslexia in Italy," *Scientific Reports*, vol. 12, p. 9010, May 2022.

[67] E. M. Miles, "Dyslexia may show a different face in different languages," *Dyslexia*, vol. 6, no. 3, pp. 193–201, 2000.

[68] European Parliament and Council of the European Union, "Regulation (EU) 2016/679 of the European Parliament and of the Council of 27 April 2016 on the protection of natural persons with regard to the processing of personal data and

on the free movement of such data, and repealing Directive 95/46/EC (General Data Protection Regulation)," 2016, Accessed: 2025-06-20. [Online]. Available: https://eur-lex.europa.eu/eli/reg/2016/679/oj

[69] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.

[70] M. C. Urdaneta-Ponte, A. Mendez-Zorrilla, and I. Oleagordia-Ruiz, "Recommendation systems for education: systematic review," *Electronics*, vol. 10, no. 14, p. 1611, 2021.

[71] G. Badaro, H. Hajj, W. El-Hajj, and L. Nachman, "A hybrid approach with collaborative filtering for recommender systems," in *2013 9th International wireless communications and mobile computing conference (IWCMC)*. IEEE, 2013, pp. 349–354.

[72] Z.-D. Zhao and M.-S. Shang, "User-based collaborative-filtering recommendation algorithms on hadoop," in *2010 third international conference on knowledge discovery and data mining*. IEEE, 2010, pp. 478–481.

[73] J. Wang, A. P. De Vries, and M. J. Reinders, "Unifying user-based and item-based collaborative filtering approaches by similarity fusion," in *Proceedings of the 29th annual international ACM SIGIR conference on Research and development in information retrieval*, 2006, pp. 501–508.

[74] B. Sarwar, G. Karypis, J. Konstan, and J. Riedl, "Item-based collaborative filtering recommendation algorithms," in *Proceedings of the 10th international conference on World Wide Web*, 2001, pp. 285–295.

[75] L. Sheugh and S. H. Alizadeh, "A note on pearson correlation coefficient as a metric of similarity in recommender system," in *2015 AI & Robotics (IRANOPEN)*. IEEE, 2015, pp. 1–6.

[76] T. D. Q. Vinh, Y. Tay, S. Zhang, G. Cong, and X.-L. Li, "HyperML: A boosting metric learning approach in hyperbolic space for recommender systems," arXiv:1809.01703, 2018, Accessed: 2025-10-20. [Online]. Available: https://arxiv.org/abs/1809.01703

[77] T. Hofmann, "Latent semantic models for collaborative filtering," *ACM Transactions on Information Systems (TOIS)*, vol. 22, no. 1, pp. 89–115, 2004.

[78] V. K. Sejwal and M. Abulaish, "A hybrid recommendation technique using topic embedding for rating prediction and to handle cold-start problem," *Expert Systems with Applications*, vol. 209, p. 118307, 2022.

[79] D. Cosley, S. K. Lam, I. Albert, J. A. Konstan, and J. Riedl, "Is seeing believing? how recommender system interfaces affect users' opinions," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, ser. CHI '03. New York, NY, USA: Association for Computing Machinery, 2003, p. 585–592.

[80] A. I. Schein, A. Popescul, L. H. Ungar, and D. M. Pennock, "Methods and metrics for cold-start recommendations," in *Proceedings of the 25th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval*, ser. SIGIR '02. New York, NY, USA: Association for Computing Machinery, 2002, p. 253–260.

[81] M. Fernández, A. Bellogín, and I. Cantador, "Analysing the effect of recommendation algorithms on the amplification of misinformation," arXiv:2103.14748, 2021, Accessed: 2025-10-20. [Online]. Available: https://arxiv.org/abs/2103.14748

[82] A. Said, A. Bellogín Kouki, and A. de Vries, "A top-n recommender system evaluation protocol inspired by deployed systems," in *2013 ACM RecSys Workshop on Large-Scale Recommender Systems*, Oct. 2013.

[83] N. Joorabloo, M. Jalili, and Y. Ren, "A probabilistic graph-based method to solve precision-diversity dilemma in recommender systems," *Expert Systems with Applications*, vol. 184, p. 115485, 2021.

[84] B. Xie, H. Liu, R. Alghofaili, Y. Zhang, Y. Jiang, F. D. Lobo, C. Li, W. Li, H. Huang, M. Akdere, C. Mousas, and L.-F. Yu, "A review on virtual reality skill training applications," *Frontiers in Virtual Reality*, vol. 2, 2021.

[85] G. Lampropoulos and Kinshuk, "Virtual reality and gamification in education: a systematic review," *Educational technology research and development*, vol. 72, no. 3, pp. 1691–1785, Jun. 2024.

[86] A. Neugebauer, N. Castner, B. Severitt, K. Stingl, I. Ivanov, and S. Wahl, "Simulating vision impairment in virtual reality: a comparison of visual task performance with real and simulated tunnel vision," *Virtual Reality*, vol. 28, no. 2, 2024.

[87] D. Passig, "The impact of immersive virtual reality on educators' awareness of the cognitive experiences of pupils with dyslexia," *Teachers College Record: The Voice of Scholarship in Education*, vol. 113, no. 1, pp. 181–204, Jan. 2011.

[88] D. Passig, S. Eden, and V. Rosenbaum, "The impact of virtual reality on parents' awareness of cognitive perceptions of a dyslectic child," *Education and Information Technologies*, vol. 13, no. 4, p. 329–344, Oct. 2008.

[89] E. Wadlington, C. Elliot, and J. Kirylo, "The dyslexia simulation: Impact and implications," *Literacy Research and Instruction*, vol. 47, no. 4, p. 264–272, Sep. 2008.

[90] G. Morciano, J. M. Alcalde Llergo, A. Zingoni, E. Yeguas Bolívar, J. Taborri, and G. Calabrò, "Use of recommendation models to provide support to dyslexic students," *Expert Systems with Applications*, vol. 249, p. 123738, 2024.

[91] L. Lukov, N. Friedmann, L. Shalev, L. Khentov-Kraus, N. Shalev, R. Lorber, and R. Guggenheim, "Dissociations between developmental dyslexias and attention deficits," *Frontiers in Psychology*, vol. 5, Jan. 2015.

[92] S. Caldani, M. Baghdadi, H. Peyre, E. Khoury, R. Delorme, and M. P. Bucci, "Poor visuo-spatial orientation and path memorization in children with dyslexia," *Nordic Journal of Psychiatry*, vol. 76, no. 3, Jun. 2021.

[93] S. S. Lie, K. Røykenes, A. Sæheim, and K. S. Groven, "Developing a virtual reality educational tool to stimulate emotions for learning: Focus group study," *JMIR Formative Research*, vol. 7, p. e41829, Mar. 2023.

[94] Government of Spain, "Organic Law 3/2018, of December 5, on the Protection of Personal Data and Guarantee of Digital Rights," 2018, Accessed: 2025-01-08. [Online]. Available: https://www.boe.es/eli/es/lo/2018/12/05/3/con

[95] W. M. Association, “World medical association declaration of Helsinki: Ethical principles for medical research involving human subjects,” *JAMA*, vol. 310, no. 20, pp. 2191–2194, Nov. 2013.

[96] X. Tong, D. Gromala, S. P. K. Ziabari, and C. D. Shaw, “Designing a virtual reality game for promoting empathy toward patients with chronic pain: Feasibility and usability study,” *JMIR Serious Games*, vol. 8, no. 3, Sep. 2020.

[97] L. Bryant, M. Brunner, and B. Hemsley, “A review of virtual reality technologies in the field of communication disability: implications for practice and research,” *Disability and Rehabilitation: Assistive Technology*, vol. 15, no. 4, p. 365–372, Jan. 2019.

[98] X. Lin, R. Li, Z. Chen, and J. Xiong, “Design strategies for vr science and education games from an embodied cognition perspective: a literature-based meta-analysis,” *Frontiers in Psychology*, vol. 14, Jan. 2024.

[99] Y. Jin, S. Lee, S. Kim, J. Seo, K. Jung, H. Lim, and J. Lee, “Divrsity: Design and development of group role-play vr platform for disability awareness education,” in *Proceedings of the 2023 ACM Designing Interactive Systems Conference*, ser. DIS ’23. ACM, Jul. 2023, p. 161–174.

[100] W. P. Morgan, “A case of congenital word blindness,” *BMJ*, vol. 2, no. 1871, pp. 1378–1378, Nov. 1896.

[101] A. Artiles, D. Rose, T. González, and A. Bal, *Biology and culture in learning disabilities research: Legacies and possible futures*, May 2020, pp. 168–177.

[102] J. J. Tree and J. Kay, “Phonological dyslexia and phonological impairment: An exception to the rule?” *Neuropsychologia*, vol. 44, no. 14, pp. 2861–2873, 2006.

[103] J. Marshall, K. Patterson, and M. Coltheart, “Surface dyslexia: Neuropsychological and cognitive studies of phonological reading,” Jan. 1987.

[104] S. Z. Rapcsak, P. M. Beeson, M. L. Henry, A. Leyden, E. Kim, K. Rising, S. Andersen, and H. Cho, “Phonological dyslexia and dysgraphia: Cognitive mechanisms and neural substrates,” *CORTEX*, vol. 45, no. 5, pp. 575–591, May 2009.

[105] M. P. Alexander, R. B. Friedman, F. Loverso, and R. S. Fischer, “Lesion localization of phonological agraphia,” *Brain and Language*, vol. 43, no. 1, pp. 83–95, 1992.

[106] R. E. P. Maculada, A. R. Caballero, C. G. Villarin, and E. M. Albina, “Funologo: An android-based mobile virtual reality assisted learning with speech recognition using diamond-square algorithm for children with phonological dyslexia,” in *2023 8th International Conference on Business and Industrial Research (ICBIR)*, 2023, pp. 403–408.

[107] J.-A. Jordan, G. McGladdery, and K. Dyer, “Dyslexia in higher education: Implications for maths anxiety, statistics anxiety and psychological well-being,” *Dyslexia*, vol. 20, no. 3, pp. 225–240, Jun. 2014.

[108] D. Britton, “Dyslexia - typographic design,” 2015, accessed: 2025-06-20. [Online]. Available: https://danielbritton.info/dyslexia/

[109] T. Muehling, I. Spaeth, J. Backhaus, N. Milke, S. Oberdoerfer, A. Meining, M. E. Latoschik, and S. Koenig, “Virtual reality in medical emergencies training: benefits, perceived stress, and learning success,” *Multimedia Systems*, vol. 29, no. 4, pp. 2239–2252, Aug. 2023.

[110] R. N. Spreng, M. C. McKinnon, R. A. Mar, and B. Levine, "The toronto empathy questionnaire: Scale development and initial validation of a factor-analytic solution to multiple empathy measures," *Journal of Personality Assessment*, vol. 91, no. 1, p. 62–71, Jan. 2009.

[111] H. K. Kim, J. Park, Y. Choi, and M. Choe, "Virtual reality sickness questionnaire (vrsq): Motion sickness measurement index in a virtual reality environment," *Applied Ergonomics*, vol. 69, p. 66–73, May 2018.

[112] M. Usoh, E. Catena, S. Arman, and M. Slater, "Using presence questionnaires in reality," *Presence: Teleoperators and Virtual Environments*, vol. 9, no. 5, pp. 497–503, 2000.

[113] S. Baron-Cohen and S. Wheelwright, "The empathy quotient: An investigation of adults with asperger syndrome or high functioning autism, and normal sex differences," *Journal of Autism and Developmental Disorders*, vol. 34, no. 2, pp. 163–175, 2004.

[114] F. Youssef, P. Nunes, B. Sa, and S. Williams, "An exploration of changes in cognitive and emotional empathy among medical students in the caribbean," *Int J Med Educ*, vol. 5, pp. 185–192, 2014.

[115] S. I. Innes and J. K. Simpson, "Empathy levels in australian chiropractic students," *Journal of Chiropractic Education*, vol. 36, no. 2, pp. 110–116, Mar. 2022.

[116] R. S. Kennedy, N. E. Lane, K. S. Berbaum, and M. G. Lilienthal, "Simulator sickness questionnaire: An enhanced method for quantifying simulator sickness," *The International Journal of Aviation Psychology*, vol. 3, no. 3, pp. 203–220, 1993.

[117] B. G. Witmer and M. J. Singer, "Measuring Presence in Virtual Environments: A Presence Questionnaire," *Presence: Teleoperators and Virtual Environments*, vol. 7, no. 3, pp. 225–240, Jun. 1998.

[118] K. S. Baig, M. K. Hayat, M. A. A. Khan, U. Humayun, Z. Ahmad, and M. A. Khan, "Empathy levels in medical students: A single center study," *Cureus*, May 2023.

[119] K. A. Bin Abdulrahman, M. A. Alsharidah, B. A. Alobaida, Y. N. Alabbadi, F. Almohsen, I, T. A. Abahussain, and F. S. Alahmari, "Empathy level among saudi medical students using the toronto empathy scale," *World Family Medicine*, vol. 20, no. 11, pp. 172–180, Nov. 2022.

[120] T. Totan, T. Dogan, and F. Sapmaz, "The Toronto Empathy Questionnaire: Evaluation of psychometric properties among turkish university students," *Eurasian Journal of Educational Research*, vol. 12, no. 46, pp. 179–198, Dec. 2012.

[121] S. Rodríguez Cano, V. Delgado Benito, R. Casado Muñoz, E. Cubo Delgado, V. Ausín Villaverde, and G. Santa Olalla Mariscal, "Tecnologías emergentes en educación inclusiva: realidad virtual y realidad aumentada: Proyecto europeo FORDYS-VAR," *Revista INFAD de Psicología. International Journal of Developmental and Educational Psychology.*, vol. 2, no. 1, pp. 443–450, Aug. 2021.

[122] D. Saredakis, A. Szpak, B. Birckhead, H. A. D. Keage, A. Rizzo, and T. Loetscher, "Factors associated with virtual reality sickness in head-mounted displays: A systematic review and meta-analysis," *Frontiers in Human Neuroscience*, vol. 14, 2020.

[123] M. Materazzini, G. Morciano, J. M. Alcalde-Llergo, E. Yeguas-Bolívar, G. Calabrò, A. Zingoni, and J. Taborri, "Combine virtual reality and machine-learning to identify the presence of dyslexia: A cross-linguistic approach," *Information*, vol. 16, no. 9, 2025.

[124] J. M. Alcalde-Llergo, P. Aparicio-Martínez, A. Zingoni, S. Pinzi, and E. Yeguas-Bolívar, "Fostering inclusion: A virtual reality experience to raise awareness of dyslexia-related barriers in university settings," *Electronics*, vol. 14, no. 5, 2025.

[125] J. M. Alcalde-Llergo, A. Zingoni, P. Aparicio-Martínez, S. Pinzi, and E. Yeguas-Bolívar, "Design and evaluation of a serious game in virtual reality to increase empathy towards students with phonological dyslexia," *Multimedia Systems*, vol. 31, no. 5, Aug. 2025.

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