ID N. 26

UNIVERSITÀ CAMPUS BIO-MEDICO DI ROMA

DEPARTMENT OF ENGINEERING

UNIVERSITÀ DEGLI STUDI DELLA TUSCIA

DIPARTIMENTO DI ECONOMIA, INGEGNERIA, SOCIETÀ E IMPRESA

Italian National Ph.D. in Artificial Intelligence

Health and Life Sciences

XXXVII Cycle

Study, design and implementation of customized digital support tools for students with dyslexia, using machine learning

Supervisors

Andrea Zingoni

Co-supervisor: Stefano Rossi

Candidate

Gianluca Morciano

December, 2024

A tutti i miei cari,
siete importanti in modi che non immaginate.

Acknowledgements

I am deeply grateful to all those who have contributed to the completion of this thesis. Their support, guidance, and encouragement have been invaluable throughout this journey. First and foremost, I would like to express my heartfelt gratitude to my advisor, Andrea Zingoni, for the guidance, insightful feedback, and constant encouragement. The expertise and patience have been instrumental in shaping this research and bringing it to fruition. To my colleagues, thank you for your camaraderie, stimulating discussions, and encouragement during both challenging and rewarding times. Finally, I am profoundly grateful to my family for their unwavering love, patience, and sacrifices. This thesis is a testament to the support and kindness I have received from so many people, and I dedicate it to all those who have inspired and supported me along the way.

Abstract

Dyslexia is a neurodevelopmental disorder that significantly affects cognitive abilities, particularly in areas such as reading, memory retention, and attention span. Individuals with dyslexia often struggle with fluent reading, accurate word recognition, and spelling, which can impede their academic performance and self-confidence. Additionally, dyslexia commonly coexists with other neurodevelopmental disorders, such as autism spectrum disorder and attention-deficit/hyperactivity disorder. This comorbidity can compound learning challenges, making educational progress more complex and requiring a multifaceted approach to support. Early diagnosis is crucial, as numerous studies have shown that identifying dyslexia in childhood allows for timely intervention. Early interventions often enable children to access specialized tools and strategies that can alleviate or mitigate some of the difficulties they encounter in the classroom and daily life. However, in cases where diagnosis is delayed or missed entirely, individuals are left without formal support, which heightens the importance of alternative support tools and strategies to aid in their learning. To address these challenges, research efforts are increasingly focused on determining the most effective support mechanisms. One promising area is artificial intelligence, which has shown potential to transform the way dyslexia is diagnosed and managed. Artificial intelligence can provide precise, individualized assessments, which can then guide the creation of custom support tools tailored to each student's unique needs and learning profile. However, most existing studies concentrate on adolescent students, often neglecting the unique challenges that university students with dyslexia face. In response to this gap, the VRAILEXIA project was founded. This initiative seeks to combine the immersive capabilities of virtual reality with the diagnostic and adaptive powers of artificial intelligence to develop innovative, personalized study aids. These tools are intended to address the specific needs of each student, helping them navigate their educational journey more effectively. This thesis will delve into the various studies conducted design methods to help dyslexic students, analyzing the methodologies used and discussing the insights and outcomes achieved. Through this exploration, the goal is to highlight the potential of artificial intelligence in creating a more inclusive and supportive educational environment for individuals with dyslexia

Contents

List of Figures

List of Tables

List of Algorithms

Chapter 1

Dyslexia: origins, characteristics and methods of intervention

1.0.1 Specific Learning disorders

Specific Learning disorders (SLDs) are a group of neurodevelopmental disorders characterized by a persistent impairment in learning academic skills such as reading, writing and mathematics but do not compromise global intelligence [86]. In the Diagnostic and Statistical Manual of Mental Disorders (DSM-5), it is reported that around 5% to 15% of school-aged children from different languages and cultures have a SLD [2] and the prevalence is equally distributed among males and females [115]. Over the years, various factors have emerged that can be considered as possible causes of SLD. In [104], it was proposed that the SLD is mainly caused by a deficit in phonological processing. This theory suggests that dyslexics have an impairment in the representation, storage or retrieval of speech sounds. In order to learn to read an alphabetic system, grapheme-phoneme correspondence (the correspondence between letters and constituent sounds of speech) must be learned. Therefore, if the subject has a difficulty in representing, storing or retrieving the grapheme-phoneme correspondence, reading will be negatively affecte [119]. Indeed, a study showed that 100% of all the people considered in the study had a phonological deficit while the influence of visual, motor and auditory deficits is limited [105]. Another possible cause for the SLD disorder is the deficit in the perception of short or rapidly varying sounds [123]. This means that the auditory system fails to process the sound and, as a consequence, dyslexics develop a phonological deficit. Another theory is that the SLD are caused by magnocellular system disorders [121]. This theory implies that, in SLD subjects, the magnocellular pathway, responsible of responding to rapid visual changes in stimulation, has a reduced sensitivity. As a consequence, people with SLD have difficulties in cognitive areas such as reading and word recognition.

These theories however, propose ”core deficit” symptoms and secondary symptoms [91], a view that has been criticised [22]. Indeed today, a wide agreement has been reached on the fact that SLDs have a multifactorial origin [12]. Following this assumption, Wolf [137] introduced the concept of a ”pyramid” to describe reading behaviors (as shown in Figure 1.1. This model can be visualized as an iceberg, where the visible tip represents the observable difficulties children experience. These difficulties, influenced by environmental factors such as education and socio-cultural context, can appear despite the child's overall good cognitive abilities and may affect reading or other basic learning skills. The hidden portion of the pyramid includes the fundamental cognitive processes—such as perception, language, motor skills, memory, and attention—as well as executive functions. These processes influence performance as measured in neuropsychological evaluations. The complexity and variety of these processes and their interactions explain how similar symptoms (such as difficulties in reading or writing) can arise from different causes and combinations of factors. Deeper within the pyramid are the neural networks, composed of neurons and their synaptic connections. At the very foundation of the pyramid lies the genetic basis, which governs the development of body cells in conjunction with the individual's specific life environment.

Several studies show that SLDs have a genetic origin. It has a relatively strong heritability component, and usually, 40% to 70% of SLD subjects inherit the genes from family members [49]. Indeed in [21], the authors studied the genes of 37 subjects with SLD, 21 of whom were young subjects with SLD. 15 gene candidates were considered and, among those, a single-nucleotide polymorphism (SNP) variant was found in the DGKI, DIP2A, KIAA0319 and PCNT genes. In all cases the mutation was transmitted by one of the two parents who reported having language difficulties. The genetic framework of SLDs is intricate and involves a blend of genetic elements that contribute to an individual's vulnerability to these conditions. Important features include its polygenic nature, the presence of both common and rare variants, which frequently converge on particular biological pathways and networks associated with brain development, neurotransmitter function, and neuronal communication [21]. Over the last decade, various candidate genes have been discovered that may influence the risk of developing SLD. These genes are DCDC2, DYX1C1, KIAA0319, and ROBO1 and are thought to be involved in crucial biological processes, including neuron migration during brain development [34]. These genes are believed to regulate neuronal migration and the growth of dendrites and axons by influencing primary cilia formation and function. This suggests that the predisposition to SLD might be considered the least severe expression within a spectrum of neuronal developmental disorders, which at its most extreme, leads to significant brain malformations and profound intellectual disability.

Although the genetic predisposition to SLD exists from birth, the manifestations of these

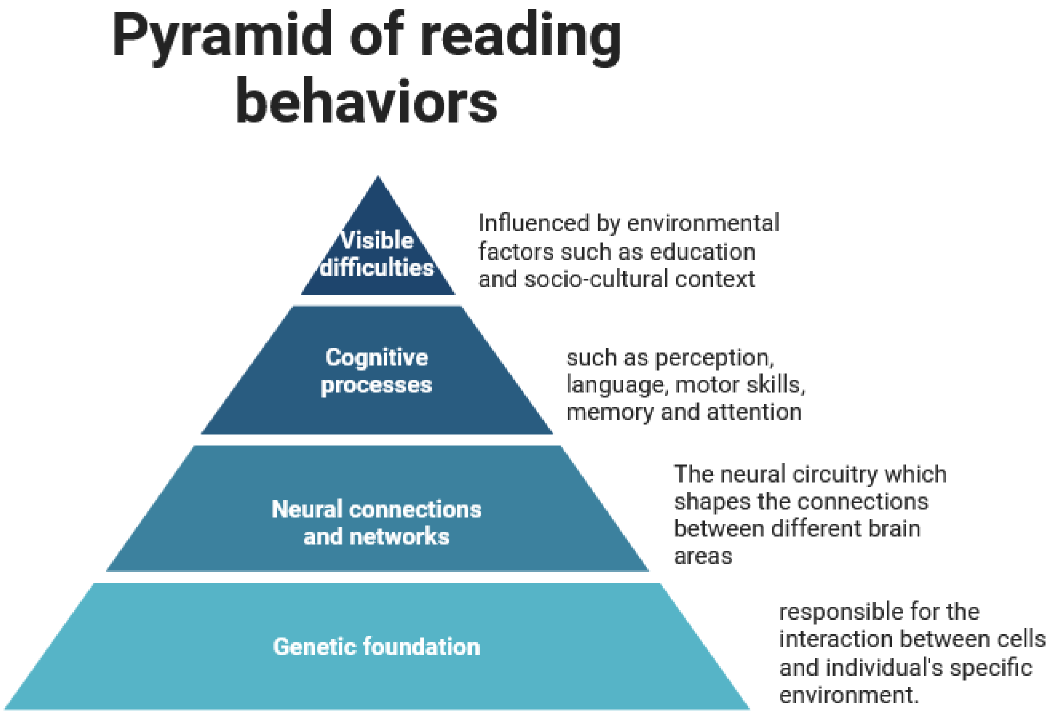


Figure 1.1: The Pyramid of reading behaviors proposed by Wolf in 2007. This theory better represent the complexity of SLD and their cognitive difficulties.

disorders often become more apparent during the school years. While some signs may be noticeable in the preschool years or even earlier, it is typically during formal education that children exhibit significant difficulties in areas such as reading, writing, comprehension, number perception, and calculation [90]. These challenges frequently result in academic performance that falls below the expectations for their age, highlighting the impact of SLD on educational attainment. drag the child's academic performance below what would be expected for his or her age.

Based on the type of impaired cognitive ability, it is possible to distinguish between several specific learning disabilities: dyslexia, dyscalculia, dysgraphia, and dysortography. Dyslexia is characterized by difficulties in reading, including trouble with accurate or fluent word recognition and poor spelling abilities. Dyscalculia involves challenges with arithmetic operations, such as understanding numbers, learning how to manipulate numbers, and performing mathematical calculations. Dysgraphia affects writing abilities, manifesting in problems with spelling, poor handwriting, and difficulty putting thoughts on paper. Dysortography refers to specific difficulties in writing, particularly with spelling and constructing grammatically correct sentences. Among these disorders, dyslexia has the highest prevalence [131]. As a consequence, dyslexia has been the most studied among the SLDs and was the focus of our works. Through time, four main theories have been proposed to explain the origins of dyslexia. The most widely accepted theory is the phonological theory [110], which posits that the cognitive deficits experienced by dyslexic individuals are primarily caused by poor phonological skills, including difficulties with phonemic awareness and limitations in short-term memory. As a proof for this hypothesis, several studies have demonstrated that dyslexics have impairments in both word and non-word repetition, suggesting a short-term memory deficit which is associated to a poor phonological representation [103]. In addition, imaging studies have revealed that phonological impairments in individuals with dyslexia are related to notable irregularities in both brain connectivity and cortical structure, especially within the language network of the left hemisphere [138]. This theory highlights the challenges in processing the sounds of language as the core issue in dyslexia. Another theory is the visuo-spatial hypothesis [128], which emphasizes the role of visual processing deficits in dyslexia. According to this hypothesis, dyslexic individuals have a reduced perceptual span and slower visual information processing speeds, making it difficult for them to efficiently decode written text. The cerebellar theory offers a different perspective, suggesting that the phonological deficits seen in dyslexic individuals are actually a result of motor deficits [43]. This theory implicates the cerebellum, a brain region traditionally associated with motor control, proposing that impairments in this area affect the articulatory coding required for reading. Finally, the auditory hypothesis suggests that dyslexia is primarily caused by an auditory deficit [122]. According to this theory, difficulties in processing auditory information lead to problems with categorical perception, the ability to distinguish between different phonetic categories, which is crucial for reading development.

These theories highlight the complex interplay between different cognitive and neurological factors in dyslexia, emphasizing how deficits in areas such as articulatory coding and auditory processing can disrupt reading development. However, dyslexia rarely exists in isolation. It is increasingly recognized that there is a high comorbidity of dyslexia with other neurodevelopmental disorders, such as ADHD and autism [16]. Regarding the comorbidity between dyslexia and ADHD, it has been estimated that around 20% to 40% of children with ADHD also have dyslexia [50]. Several studies have identified common genetic patterns between the two disorders. In particular, some of the genes involved were the DYX1, 2, 4, 5 and 8 [30]. These genetic similarities may explain similar brain abnormalities as revealed by neuroimaging studies. For instance, in both dyslexic and ADHD subjects it was found a reversed asymmetry of different hemisphere structures such as the planum temporale, caudate nuclaus and frontal lobes. Moreover, lower cerebellar volumes and less gray matter volumes were found in both dyslexic and ADHD subjects [50]. The genetic and brain abnormalities may explain why some cognitive deficits are shared between dyslexic and ADHD subjects. For instance, in both these disorders the sustained and selective attention is reduced, resulting in a higher difficulty in concentrating for long. This may reflect a deficit in working memory and processing speed, negatively influencing tasks like reading, writing and problem-solving [73]. In contrast to ADHD, where attentional deficits are most prominent, the comorbidity between dyslexia and autism typically presents challenges in social communication, rigid thinking, and sensory and language processing [16]. These difficulties are linked to anomalies in specific genes, particularly DYX2 and DRD2, which are found in individuals with both dyslexia and autism [37]. These genetic factors may play a significant role in the cognitive challenges associated with these disorders.

For instance, individuals with this comorbidity often experience heightened difficulty with phonological processing, a core issue in dyslexia that affects their ability to decode words and read fluently. A similar challenge is intensified in autistic subjects by difficulties in understanding and producing language within social interactions, making communication particularly difficult. Sensory processing issues are shared between dyslexia and autism. While autistic individuals may experience sensory sensitivities that make certain environments overwhelming, those with dyslexia may struggle with auditory processing difficulties, especially in noisy settings. This dual sensory challenge can make traditional learning environments particularly challenging, requiring tailored interventions that address both sensory and cognitive needs.

The recognition of dyslexia's frequent comorbidity with other neurodevelopmental disorders, such as ADHD and autism, underscores the complex dynamics of genetic and neurological factors that greatly contribute to the the cognitive challenges faced by individuals with dyslexia. These overlapping deficits in areas like attention, reading, social communication, and sensory processing can significantly hinder a person's ability to succeed in academic and social environments. In addition, people with dyslexia can have poor mental health by having an increased risk of developing generalized anxiety [77], low self-esteem [92], and depression [89]. Given the wide-ranging difficulties that dyslexia can impose, especially when compounded by other disorders, a timely diagnosis becomes of utmost importance. Early identification allows for the implementation of targeted interventions that can address these multifaceted challenges, ultimately improving long-term outcomes for those affected.

1.0.2 The diagnose of dyslexia

Given all the difficulties that can be encountered by children with dyslexia, it appears evident how crucial it is to perform an early screening and diagnosis that can lead to identifying the best support measures. To favor this process, schools and professionals should intervene as soon as possible, in order to mitigate the potential disparities between dyslexic children and non-dyslexic children. Indeed, when screening is done in kindergarten and the appropriate support is given, the outcome is better [127] compared to children diagnosed later in life [74] or in adolescence [130]. Therefore, early screening can favor appropriate support that can help to mitigate the cognitive symptoms as well as improving the psychological well-being of individuals affected by dyslexia. Early screening and diagnosis is usually performed using different cognitive tests aimed at evaluating specific cognitive abilities that may be impaired in dyslexic children.

Cognitive tests

The most common method used to diagnose dyslexia, is the application of cognitive tests [112]. These tests are generally composed of a set of pre-selected items designed to measure specific psychological traits and cognitive abilities in the individual tested. Through cognitive tests, it is possible to examine general cognitive abilities using the Wechsler Adult Intelligence Scale (WAIS) for adults or the Wechsler Intelligence Scale for Children (WISC) [134] for children, as well as specific cognitive abilities such as verbal and phonological processing [101], mental disorders such as depression [63], and psycho-physical traits such as stress [54]. As mentioned earlier, it is preferable to screen and diagnose dyslexia as early as possible in order to provide the necessary support. To this end, several tests of varying lengths have

Test	Age	Cognitive abilities tested
DEST [42]	4-6 years old	phonological skills, reading, spelling, motor skills, short-term memory
BDT [84]	7 years old to adulthood	reading, spelling, phonological processing, memory and motor skills
LSC-SUA [26]	18 years old to adulthood	reading, writing, comprehension, mathematics
DAST [41]	16 years old to adulthood	reading, spelling, motor skills, memory
BDA [25]	16 years old to adulthood	reading, writing and comprehension

Table 1.1: Brief summary of the presented pen-and-paper cognitive tests used to diagnose dyslexia.

been created, as shown in Table 1.1.

An example of a dyslexia screening test is the Dyslexia Early Screening Test (DEST). This test evaluates various tasks including rapid naming, phonological discrimination, digit span, letter and digit naming, motor skills, and postural stability. Each child is assigned a score that indicates a "high risk," "moderate risk," or "neutral" risk to be dyslexic. At-risk children are referred to psychologists to administer additional tests in order to produce a timely diagnose of dyslexia. Another well-known test for assessing dyslexia is the Bangor Dyslexia Test (BDT). Since dyslexia is considered to arise from phonological processing deficits rather than literacy skills, the BDT focuses on skills that require verbal and phonological processing. The test is designed to be an easy-to-administer screener for children from 7 years old to adults and consists of 10 subtests that do not directly assess reading and spelling skills. For instance, one substest measures the awareness of left and right using body parts, another one tests the ability to repeat polysyllabic words such as "foreboding", "passionately" or "apprehensively". Other subtests is focused on reciting the months of the year in the correct order and in reverse or repeating digits in the correct order on in reverse. All of these subtests allow to have an indirect understanding of crucial cognitive skills such as verbal working memory, attention, spatial awareness and arithmetic skills.

If dyslexia is not detected during childhood, it is important to perform a diagnosis as soon as possible. This is why some tests have been developed to assess dyslexia in adolescents and adults. The cognitive development and strategies used by dyslexic individuals to compensate for their difficulties may differ between children and adults, requiring tests that are tailored accordingly [69]. Examples of widely used tests for adolescents and adults include the LSC-SUA, the Adult Dyslexia Battery, the BDT, and the Dyslexia Adult Screening Test (DAST).

These tests are designed to evaluate dyslexia in the age range of adolescence to adulthood and assess specific skills negatively affected by dyslexia, such as reading, writing, comprehension, and memory. For instance, the LSC-SUA test is divided in 4 areas such as reading, in which the subject has to read a text, words and non-words; comprehension, involves questions about two different texts; writing of words and numbers and calculus. The BDA investigates, thanks to different tests, the reading ability and flexibility of the testee during silent and vocal reading, it's writing skills and comprehension abilities. It consists of different reading tests, such as words, non-words, text and silent reading; two writing tests such as dictate texts and sentences and one comprehension assessment.

While the BDT focuses more on verbal and phonological processing, the DAST has a broader scope, as it assesses not only reading and verbal fluency but also postural stability, working memory, non-verbal reasoning and semantic fluency. The last two assessments measure the relative strengths of the testee and this serves two purposes, on one hand, allows to avoid deliberate underperformance from the testee, hence decreasing the diagnostic ability of the test, and on the other hand, allows a more representative understanding of the weaknesses and strengths of each individual.

Neuroimaging

The tests described earlier are useful for assessing the cognitive difficulties caused by dyslexia. However, they provide an incomplete understanding of the effects of dyslexia on brain morphology, structure, and functioning. To investigate the neural correlates of dyslexia and potentially find new ways to diagnose it, a widely used method is the magnetic resonance imaging (MRI) or the functional magnetic resonance imaging (fMRI) [85]. MRI is a non-invasive imaging technique that examines the morphology of the brain through the use of magnetic fields [93], while fMRI analyzes the differences in blood oxygenation to assess brain activity [72].

MRI studies have revealed that dyslexic individuals have decreased brain volume and reduced gyrification compared to non-dyslexic individuals [24]. One indicator of brain volume is gray matter volume, which represents the amount of nervous cells involved in routing and analyzing stimuli in the central nervous system [100]. In dyslexic individuals, gray matter volume is reduced in the left temporal lobe, frontal lobe, thalamus, and cerebellum [17]. Gray matter abnormalities in dyslexia have also been studied in relation to age and sex differences [38]. The study examined four groups: 28 men (mean age 43 years), 26 women (mean age 34 years), 30 boys (mean age 10 years), and 34 girls (mean age 10 years). The men exhibited reduced gray matter volume in the left temporal gyrus and right supramarginal gyri, while the women showed reduced gray matter in the medial frontal gyrus. The boys had decreased gray matter in the left inferior parietal cortex, and the girls had reduced gray matter volume in the right central sulcus and left primary visual cortex.

While brain morphology provides useful information for diagnosis, it does not directly reveal brain activity. However, fMRI can be used to study brain functioning. For example, in a study [129], a functional disconnection of the left occipito-temporal cortex was observed in children with dyslexia. fMRI has also provided evidence supporting the theory that dyslexic children have a specific deficit in phonological processing [118]. In Temple et al.'s study [124], phonological processing was examined in a group of 15 dyslexic children compared to a group of 24 non-dyslexic children. The authors not only reported a phonological processing deficit in dyslexic children but also reduced activity in the left-hemisphere temporo-parietal area, consistent with existing literature [114, 18].

In addition to assessing brain activity, fMRI has been used to detect abnormalities in cognitive skills such as working memory [36], attention [27], mathematics [5], and problem-solving [3]. These skills can be negatively influenced by dyslexia. For example, in [10], dyslexic and non-dyslexic children were compared in three working memory tasks. The dyslexic group showed significantly impaired performance compared to the control group. Although both groups exhibited similar patterns of brain activation, the intensity of activation differed. The control group showed greater activity in the left cerebellum, middle frontal gyrus, and superior parietal lobule. This suggests that the intensity of activation, rather than the pattern of activation, may contribute to working memory deficits in dyslexic individuals.

The benefits of using fMRI are not limited to potential dyslexia diagnosis but also extend to monitoring the effects of treatment. Early screening and diagnosis of dyslexia are crucial for implementing necessary support tools and services. However, it is essential to validate the efficacy of these tools and potentially redesign treatments to enhance their effectiveness. fMRI can be utilized in this process. In a study [107], 18 children with dyslexia and 21 without dyslexia were examined during a phoneme mapping task. Children with dyslexia exhibited altered functional connectivity in the left inferior gyrus and its correlations with the right and medial frontal gyrus, right frontal gyrus, and right supplemental motor area. However, when dyslexic children participated in a 3-week program aimed at enhancing linguistic awareness, decoding, and spelling, these functional differences were nullified, indicating that treatment can produce functional benefits for dyslexic children. Another example of fMRI being used to monitor the effects of treatment on the brain can be found in [47]. The brain activation of a group of dyslexic children was compared to that of a group of non-dyslexic children while listening to rapid and slow acoustic stimuli. The non-dyslexic children showed a transition of activation in the prefrontal cortex between rapid and slow stimuli, which was not observed in the dyslexic group. Interestingly, after an 8-week program designed to enhance linguistic and phonological processing, the dyslexic group exhibited the same activation pattern found in the control group. These findings demonstrate the utility of fMRI for both potential diagnosis and monitoring of dyslexia treatments.

EEG

The electroencephalogram (EEG) is utilized to assess brain activity, with a particular focus on its temporal dimension [67]. Temporal information is a crucial parameter that provides insights into neuronal communication [125] and offers valuable perspectives on the functioning of dyslexic brains. For instance, in [4] analyzed the brain activity of 19 dyslexic children and 19 non-dyslexic children during various language tests, including rapid letter naming, phoneme detection, spelling, and articulation. The authors discovered that the dyslexic group exhibited increased slow activity in the frontal and temporal regions of the brain compared to the control group. These differences were interpreted as potential compensatory mechanisms employed by dyslexic individuals to overcome their difficulties [4]. This finding aligns with other studies that have also highlighted the presence of compensatory mechanisms in dyslexia [106].

Neuronal networks oscillate in different frequency bands, including delta (0.5-4 Hz), theta (4-7 Hz), alpha (8-12 Hz), beta (13-30 Hz), and gamma (above 30 Hz) [20]. Several studies have consistently reported abnormalities in these oscillations, which can be used to diagnose dyslexia. Dyslexic individuals tend to exhibit increased delta and theta oscillations, while beta and alpha oscillations are decreased [96]. These differences in oscillatory activity suggest delayed cerebral maturation and specific phonological processing deficits in dyslexia [60].

EEG can be combined with functional magnetic resonance imaging (fMRI) to gain a more comprehensive understanding of brain activity. This combination overcomes the limitations of each technique, as fMRI lacks temporal resolution, while EEG lacks spatial resolution [82]. Grunling et al. employed this integrated approach to analyze a group of dyslexic children and a control group during a pseudoword rhyming task [52]. The results revealed reduced amplitudes and latencies in fronto-central and temporo-parietal areas of dyslexic children, indicating phonological processing deficits [52]. Furthermore, fMRI data showed dyslexia-specific overactivation in the inferior frontal region, which corresponded to the phonological deficit observed in the EEG findings [52].

Lehongre et al. investigated auditory cortical oscillations and activations in dyslexic individuals and control subjects using EEG and fMRI [71]. The study revealed distinct patterns of dominant gamma oscillations in the left hemisphere and prevalent delta-theta oscillations in the right hemisphere in the control group. In contrast, dyslexic individuals exhibited disrupted distinctions in these oscillatory patterns, suggesting altered auditory processing in dyslexia [71].

In summary, EEG provides valuable insights into brain activity, particularly its temporal aspects. Dyslexic individuals often exhibit deviations in neuronal oscillations, which contribute to our understanding of the phonological deficits observed in dyslexia. The combination of EEG and fMRI offers a holistic perspective by integrating temporal and spatial information, enabling a comprehensive exploration of dyslexia-related neural mechanisms. These advanced techniques help unravel the complex nature of dyslexia and provide valuable insights for diagnosis and potential interventions [82].

Eye-tracking

Dyslexia, characterized by a significant reading deficit, can be better understood by studying the connection between visual attention and eye movement during reading, which can aid in the development of new screening and diagnostic methods for specific learning disorders like dyslexia [113]. Studies utilizing eye-tracking technology have demonstrated that dyslexic individuals exhibit distinct saccade patterns compared to non-dyslexic individuals [31, 75], including single fixations for a limited number of words, multiple fixations for other words, and modulation of gaze duration based on word length [8]. These differences may be attributed to oculomotor deficits [65], which could explain the impaired visuo-attentional processes observed in dyslexics [8]. These deficits are at the core of the ”sluggish attentional shifting” hypothesis [55], which proposes that once dyslexic individuals fixate their attention, it becomes difficult for them to disengage and shift their attention elsewhere. This attentional deficit extends to various sensory modalities, as dyslexic children demonstrate deficits in orienting and focusing spatial attention across auditory and visual domains [39]. These difficulties have a detrimental impact on phonological representation, which is considered the primary deficit in dyslexia [94].

1.0.3 Technologies to support dyslexic students

In the previous section, the importance of a timely and effective diagnosis was emphasized. This is crucial because dyslexia introduces a range of challenges that extend beyond cognitive impairments to impact the psychological well-being of those affected. Early diagnosis is key, as it can help reduce the disparities between dyslexic and non-dyslexic children. However, when diagnosis occurs later in life or is missed altogether, it becomes essential to employ support tools to assist dyslexic individuals in managing their difficulties. Many of these support tools are digital, such as specialized fonts designed to aid reading or text-to-speech features that allow users to listen to written content. In the following sections, the use of digital tools in education will be discussed, followed by an in-depth exploration of how these tools specifically benefit dyslexic individuals.

Digital tools in education

In today's rapidly evolving educational landscape, digital tools have emerged as powerful catalysts for transforming the way students learn and educators teach. Traditional classroom teaching does not provide an immediate learning environment, faster assessment and greater engagement. In contrast, digital learning tools and technology fill this gap. Therefore, these tools have become integral components of modern education, reshaping traditional methods and offering innovative solutions to long-standing challenges [29]. As technology continues to impact the learning environments, it brings with it a host of benefits that provide help to subjects with different learning styles, abilities, and needs. From interactive software that enhances student engagement to adaptive learning platforms that personalize education, digital tools are redefining what is possible in the classroom and beyond [48]

An example of a digital tool is the e-learning. E-learning is the application of information and communication technologies to favor web-based, computer, digital or online learning [81]. This tool brings several benefits to the students, for instance it allows the creation of self-directed learning tools. In [68], the authors created an e-learning module to assist master and post-graduate students in developing their knowledge before enrolling in a course. The e-learning module consisted of audiovisual presentation, graphical theme, animations and case-based learning. The results show that the e-learning module increased the engagement of the students as well as their learning outcomes. Another significant benefit of e-learning is the ability to revisit and repeat content. In traditional classrooms, students must absorb what the lecturer explains while simultaneously taking notes. Once the lecture ends, students are left with only their notes to review, missing out on the full lecture content. In contrast, e-learning platforms often provide tools like repositories with recorded lectures, enabling students to interact with and review the material as many times as they wish. Moreover, recorded lectures accommodate various learning styles. For instance, some students learn more effectively in the evening [98], a time when traditional classes are unavailable, whereas online content can be accessed at any time. Additionally, e-learning offers the flexibility to adapt content to various curricula, allowing it to meet the specific needs of different educational programs.

Another type of digital tool available to students is the smartphone and tablet. These devices offer important benefits such as portability, widespread use and access to the internet, granting therefore the access to e-learning platforms. Its wide acceptance among young people have made mobile devices an emerging tool capable of expanding the frontiers of education beyond the classroom. Research on the possible uses and potentialities of mobile technologies is growing. For instance, in [28] the author designed an application for tablet to support elementary students in their learning of the concept of angle. The students used their devices to identify and photograph angle- like shapes that appeared in their environment (for example in a tree stump or in the corner of a table); the students then analyzed these images using the application contained in their tablets. In this way the students analyzed whether the angles that occurred in their physical environment actually conformed to the mathematical properties of an angle. The result of this method is that the students reported a greater understanding of the concept of angle and also payed more attention to the mathematical properties rather than to their visual appearance. In another study [136], the authors created a mobile phone game, "MobileMath", to allow students to learn geometry. This game is location-based and uses the GPS the track the movements of the users. The scope of the game was to create and explore the quadrilaterals and their properties on a real playing field outside the classroom. The researchers found that certain features of this game (like the fact that the game in itself as a whole is competitive) result in quite an engaging experience for the students; in addition, the game allows students to notice geometrical aspects of the real world.

Massive Open Online Courses (MOOCs) are among the most popular types of e-learning platforms. MOOCs typically employ a multimedia format, utilizing various resources, most commonly in the form of concise videos focused on specific topics with clearly defined learning objectives. A notable feature of MOOCs is the opportunity they provide for students to connect and collaborate with their peers. This interactive aspect allows learners to ask questions about concepts that may be unclear, exchange additional resources, and enhance their overall learning experience. A significant advantage of MOOCs is that they usually do not impose a limit on the number of participants and are accessible to anyone interested in acquiring knowledge on a particular subject. Participants have the freedom to engage with as much or as little of the course content as they choose [15]. Furthermore, MOOCs can serve as supplementary material for topics covered in traditional classrooms, offering learners the chance to understand the same concepts from different perspectives, as explained by various instructors. A practical example of integrating a MOOC into traditional classroom settings is discussed in [59]. In this instance, 26 students participated in a MOOC designed to introduce them to the fundamentals of databases. Alongside this online course, they also attended an on-campus computer science class. In the physical classroom, the teacher concentrated on facilitating in-class activities, overseeing projects, conducting assessments, and addressing specific student queries. The findings indicate that most students engaged with at least half or the entirety of the online course, and the time they spent with study materials increased in this blended learning environment compared to conventional classroom teaching. In another study [59], over 15,000 students enrolled on three college preparatory MOOCs, covering remedial algebra, college-level algebra and college-level statistics. This study included both matriculated and non-matriculated students. The results show that matriculated students generally performed better than non-matriculated ones. Success was linked to student effort, particularly in completing problem sets and watching video lectures. For the statistics course, passing rates correlated with the amount of video content viewed, with students needing to watch over 223 hourse to have a 50% chance of passing.

As the benefits of MOOCs in enhancing student learning experiences continue to be assessed, another advanced digital tool is garnering significant attention in the educational field—virtual reality (VR). VR technology, as described by [83], allows users to be "fully immersed in, interact with, and experience in real-time a three-dimensional simulated environment that can represent realistic or imaginative scenarios". By utilizing VR, educators are able to present educational content to students in an entirely new and captivating way. For instance, [40] discusses the development of VR-based software designed to aid medical students in understanding the anatomy of the heart using 3D models. In this study, students engaged with the VR system to virtually dissect different heart structures, enabling them to explore the various components of the heart in detail. They could interact with the models by rotating, enlarging, and minimizing the heart's structures. After the VR sessions, students were administered a 25-question quiz. The findings revealed that students displayed significantly higher levels of engagement compared to traditional textbook-based methods and exhibited a deeper comprehension of heart function. Another study by [1] involved 48 engineering students using VR to learn engineering concepts and the mathematical principles behind the operation of specific engine parts. Following these sessions, students completed quizzes that tested their mathematical skills and understanding of the concepts covered in the VR lectures. The results demonstrated that the use of VR substantially enhanced the students' performance compared to those who did not utilize the VR tool. Specifically, the heightened level of immersion provided by VR enabled students to visualize the individual components of engines and progressively grasp how these parts interact, thereby enhancing their overall understanding.

This section provided an overview of the digital tools currently being explored to support students in their learning journey. The studies cited here demonstrate that the integration of these new technologies can significantly accelerate students' learning across various disciplines. Consequently, digital tools are also being employed to assist students with neurodevelopmental disorders, such as ADHD, autism, and dyslexia. Beyond boosting the learning rates of students facing challenges, these tools also contribute to narrowing the gap between students with neurodevelopmental disorders and their neurotypical peers, thereby fostering a more inclusive educational environment.

Digital tools in dyslexia

Dyslexia is characterized by a constellation of deficits that not only include cognitive difficulties but also psychological ones. For this reason, the use of digital tools to support dyslexic students is currently being investigated. As an example, e-learning represent a valid option in the creation of supporting tools for education. This is also true for children with dyslexia. For instance, in [99], the authors designed a web-based e-learning platform aimed at improving the reading difficulties of dyslexic children. The platform was composed of six major modules such as the learner profile module, the content repository module , learner goals module, the assistive learning engine module, the transformation base module and the monitoring module. Based on the learning goals and the learner profile, the content was transformed, through the assistive learning engine, into a format that suited the best the user. This tool was positively valued by dyslexic children and represent an attempt to customize the learning experience of users with SLDs. A major limit of this platform, however, is that it only focused on the reading difficulties of dyslexics. The main disadvantage of the platform was that it was focused only on the reading difficulties of dyslexics, while it did not take into account the other difficulties that dyslexics can experience. In [11] however, the authors designed a platform that considered the characteristics of each learner. The system indeed, took into account several factors such as the learner cognitive profile, learning style preference, learning goals, specific difficulties, the most frequent errors that the user does. By testing the platform on children with and without dyslexia, the authors observed that the children with dyslexia had different profiles with respect to the errors done, the learning goals and preferred learning style. This work confirms the importance of a customized e-learning environments to help dyslexics to mitigate some of their issues.

Another promising tool discussed in the previous section is the smartphone. Indeed, its ease of use and widespread adoption make the smartphone a useful device for reaching as many dyslexic children as possible. In addition, the use of smartphones does not only facilitates a wide screening but also offers a potential engaging platform to improve the cognitive difficulties encountered by dyslexics. For instance in [6] the authors developed a mobile application to screen and train individuals with dyslexia and dysgraphia. The subjects had to read and pronounce 15 words and had to write 15 numbers with increasing levels of difficulty. The mobile application then, compared the progress made during the time and provides feedbacks to the users. In another work [117], children were trained in four categories using mini-games: ”word” category with the goal of supporting the children’s reading skills and enrich their vocabulary, ”numbers” category which focuses on supporting the mathematical abilities of the children, ”memory” category aimed at improving children’s short-term memory and attention and, lastly, the ”book” category with the goal of strengthening children’s concentration through reading and increase their interest in reading. The results showed that most of the users had higher performance compared to their performance before the training phase. Also, they no longer needed a constant assistance when reading or writing since their word recognition and phonological decoding improved. Similar results were found in [13], where a mobile game application was designed as an alternative method to support dyslexic students in three cognitive domains that are usually negatively affected, visual, auditory and working memory. The application demonstrated to be an efficient method to encourage and motivate children to overcome their difficulties and provided a useful tool for learning.

Another tool useful to help dyslexic students is the VR. Indeed, thanks to this device it is possible to test, screen and support dyslexic subjects in a new way. For instance, in [79] 28 children with dyslexia were enrolled in a program to study if the use of VR could ameliorate the difficulties associated with dyslexia. The group was divided in two, the first underwent a conventional neuropsychological treatment while the second one performed a VR training. The results showed that the group who was treated with the VR training improved their word reading scores. In addition, children using the VR showed greater engagement, motivation and enjoyment which allowed for longer training sessions.

Another example of the VR used to enhance specific cognitive skills such as executive functions and memory can be found in [33] and [64]. In the former, 24 children with SLDs underwent a six-weeks program aimed at improving their executive functions. The assessment was done at the beginning of the training, at the end of it and after 6 months from the end of the program. The results showed that thanks to this VR training, the children increased their scores in visual attention, inhibition, flexibility and planning. In addition, most of these enhancements were maintained after 6 months from the end of the training. In the latter study instead, the authors tested memory performance of dyslexic students with VR device. The results were interesting because showed that undergraduate dyslexic students do not differ significantly from non-dyslexic students, highlighting the development and successful use of compensatory strategies. Another study [95], used a VR-based mini-game to improve reading abilities in dyslexic children. Children were tested in three different tasks before and after the test. The tasks were: reading of words/non-words, attentional blink test (in which the subject had to identify the colored letter) and Posner’s task (in which the participant had to press a button when a target appeared. The results show that the reading time were decreased but still higher than non-dyslexic children. This suggests that a more prolonged exposure time with the rehabilitation device might be necessary to further enhance the reading capabilities of dyslexic children but that it can be a future direction.

Beyond the digital landscape, there are also more straightforward yet impactful tools that can make a significant difference in how dyslexic children interact with text. One such tool is the use of dyslexia-friendly fonts. By incorporating these fonts, which are specifically crafted to reduce letter confusion and improve readability, it is possible to support dyslexic students both in and out of immersive digital spaces. An example is the use of the font "Dyslexie" [35]. The rationale behind this font is that people with dyslexia tend to confuse similar-looking letters such as b and d for instance. Therefore by using thicker lines, above-average spacing between the words, Dyslexie can ameliorate the difficulties that dyslexics have when reading. In a study [80], 39 dyslexic children were asked to read texts presented in either Dyslexie or Arial font. The findings revealed that participants read 7% faster when using the Dyslexie font compared to Arial. Additionally, the study highlighted that the increased spacing between words significantly contributed to faster reading times, whereas the thickness of the lines did not have a notable impact on reading speed. Another widely studied font is the "OpenDyslexic" font [135]. For instance, in [46] the authors measured the eye movements of adults with and without dyslexia during the reading of a set of standardised texts. OpenDyslexic improved the reading comprehension in dyslexics and non-dyslexics. These improvements were greater for dyslexics. However, reading speed was not affected by the use of a specific font. OpenDyslexic yielded increases in visual search intensity and visual ease in the form of decreases in median fixation duration and fixation to saccade ratio as well as a smaller number of falsely programmed forward saccades.

The tools discussed in this section may be useful in addressing some of the challenges faced by individuals with dyslexia, but they do not take into account differences between individuals. Each person is unique, and the severity of cognitive and psychological difficulties can vary from one student to another. It is crucial to tailor the learning experience to the specific needs and goals of each individual, as this enables the creation of a personalized set of tools that supports a customized learning journey. One way to achieve this is through the use of Artificial Intelligence (AI) and Machine Learning (ML).

1.0.4 The role of AI and ML in dyslexia

Today, we are witnessing a new technological revolution driven by the increasing popularity and application of AI and ML algorithms in a wide range of fields, including biology, psychology, medicine, finance, sports and agriculture [76]. But what exactly means the terms ML and AI? ML involves the design of mathematical models that can learn and improve from data without being explicitly programmed [116]. It falls under the domain of artificial intelligence (AI), which aims to simulate human cognitive abilities such as learning, reasoning and problem-solving [56]. These technologies are growing in popularity due to their ability to analyze large volumes of diverse data, integrate different types of information, and detect patterns that may be difficult for humans to identify. In order to to this, mathematical models are used. As described in [32], the most used algorithms are:

- Artificial Neural network (ANN): ANNs are a type of machine learning model that mimics the way human brains process information. They consist of layers of artificial neurons, where each neuron takes input, processes it, and passes it on to the next layer. The model is made up of an input layer, one or more hidden layers, and an output layer. Neurons in each layer are connected to neurons in the next layer, with each connection having a weight. The model learns by adjusting these weights based on the error in its predictions, using an algorithm called backpropagation.

- Decision tree (DT): A decision tree is a tree-structured model where each internal node represents a "decision" or test on a feature, each branch represents the outcome of the test, and each leaf node represents a final decision or classification. The model recursively splits the data into subsets based on the most significant feature at each step. The goal is to divide the data in a way that best separates the different classes (or outcomes), often using metrics like Gini impurity or information gain to determine the best splits.

- Naive Bayes (NB): Naive Bayes is a probabilistic classifier based on Bayes' Theorem, which calculates the probability that a given data point belongs to a particular class. The "naive" assumption is that all features are independent of each other, which simplifies the calculations. It computes the likelihood of each feature contributing to a class and combines them to make predictions. Despite the unrealistic assumption of independence, Naive Bayes works surprisingly well in many practical situations, especially when dealing with large datasets and high-dimensional feature spaces.

- Random Forest (RF): Random forest is an ensemble learning method that builds multiple decision trees during training and aggregates their results to make more accurate and stable predictions. Each tree in the forest is built on a random subset of the data and selects random subsets of features at each split. This randomness helps reduce the likelihood of overfitting and increases the model's ability to generalize. The final output is the majority vote (classification) or the average (regression) of the individual trees' predictions.

- Support Vector Machine (SVM): An SVM is a powerful supervised learning algorithm primarily used for classification tasks. It works by finding the optimal hyperplane that best separates different classes of data points in the feature space. SVM tries to maximize the distance between the closest points of the classes (called support vectors) and the separating hyperplane. For non-linearly separable data, SVM uses a technique called the "kernel trick" to map data into a higher-dimensional space where it can find a linear boundary.

- Linear Regression (LIR): Linear regression is a simple yet powerful statistical method for predicting a continuous outcome based on one or more input features. It assumes a linear relationship between the dependent variable (the target) and the independent variables (the features). The model finds the best-fit line through the data by minimizing the sum of squared differences between the actual and predicted values.

- Logistic Regression (LR): Logistic regression is used for binary classification problems, where the goal is to predict whether an instance belongs to one of two classes (e.g., yes/no, true/false). Logistic regression uses the sigmoid function to map predicted values to probabilities between 0 and 1. The model outputs the probability of the instance belonging to the positive class. A decision threshold is used to classify instances.

As previously said, these algorithms are growing in popularity and their adoption is widespread in virtually every human-related field. The education sector for children with special needs is no exception, as a growing body of research is investigating how AI and machine learning can be leveraged to improve early screening for developmental disorders like dyslexia and to boost the learning outcomes of affected children. The significance of timely and accurate diagnosis has already been discussed in previous sections. Consequently, a substantial number of studies are dedicated to this area of focus. For instance, in a recent study by Wang et al. [133], an artificial neural network (ANN) combined with a genetic algorithm was used to assess the most significant factors in predicting dyslexia in Chinese children. The model achieved an impressive accuracy of 94% and highlighted reading accuracy as the most critical factor in diagnosis. Other relevant deficits included phonological awareness, reading fluency, rapid digit naming, and reaction times. Another example can be found in the study by Le et al. [70]. They conducted comprehensive assessments on dyslexic and non-dyslexic children, encompassing tasks related to reading, spelling, memory, attention, phonological skills, movement, visual attention, and hearing. Through a principal component analysis (PCA), they identified the most informative tasks for dyslexia diagnosis, which included reading and spelling tasks, phonological tasks, visuo-attentional tasks, and auditory tasks. By employing logistic regression solely on the performance of these tasks, the classification model achieved an impressive accuracy of 94% in diagnosing dyslexic children. It is worth noting that cognitive performance and reported difficulties are not the sole parameters amenable to analysis for dyslexia diagnosis. Handwriting analysis can also be an effective screening tool. For example, Yogarajah et al. [139] compared the handwriting of dyslexic and non-dyslexic children using a convolutional neural network (CNN). This method yielded an average accuracy of 86% in detecting subjects with and without dyslexia with no need of cognitive tests.

While the use of machine learning for diagnosing dyslexia is crucial for ensuring early intervention and proper support, the role of these technologies does not end there. Beyond diagnosis, machine learning is also being utilized to assist dyslexic individuals in their learning journey. With personalized, adaptive tools, ML can help address the unique challenges faced by these individuals, offering tailored solutions to enhance both their reading and writing skills. For example, in [120], the authors conducted a comprehensive evaluation of four machine learning (ML) models—Random Forest (RF), Decision Tree (DT), Naive Bayes (NB), and Support Vector Machine (SVM)—to predict the academic performance of students from 22 high schools. Among these models, the Random Forest (RF) model achieved the highest classification accuracy, while Naive Bayes (NB) performed the worst. To further enhance their analysis, the authors integrated a principal component analysis (PCA) into each of the models and examined the impact on their performance. The addition of PCA resulted in hybrid models that exhibited improved accuracy compared to their baseline versions, indicating a significant enhancement in predictive capability. The results clearly demonstrate that ML models, particularly when augmented with techniques like PCA, can be effectively employed to predict academic performance. By leveraging predictions of student performance, teachers can gain valuable insights into both the strengths and weaknesses of their students, enabling them to implement more targeted strategies to improve learning outcomes. Moreover, predicting student performance plays a crucial role in tracking academic progress and, if necessary, triggering timely pedagogical interventions to ensure students successfully complete their courses. The ability to anticipate academic difficulties provides instructors with the opportunity to address learning gaps early on, ultimately helping students achieve better educational outcomes and promoting a more personalized learning experience for each individual. Another example of using ML to assist dyslexic children is discussed in [97]. In this case, the reading abilities of 622 children (388 with dyslexia) were mapped onto an ANN to replicate the process through which children learn to read. The model was then compared to the actual reading results of these 622 children using the exact same words the children read. This approach allowed researchers to explore how deficits in components of the reading network might predict individual differences in reading ability across three areas: efficiency of the orthographic lexicon, accuracy in phoneme activation, and vocabulary score, which measured each child's lexicon. The findings demonstrated that the model effectively simulated both typical and impaired reading development based on performance in these categories. Furthermore, using the reading performance in just three categories was enough for the model to predict learning outcomes in children with and without dyslexia. Tracking the difficulties encountered by dyslexic children is an important activity to ensure that adequate support is given. An example of this can be found in [88]. Here, the authors tracked and collected the difficulties of dyslexic children in phonology, writing and reading through a computer-based video-game. Then, they have developed a Hidden Markov model to recognize the difficulties of each user and propose a teaching path that is based on those. Thanks to this approach, 60% of the children affected with dyslexia improved their skills with respect to standard support tools. Another approach was followed in [102], where object character recognition (OCR) was mixed with ML in order to help dyslexic children in reading. Specifically, a smartphone application was developed to utilize the phone's camera for capturing the text being read by the user. The application then allowed users to modify the text by adjusting the font style and size, altering the background color, highlighting challenging words, and requesting simpler synonyms for difficult terms. Machine learning, particularly through an artificial neural network (ANN), was employed to track complex and unfamiliar words for each individual user. This approach enabled the algorithm to anticipate difficult words and autonomously suggest easier synonyms, reducing the difficulties faced by dyslexic users without needing their direct input. As a result, it effectively alleviated some of the challenges associated with reading for individuals with dyslexia. In [126] instead, the focus is on enhancing both reading and writing abilities in dyslexic students. This is achieved through the use of a SVM predictor that undergoes continuous training based on the students' performance in serious educational games and targeted exercises. These games and exercises are designed to be adaptive, with their types and difficulty levels dynamically adjusted according to the real-time performance data gathered from the students. As a result, the system is able to provide personalized learning experiences that evolve with the individual student's progress. Notably, this method has shown significant improvements not only in the students' overall reading and writing skills but also in their level of engagement and motivation in the learning process. Furthermore, this approach offers additional benefits by enhancing the ability of parents and therapists to monitor and track the students' ongoing progress, providing valuable insights and allowing for more effective interventions and tailored support plans.

The studies reported here, underscore the crucial role that ML plays in the development of support tools for individuals with dyslexia. These tools have the potential to significantly enhance the educational experience and outcomes for dyslexic learners by providing personalized assistance and tailored interventions. However, it is important to note that the majority of existing research predominantly concentrates on children and adolescents with dyslexia. This focus has resulted in a substantial body of knowledge regarding the effectiveness of various support tools for younger students. Despite these advancements, there has been relatively little attention given to the development of similar support tools for university students who have dyslexia. As a result, there is a notable gap in our understanding of how best to support dyslexic individuals at the higher education level. The specific challenges faced by university students with dyslexia can differ significantly from those encountered by younger students, such as the increased demands for advanced reading comprehension, academic writing, and time management. Consequently, addressing this gap is essential for ensuring that university students with dyslexia receive the appropriate resources and accommodations needed to succeed academically and achieve their full potential.

In response to this gap in support for university students with dyslexia, we have developed an innovative framework known as VRAILEXIA. This cutting-edge framework integrates VR with AI to create specialized support tools tailored specifically for higher education students facing dyslexia. The primary goal of this initiative is twofold: first, to design and implement support tools that are meticulously crafted to address the unique challenges encountered by university students with dyslexia; and second, to ensure that these tools are highly personalized to meet the individual needs of each student.

Chapter 2

VRAILEXIA: a framework to support dyslexic students during their learning path

2.0.1 What is VRAILEXIA? - An introduction to the project

The development of support tools for dyslexia is essential, especially when early diagnosis is either missed or delayed. With advancements in technology, we now have the opportunity to utilize the computational power and adaptability offered by mathematical models capable of learning and making predictions. These models, which fall under the categories of ML and AI, are increasingly being applied in educational settings. While much of the current research focuses on children and adolescents with dyslexia, there is a notable lack of support for dyslexic students in higher education, such as universities. The VRAILEXIA project—standing for Virtual Reality and Artificial Intelligence Applied to Dyslexia—emerges from the need to address this gap. Several factors contribute to this necessity. Firstly, the volume and nature of study at the university level differ significantly from that of primary and secondary education. Secondly, the complexity and depth of material encountered in higher education present greater challenges. Lastly, it is likely that different study techniques and strategies are required in the university context compared to earlier educational stages. By harnessing the advanced capabilities of AI and ML, VRAILEXIA provides a dynamic and adaptive learning experience. Each student will benefit from a personalized learning path that evolves over time, continuously adjusting to their progress and changing requirements. This means that as students advance in their studies and encounter new challenges, the tools provided will adapt in real-time, offering ongoing, customized support that aligns with their evolving academic needs and learning styles. Through this approach, VRAILEXIA aims to bridge the

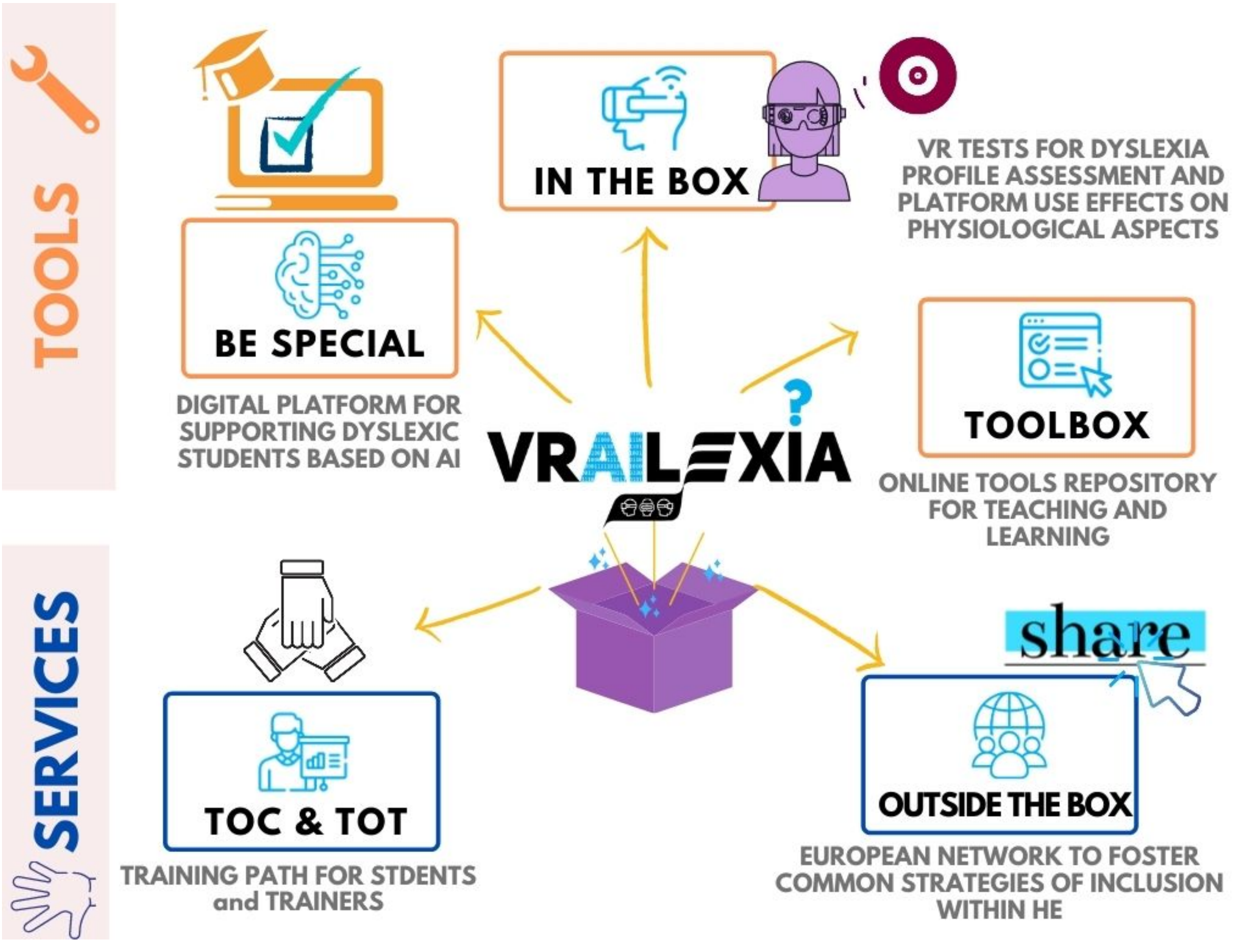


Figure 2.1: The building blocks of the VRAILEXIA project.

existing support gap and enhance the academic experience for dyslexic students in higher education, ensuring they have the resources and flexibility needed to thrive in their studies and achieve their full potential.

To do so, the VRAILEXIA project is structured around two main modules: "Tools" and "Services" (Figure 2.1). The "Tools" module includes three key components aimed at alleviating the challenges faced by dyslexic students. The first component, "In the Box," focuses on developing VR tests specifically designed for dyslexia profile assessment. Unlike traditional assessment methods, these VR tests create an immersive, interactive environment that not only engages students but also accurately monitors and tracks their individual difficulties. By gaining a more nuanced understanding of each student's unique challenges, the project can offer highly targeted support strategies that are far more effective than one-size-fits-all solutions. Moreover, the dynamic and adaptable nature of VR assessments means they can evolve with new research findings and student needs, ensuring ongoing relevance and effectiveness in providing support. The second component is "Be Special" which is the core of this thesis dissertation. This unit is dedicated to the creation of ML models that aid dyslexic students throughout their learning journey. ML algorithms have the power to analyze large amounts of data, identify patterns, and adapt in real time, making them exceptionally well-suited for this purpose. By harnessing this technology, "Be Special" offers tailored, data-driven interventions that adapt to the individual learning patterns of each student. These interventions can evolve alongside the students, providing personalized recommendations and support that help them overcome specific obstacles as they progress through their studies. For example, by continually analyzing a student's performance and behavior, the ML models can suggest optimal learning strategies, study techniques, and even content modifications. This adaptive learning environment not only empowers students to tackle their unique challenges but also promotes a more inclusive and flexible educational experience. Finally, the "Toolbox" serves as an online repository, offering teachers and students additional resources that can be readily accessed. This repository is more than just a collection of tools; it is a dynamic platform aimed at fostering a deeper understanding of dyslexia among educators and providing them with practical strategies to adapt their teaching methods. By including resources such as lesson plans, teaching strategies, and adaptive learning materials, the "Toolbox" helps bridge the knowledge gap, ensuring that teachers are equipped to address the diverse needs of dyslexic students. On the other hand, the "Services" module focuses on the practical application and dissemination of the tools and strategies developed within the project. It comprises two units: "Toc & Tot" and "Outside the Box." "Toc & Tot" is designed as a training environment for both students and teachers. This training is not a one-time event but an ongoing process aimed at refining teaching methods based on real-world data and outcomes. After completing the "ToT" sub-unit, teachers are tasked with designing and implementing lectures in the subsequent semester, using the latest data collected from the "Be Special" unit. This iterative process ensures that the teaching methods are continually evolving, informed by up-to-date insights into the learning needs and progress of dyslexic students. This data-driven approach promotes a responsive and adaptive educational environment, where instructional strategies are consistently aligned with the students' evolving needs. The second unit, "Outside the Box," aims to establish a collaborative network of European university partners (as shown in Figure 2.2). This aspect of the project is crucial as it addresses the need for a unified, international approach to supporting dyslexic students. By fostering an exchange of information, best practices, and resources among partner universities, "Outside the Box" encourages the development of innovative and inclusive strategies tailored to the challenges dyslexic students face in higher education. This network not only facilitates the sharing of expertise and knowledge but also strengthens the collective ability to devise new solutions. Through this collaborative effort,

Figure 2.2: The European partners of the VRAILEXIA project

the VRAILEXIA project aims to promote an inclusive academic environment for dyslexic students

As outlined in the previous section, this thesis dissertation focuses on the "Be Special" unit, which seeks to leverage the potential of ML to develop personalized support tools for dyslexic students. The initial analysis began with an exploratory study conducted at the University of Tuscia in Viterbo. This study aimed to identify the number of dyslexic students enrolled across various courses and evaluate the nature and severity of the challenges they faced. The objective was to pinpoint the key difficulties encountered by university students with dyslexia and identify potential strategies to alleviate these obstacles. Subsequently, a suite of ML algorithms was employed to recommend the most suitable learning tools and study techniques tailored to each student's needs. The algorithms used in this process included RF, LR, LIR, k-nearest neighbors (kNN) and SVM, along with both collaborative and content-based recommendation systems. The following subsections of this chapter will delve into the rationale and methodologies employed in these studies, providing a detailed overview of the processes involved. Chapter 3 will then present the results derived from each study, offering insight into the effectiveness of these ML-driven support tools and strategies.

2.0.2 The explorative analysis - understanding the needs of the students

In order to design, create and implement the suite of ML models to support dyslexic students data were collected and analyzed. To do this, a questionnaire was administered to Italian students with dyslexia who fulfilled two prerequisites: 1) being at least 18 years old and 2) attending university or left it at most 5 years earlier. The questionnaire underwent a double conformity check. After a validation conducted by the ethics committee of the University of Tuscia, the research proposal was sent to the National University Conference of Disability Delegates (CNUD) for a second approval. A total of 66 Italian universities took part on this study and the students who took part had a diagnosis of SLD issued no later than 3 years ago. As shown in Table 2.1, the questionnaire was composed of three sections, namely "Demographic Information", "Dyslexia status and history" and "Issues and support methodologies". The last section was composed of additional threes sub-units, "Experienced issues", "Support tools" and "Support strategies". The first section collected demographic information such as age, gender, high school enrolled and attended university degree course. The second section was related to the dyslexia status of each student. Some of the questions were about the year of the diagnosis, comorbidity with other SLDs or other difficulties. The third section instead is focused on the specific issues encountered by students during their learning path and on the learning tools and study strategies they found particularly useful or useless.

This section was divided into three sub-sections: the first focused on the issues experienced, the second on learning tools, and the third on study strategies. Participants were asked to rate each item on a scale from 0 to 5 (only integer values were permitted). A

		Issues and support methodologies		
Demographic Information	**Dyslexia status and history**	**Experienced issues**	**Support tools**	**Support strategies**
Age	Year of the diagnosis of dyslexia	Reading	Audiobook with human voice	Rehearsing
Gender	Other difficulties besides dyslexia	Writing	Words with different colors	Self-made schemes
Type of high school	Type of support received	Text comprehension	Fonts	Self-made maps
University degree	Other relatives with dyslexia	Uncommon words	Using a tablet to takes notes	Highlighting keywords
Year of university		Concentration	Clear layout of the material	Highlight with different colors
Non-resident student		Focused attention	Highlighted keywords	Study group

Table 2.1: Brief overview of some of the questions contained in the questionnaire.

score of 0 indicated a "not experienced" issue or a "useless tool/strategy," while a score of 5 indicated a "strong difficulty" or a "very useful tool/strategy." These three sub-sections were developed through face-to-face interviews with 25 students with dyslexia. During these interviews, every issue they encountered was documented, including those that were only partially experienced or occurred briefly. Additionally, the lists included all support tools and strategies the students had tried or expressed an interest in trying. This thorough method provided a comprehensive overview of their experiences and needs. To ensure completeness, a blank space was included for participants to add any issues, tools, or strategies they felt were missing. Notably, the questionnaire was designed to take less than 10 minutes to complete. This was intended to keep the survey brief and avoid the lengthy, repetitive tasks that can be particularly challenging for individuals with dyslexia. The questionnaire was administered online, and it received responses from 1,261 dyslexic students from across Italy. Out of these, 72 responses were excluded because the participants were either outside the study's age range or did not have a clinical diagnosis of dyslexia. As a result, the final database for analysis consisted of 1,189 questionnaires.

In this study [9], an agglomerative algorithm was employed to conduct a cluster analysis, a multivariate statistical method designed to group a set of units in such a way that those within the same group (referred to as a cluster) are more similar to each other than to those in other groups (clusters). Agglomerative clustering is the most prevalent form of hierarchical clustering, widely used for its effectiveness in creating typological groupings that are both distinct from one another and internally consistent [53]. This makes it particularly well-suited for identifying clusters that are cohesive yet separate. In this context, the units of analysis were the students who participated in the survey. Agglomerative hierarchical clustering works through a series of successive mergers. The process begins with each individual unit as its own cluster, meaning that initially, the number of clusters equals the number of units. The algorithm then iteratively merges the most similar units into groups, combining these groups based on their similarities. This merging process continues until all units are ultimately fused into a single cluster as the similarity thresholds diminish. In this way, it creates a hierarchical structure of clusters. To measure the similarity between units, we utilized the Gower distance [51]. The Gower distance is a versatile metric specifically designed to calculate the dissimilarity between two items that contain a mix of numeric and categorical data. Also known as Gower dissimilarity, this measure is particularly favored for datasets involving mixed-type variables because it normalizes the differences, providing a dissimilarity score that ranges from 0 to 1. This score is essentially an average of the scaled distances calculated for each variable individually. The Gower distance serves as the complement to one of Gower's similarity coefficients:

$$d_{G,ij} = 1 - s_{G,ij} = \frac{\sum_{t=1}^{p} \delta_{ijt} d_{ijt}}{\sum_{t=1}^{p} \delta_{ijt}} \tag{2.1}$$

It represents a measure of dissimilarity or distance between unit i and unit j, where $\delta_{ijt} = 1 - s_{G,ij}$ is the distance calculated for the $t-th$ variable, and $s_{G,ij}$ is the similarity between units i and j with respect to the $t-th$ variable. The value of this similarity measure depends significantly on the type of variable itself—whether it is nominal, ordinal, or continuous, among other types—since different variables may require different methods to calculate distances accurately. Once this distance measure is defined, the focus then shifts to the linkage methods, which determine how clusters are formed. Some of the primary linkage methods include single linkage (also known as minimum distance or nearest neighbor), complete linkage (maximum distance or farthest neighbor), average linkage (average distance), and Ward's linkage. Single linkage connects clusters based on the shortest distance between any two points in the clusters, while complete linkage uses the greatest distance between points, leading to more compact clusters. Average linkage considers the average distance between all points in the clusters.

Ward's method [53], in particular, is recognized as a hierarchical clustering procedure that is designed to minimize the "loss of information" that results from merging two clusters. This "loss of information" is quantified as an increase in the error sum of squares (ESS) criterion. Ward's method is unique in its approach to clustering, as it focuses on minimizing the total within-cluster variance. Each potential clustering step is evaluated based on the ESS criterion, ensuring that each merge results in the least possible increase in overall heterogeneity. This results in more uniform clusters that are internally cohesive, making Ward's method particularly useful in scenarios where maintaining homogeneity within clusters is crucial. Firstly, for a given cluster kk, let the sum of the squared deviations of each item in the cluster from the cluster mean (or centroid) be denoted as ESS_k. This measure reflects the internal cohesion of the cluster, indicating how closely the items within the cluster are grouped around their mean. If there are KK clusters in total, the ESS is defined as the sum of these squared deviations across all clusters, expressed as:

$$ESS = ESS_1 + ESS_2 + ... + ESS_k \tag{2.2}$$

At each iteration of the clustering process, the algorithm considers the union of every possible pair of clusters, evaluating which combination results in the smallest possible increase in the overall ESS. In other words, it seeks to merge the pair of clusters that leads to the minimal loss of information, thereby ensuring that the new clusters formed are as cohesive as possible. Initially, each cluster consists of just a single item, so if there are N

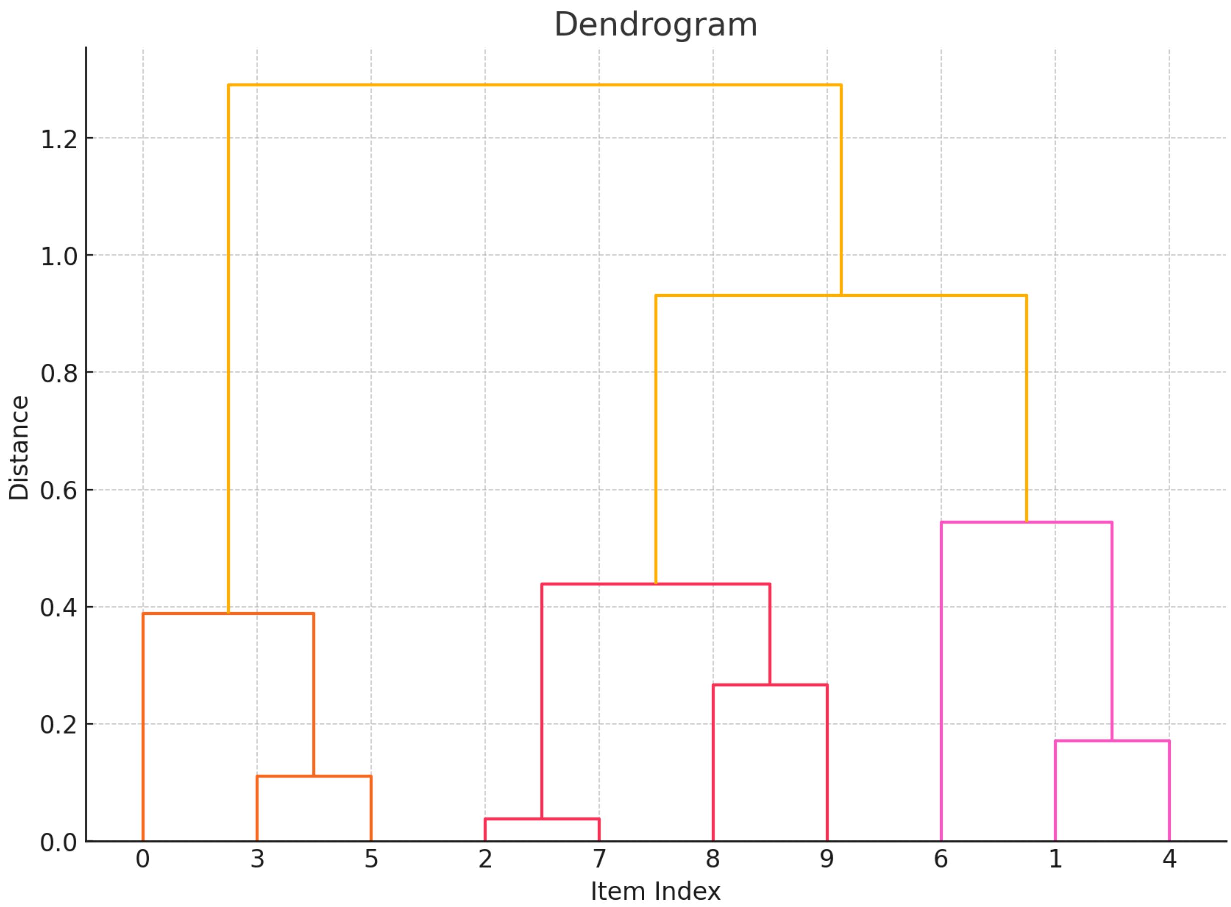


Figure 2.3: Example of a dendrogram

items, $ESS_k = 0, k = 1, 2, ..., N$ then $ESS = 0$. At the other extreme, when all individual clusters have been combined into a single group containing all items, the ESS reaches its maximum value given by $ESS = \sum_{j=1}^{N} (x_j - \overline{x})^2$. Where x_j is the multivariate measurement associated with the $j - th$ item and $\overline{x}$ is the mean of all the items in the dataset. The results of this agglomerative hierarchical clustering process can be effectively visualized using a dendrogram, a two-dimensional diagram that graphically displays the sequence of merges. The dendrogram illustrates which clusters were merged at each step and at what level of similarity or distance the merges occurred. This visual representation allows one to easily identify the structure of the data, such as the natural number of clusters, by observing where large jumps in the levels of the dendrogram occur, as shown in Figure 2.3. The horizontal lines in the dendrogram represent the clusters that were merged, while the height of each line indicates the dissimilarity between the merged clusters. Thus, the dendrogram serves as a powerful tool to understand the hierarchical relationships and the clustering process in a clear and intuitive manner.

2.0.3 The Machine learning classification model

After an initial exploratory analysis, where the results are discussed later in Chapter 3, ML algorithms were used to develop support tools for dyslexic students. Based on the collected answers to the questionnaire, the goal of this study was to use a suite of mathematical models to suggest, based on the issues reported by the students, the best learning tools and study strategies to dyslexic students [141]. Table 2.2 shows in detail the questions asked to each dyslexic student (1261 in total) and discussed in the previous section. The issues, indicated as P in Table 2.2 were used as input to train the ML models while the learning tools and study strategies (reported respectively as T and S in Table 2.2) were used as output (labels). This approach and the nature of the data available suggested the use of supervised ML algorithms. Using deep learning algorithm would have likely led to overfitting while reinforcement learning algorithms would be unsuitable due to the absence of sequential data for training [66].

An initial decision that had to be made involved determining whether to treat the output variables collectively or individually and, if collectively, how they should be grouped. This decision depended on whether the output variables, or some subset of them, were considered to be correlated with one another. Four options were meaningful: (1) all variables were considered correlated and thus were treated jointly (in this scenario, the labels would be vectors containing 39 usefulness scores assigned to the 17 tools and 22 strategies); (2) all tools and all strategies were considered intra-correlated but not inter-correlated, so the variables were divided into two groups (in this case, two predictions would be made—one using a 17-element vector with scores for the tools, and another using a 22-element vector with scores for the strategies as labels); (3) according to a correlation criterion, certain groups of variables were regarded as intra-correlated but not inter-correlated and were thus divided into n groups (in this situation, n predictions would be made, each using a vector with the scores for tools/strategies within a specific group as a label); (4) the variables were considered uncorrelated (in this case, a single prediction would be made for each individual tool/strategy, using the score given to that specific tool/strategy as the label). Although it could have been intuitively hypothesized that some of the tools or strategies listed in Table 2.2 exhibited some degree of correlation, the literature offered no evidence of interrelated support methodologies. In light of this, a cross-correlation matrix was computed by assigning a score to each response regarding the usefulness of each tool/strategy, and this score was treated as the value assumed by that variable, from 0 to 5 as described in Section 2.0.2. Spearman's correlation criterion was chosen because it was particularly well-suited for ordinal variables, such as the ones being considered. Therefore:

ID	**Difficulty/Tool/Strategy**	**ID**	**Difficulty/Tool/Strategy**
P1	Reading	T15	Audio recording of lessons
P2	Writing	T16	Video lessons
P3	Understanding difficult words	T17	Supplementing study material with internet research
P4	Understanding the lessons	S1	A person reading for him/her
P5	Concentration	S2	A map made by himself/herself
P6	Paying attention during in-presence lessons	S3	A scheme made by himself/herself
P7	Paying attention during online lessons	S4	A summary made by himself/herself
P8	Memorising recently studied concepts	S5	Repeat the studied material
P9	Remembering concepts studied during the exam	S6	Marking keywords
P10	Study time management	S7	Underlining with different colours
P11	Taking notes	S8	Having a study group
P12	Limited time available to prepare a task/question/exam	S9	Having a tutor
T1	Human voice audio book	S10	Dyslexic student group to exchange resources
T2	Robotic voice audio book	S11	Presential lessons
T3	Different colour words	S12	Online lessons available
T4	Using the EasyReading font	S13	Taking breaks during lessons
T5	Using a smart pen or tablet to take notes and record voice	S14	Lesson slides available
T6	Clearer layout of the study material	S15	Recording the lesson
T7	Having the key words of the text highlighted	S16	Taking notes
T8	Prepared concept maps	S17	Having the lesson plan in advance
T9	Prepared schemes	S18	Dividing an examination/task/ question into several parts
T10	Prepared summaries	S19	Only written tests
T11	E-Books	S20	Only oral tests
T12	Digital tutor	S21	Conducting the exams in the presence of the professor alone
T13	Images to help understand the meaning of difficult words	S22	Having an online database with notes made by other students
T14	Images that help to memorise a concept		

Table 2.2: Difficulties (P), support tools (T) and learning strategies (S) considered.

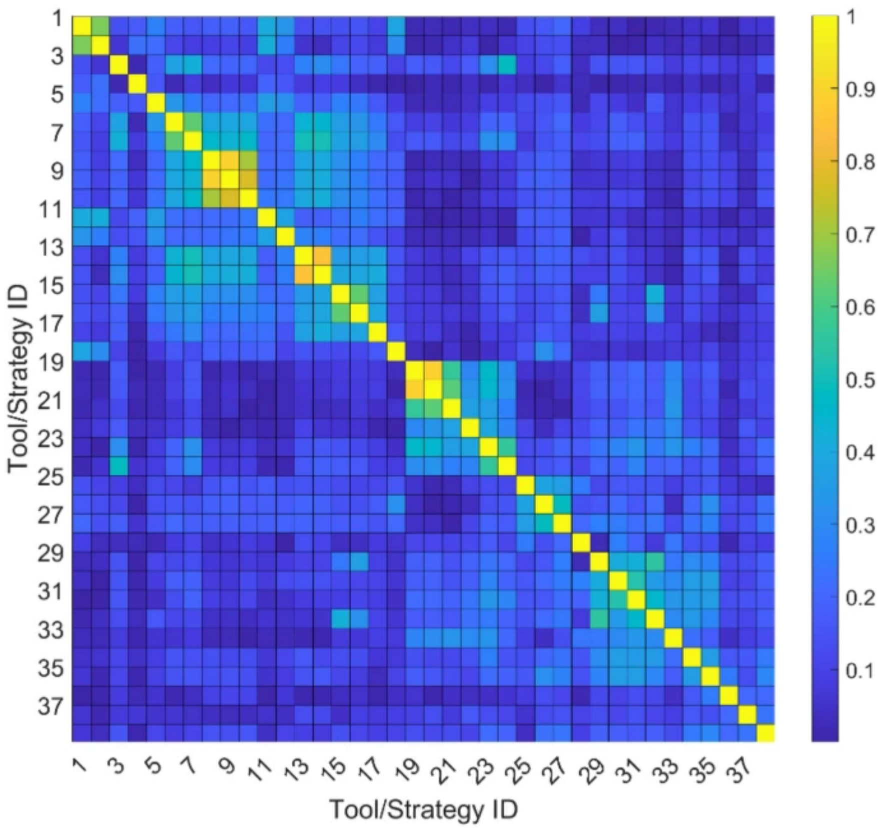


Figure 2.4: Spearman's cross-correlation (absolute value) matrix of the scores given to the usefulness of learning tools and study strategies.

$$\rho_{X,Y} = 1 - \frac{6 \cdot \sum_{i=1}^{Noss} (x_i - y_i)^2}{N_{oss} (N_{oss}^2 - 1)} \tag{2.3}$$

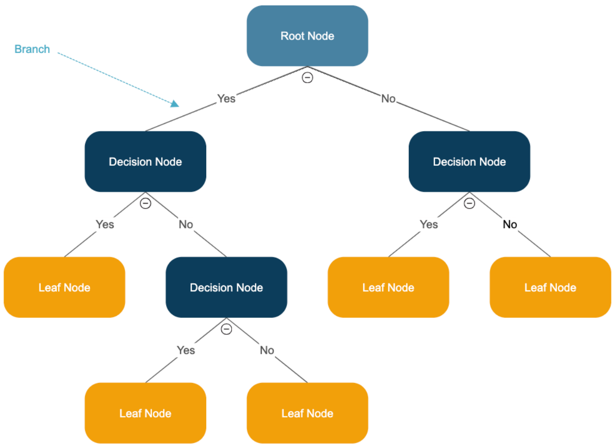
where x_i and y_i are the $i-th$ observations of two output variables, in other words are the scores given to two learning tools or study strategies, N_{oss} is the number of available observations. Figure 2.4 shows the results of the correlation. The learning tools are indicated with numbers from 1 to 17 whereas the study strategies are indicated with numbers from 18 to 39. The correlation coefficient is instead expressed with colors, whose values can be derived from the color bar on the right. Most of the variables had a weak correlation while only 4 of them had a strong correlation. From this analysis it appeared clear that the option number (4), namely considering the outputs singularly was the most meaningful choice. In addition, this choice gave the possibility to use more ML algorithms for the prediction of each variable, thus increasing the overall accuracy. In fact, one of the algorithms could have been the strongest in predicting a particular variable but weaker than another in predicting a different variable. Therefore, using only the former would have resulted in lower accuracy for the prediction of the latter, while using only the latter would have caused a loss of accuracy in predicting the former. Instead, employing the best algorithm for each specific variable led to the highest achievable accuracy. The same consideration was applied to the algorithms' setup: the optimal configuration of an algorithm for predicting one variable might not have been the best configuration for predicting another variable. Before training the algorithms, an analysis of the collected data was conducted to assess its distribution. For the input variables, which represent issues faced by dyslexic students, scores predominantly ranged from 1 to 5, with fewer 0 scores compared to other studies. This lower incidence of 0 scores is attributed to dyslexic students' tendency towards pessimism in self-evaluation, as noted by the psychologists involved. Consequently, scores of 0 were adjusted to 1, resulting in a more uniform distribution across issues. For the output variables, which represent support tools and strategies, there was a significant imbalance, with the most common score being up to 26 times more frequent than the least common score. To address this, output scores were converted into binary responses using a threshold of 2.5: scores below 2.5 indicated "useless," while scores above 2.5 indicated "useful." This midpoint ensures an even distribution between the two classes. After thresholding, the imbalance decreased to a ratio of about 1/5, with more frequent "useful" responses. To handle this imbalance during algorithm evaluation, different weights will be assigned to "useful" and "useless" predictions.

After this step, four of the most widely used supervised ML algorithms for classification were adopted to classify the data: RF, LR, kNN and SVM [62]. Supervised ML algorithms differ significantly from unsupervised ML algorithms. The key distinction is that supervised algorithms require labeled data to learn and make predictions, while unsupervised algorithms do not rely on labels. This difference is crucial in determining which type of algorithm to use for a given problem. Supervised ML models are more suitable when a complete dataset with clearly defined input-output pairs is available. In contrast, unsupervised ML models excel when the goal is to explore the dataset and identify hidden patterns or groupings without prior knowledge of the outcomes. In the context of this project, the dataset included both input features and corresponding labels, making supervised ML the most appropriate choice. By using supervised learning, we could train the model to make accurate predictions based on the labeled data. The following paragraphs will give an explanation of these models and will discuss about their application in the study.

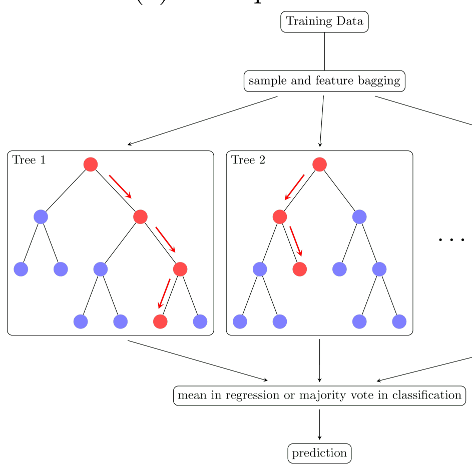
Random Forest

The RF is an ensemble method that constructs multiple DTs during training and aggregates their outputs for a final prediction (as shown in Figure 2.5b).

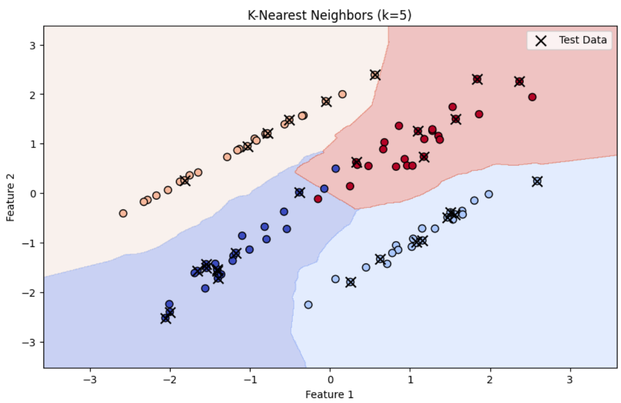
Therefore in order to understand the RF, the functioning of the DT must be briefly explained. As shown in Figure 2.5a, each DT consists of a root node, in which the tree splits



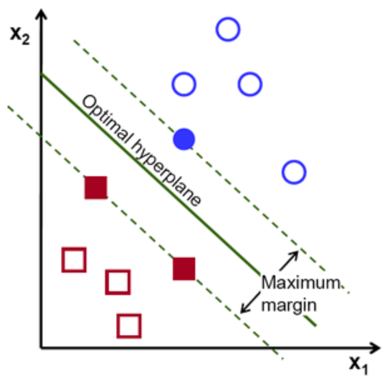
(a) Example of Decision Tree



(b) Example of Random Forest



(c) Example of k-Nearest Neighbor



(d) Example of Support vector machine

Figure 2.5: Examples of the ML models discussed

into decision nodes that represent decisions based on input features, branches that represent the outcomes of those decisions, and leaf nodes that represent the final prediction. To classify, the DT is based on the Gini impurity score and the entropy or information gain [14]. The

Gini impurity score measures how often a randomly chosen element from the dataset would be incorrectly classified if it was randomly labeled according go the distribution of labels in the subset and is calculated as

$$Gini = 1 - \sum_{i=1}^{C} p_i^2 \tag{2.4}$$

where p_i is the probability of a data point belonging to class i and C is the number of classes. The entropy instead, is calculated as follows:

$$Entropy = -\sum_{i=1}^{C} p_i log_2(p_i) \tag{2.5}$$

The tree recursively splits nodes to reduce the chosen impurity metric until the tree reaches a predefined stopping criterion. The RF combines more DT in order to classify. It is based on two main features: (i) bootstrap and (ii) random feature selection. The first, refers to the selection of a random subsets of the original dataset used to train each tree. This ensures that there is randomness while the random feature selection refers to the selection of a random subset of features at each split in the DT. The formula of the RF is:

$$\hat{y} = mode\, \{T_1(X), T_2(X), ..., T_n(X)\} \tag{2.6}$$

where $T_i(X)$ is the prediction from the i-th tree. In this study, the bootstrap technique was used by choosing 1/3 of the variables at each decision split and with a maximum of 50 DT. Three approaches were evaluated for handling the input variables: treating them as ordinal scores, as numeric values, or as binary values derived from thresholding the scores. In the binary approach, a variable is considered present if its score exceeds a specified threshold and absent if it does not. Several different thresholds (Thr) were tested: $Thr = 1.5$, $Thr = 2.5$, $Thr = 3.5$ and $The = 4.5$.

Logistic regression

Logistic Regression is used for binary classification problems. It predicts the probability that a given input X belongs to a particular class. It uses the logistic (sigmoid) function to constrain the output between 0 and 1. It is calculated as follows:

$$P(y = 1|X) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \beta_n x_n)}} \tag{2.7}$$

where $P(y = 1|X)$ is the probability that the output y is 1 given input X, $\beta_0, \beta_1, ..., \beta_n$ are model coefficients while $x_1, x_2, ..., x_n$ are input features. The decision boundary is generally set at 0.5, therefore if $P(y = 1|X) \geq 0.5$ the class is classified as 1 whereas if $P(y = 1|X) < 0.5$, the class is considered 0. The coefficients β are found by maximizing the Log-Likelihood:

$$L(\beta) = \sum_{i=1}^{N} [y_i log(P(y = 1|X)) + (1 - y_i) log(1 - P(y = 1|X))] \tag{2.8}$$

K-nearest neighbors

k-NN (an exmaple can be found in Figure 2.5c) is a ML algorithm used for both classification and regression tasks. Unlike other models, K-NN does not learn an explicit function during training. Instead, it stores the training data and makes predictions by examining the 'k' closest data points (neighbors) in the feature space for a new input. The choice of 'k' significantly affects the model's performance: a smaller 'k' can capture fine details but may be sensitive to noise, while a larger 'k' provides a smoother decision boundary but may miss finer structures. In classification, the class label is assigned based on the majority class among the 'k' neighbors, similar to the functioning of the RF. In this study, the input variables were treated both as numeric values and as binary value, as explained earlier. This was done both for the testing and for the training of the algorithm. two distances measures were used, the Euclidean distance and the Hamming distance. For two points $p = (p_1, p_2, ..., p_n$ and $q = (q_1, q_2, ..., q_n$ in an n-dimensionale space, the Euclidean distance d is calculated as follows:

$$d(p, q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + ... + (p_n - q_n)^2} \tag{2.9}$$

The Hamming distance instead, is a measure of the number of positions at which the corresponding symbols are different between two strings of equal length. It is commonly used for categorical or binary data. For two string x and y of equal length n, where each position i in the strings can be either binary or category, the Hamming distance d is calculated as:

$$d(x, y) = \sum_{i=1}^{n} 1(x_i \neq y_i) \tag{2.10}$$

where x_i and y_i are the values at position i in strings x and y respectively. 1 is the indicator function that equals 1 if $x_i \neq y_i$ and 0 otherwise. Finally, the k parameters considered in this study range from 7 to 39, with a step of 4.

Support vector machine

The SVM is a supervised learning algorithm used for classification and regression tasks. The core idea of SVM is to find the optimal hyperplane that best separates data points of different classes in a high-dimensional space (as shown in Figure 2.5d). The data points closest to the hyperplane are called support vectors. These points are crucial because they define the margin of the hyperplane. The position of these support vectors directly affects the placement of the hyperplane. The margin is the distance between the hyperplane and the nearest support vectors from each class. SVM aims to maximize this margin, which helps in achieving better generalization on unseen data. The optimal hyperplane is the one that maximizes the margin between the classes. This is achieved by solving a quadratic optimization problem. In this study, three kernels namely, linear, polynomial and radial basis function were in the training phase of the SVM. Kernels are functions used in SVM to enable the algorithm to handle non-linearly separable data by mapping it into a higher-dimensional space where a linear separation is possible. The kernel function $K(x_i, x$ computes the similarity between two data points x_i and x in the original input space. The linear functions represents the dot product in the original space $K(x_i, x) = x_i \cdot x$, while the polynomial kernel represents a polynomial function of the dot product: $K(x_i, x) = (\alpha x_i \cdot x + c)^d$ and lastly the radial basis function represents an exponential function of the squared Euclidean distance: $K(x_i, x) = exp\left(-\frac{\|x_i - x\|^2}{2\sigma^2}\right)$

Testing and analysis

Initially, the dataset was divided into two parts: 75% was allocated for training and validation, while the remaining 25% was set aside for testing. For the training and validation subset, we employed stratified tenfold cross-validation to ensure that each fold contained a proportional representation of both predictors and labels. This approach guarantees that each subset closely mirrors the overall dataset, helping to minimize any potential bias and ensuring a more reliable evaluation. The prediction algorithm that was ultimately implemented is not one of the four previously mentioned with a specific configuration. Instead, it is more of a ”super-algorithm” that predicts for each individual tool or strategy by utilizing the best-performing algorithm from the list, optimized with the most effective setup for that particular tool or strategy. In order to evaluate the perfroamnce of the algorithms, the overall weighted prediction accuracy (A) for each tool or strategy was calculated with the following formula:

$$A = 1/N_F \sum_{f=1}^{N_F}((\frac{N(C/y)_f}{N(T/y)} w_y + \frac{N(C/n)_f}{N(T/n)} w_n)) \tag{2.11}$$

where N_f is the number of folds used for cross-validation, $N(C/y)_f$ and $N(C/n)_f$ are the number of correct predictions in the case of "useful" and "useless" algorithm response, respectively $N(T/y)$ and $N(T/n)$ are the total number of tests performed in each fold, in the case of "useful" and "useless" response, respectively, and w_y and w_n are the weights used to take into consideration the imbalance of the two classes, as discussed earlier. w_y and w_n were set at the normalized inverse frequency of the "useful" and "useless" responses, so as to give a higher importance to less frequent predictions and vice versa. In addition, also F1-score was calculated, so as to include also precision and recall among the performance indexes.

The final algorithm, incorporating the most accurate machine learning algorithm with its optimal setup for each individual tool and strategy, was subsequently tested on the reserved portion of the dataset by calculating its overall accuracy. Following this, an additional evaluation was conducted in a real-world scenario. A group of students responded to the questions in Table 2.2, and their answers were fed into the classification model, which then recommended the most suitable support tools and strategies for each student. The students then tried all the suggested tools and strategies and provided feedback on which ones were helpful for their studies. The students' responses were compared with the model's output to assess its accuracy. It's important to note that study strategy S10, was not included in this evaluation because it requires a longer time frame for verification. However, a student association has already been established, and its verification is in progress. Similarly, strategies S11, S17, and S18 were not applied to an entire course but only to select topics. S11 was evaluated by teaching some topics in a traditional classroom setting and others online or through self-study materials (books and notes) without an instructor. S17 was tested by providing information about specific topics before the lessons started. Lastly, S18 was assessed by dividing topics into shorter sub-modules. In total, 43 students with dyslexia participated in this final evaluation step by completing the questionnaire.

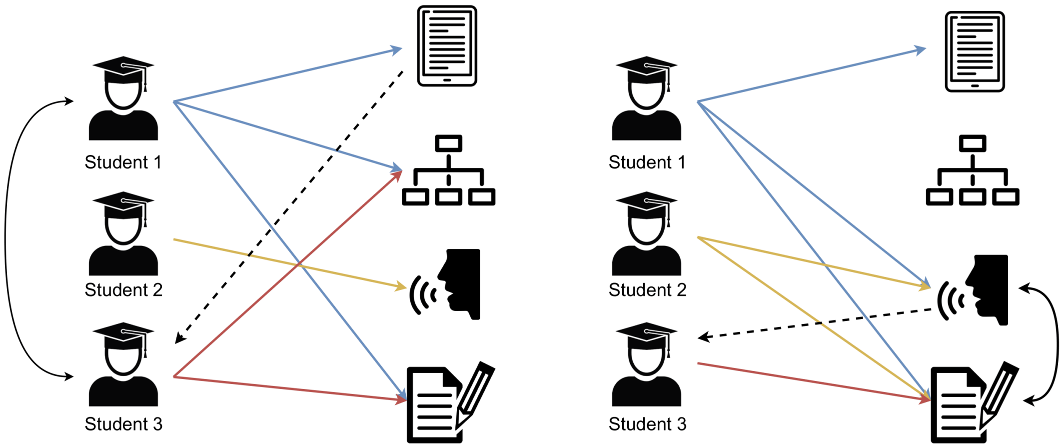
2.0.4 The use of recommendation systems

The ML algorithms described above are not the only type of algorithms that can be used to suggest the best learning tools and study strategies to students. Indeed, there is another class of models that are specifically aimed at detect user preferences and recommend items accordingly. These are the recommendation system (RS). RSs can be broadly classified into several categories, each employing different methods to suggest items to users. One of the most common categories is collaborative filtering (CF), which makes recommendations based on the preferences and behaviors of similar users. By identifying patterns in user interactions, CF algorithms can predict what a user might like by looking at the choices made by others with similar tastes [57]. Another widely used category is content-based (CB) filtering. This approach recommends items by analyzing the characteristics and features of the items themselves. Recommendations are tailored to the user by matching the user's profile or past preferences with item descriptions, such as keywords, categories, or other metadata [78]. For example, if a user has shown a preference for action movies, a content-based system might suggest other action films based on their descriptive attributes. Knowledge-based (KB) systems represent a different approach by leveraging specific knowledge about the users' needs and the domain to make recommendations. These systems take into account the explicit requirements and preferences expressed by the user, along with detailed knowledge about the items, to offer more personalized and context-specific suggestions. This approach is particularly useful in domains where user preferences are complex and cannot be easily inferred from past behavior alone [23]. Finally, hybrid systems combine elements of the aforementioned methods to create a more robust and accurate recommendation process [19]. By integrating collaborative filtering, content-based filtering, and knowledge-based approaches, hybrid systems can overcome the limitations inherent in each individual method, offering a more comprehensive and adaptable recommendation strategy. This combination allows the system to provide more relevant suggestions by drawing on multiple sources of information, thereby enhancing the overall user experience. In the realm of education, numerous RSs have been introduced to improve the students' learning experience. For example in [58], the authors integrated various RSs, including KB, CB and CF approaches, along with Web 2.0 tools, to offer teachers guidance on course design and provide students with suggestions on which activities to select, such as attending seminars, joining e-courses, reviewing subject summaries, and completing online tests. This method led to students achieving better final course outcomes. In [108], the authors developed a hybrid model by combining CF, CB, and knowledge-based algorithms to recommend learning objects to students with similar learning styles. This hybrid recommendation strategy enhanced the relevance of the educational materials suggested and significantly improved the students' learning process.

The studies reported here show a prominent role of RSs in education. However, the majority of the research on the application of RSs is directed toward students without dyslexia. Therefore, in this work the goal was to exploit RSs to customize the learning experience of students by recommending specific support tools. Specifically, three RSs were evaluated to identify which algorithm could most effectively suggest learning tools and study strategies tailored to each student's needs. Ultimately, the top-performing algorithm was utilized to recommend study strategies and learning tools for both dyslexic and non-dyslexic students. Experienced professors then assessed the learning progress of these students to measure the effectiveness of the recommendations.

The use of the CF recommendation system in dyslexia

In recent years, RSs have gained growing importance, expanding their impact across various fields, including education and learning. Within this domain, CF and CB approaches have emerged as two prominent methodologies, each offering distinct advantages and drawbacks. CB systems rely heavily on extensive information about the features of items rather than focusing on the relationships derived from user feedback and ratings. Due to this requirement, CF initially became the preferred method. The dataset used for this study is the questionnaire described in the previous sections and in [87]. The only difference is that, in this case, the Issues were not considered but only the learning tools and study strategies. Out of the 39 items included in the questionnaire, the T4 learning tool (Using the Easy Reading font) was excluded because more than 48% of the participants were unfamiliar with it. As a result, the final count of learning tools was reduced to 16, with an additional 22 study strategies, bringing the total number of items to 38. The data were divided such that 75% were used for training the model, while the remaining 25% were set aside for testing. A 10-fold cross-validation was then performed on the training dataset to fine-tune the model's configuration parameters before evaluating its performance on the test set. Data were analyzed using three types of CF RSs as implemented by [7]. The three CF systems included: a user-based approach, where recommendations are driven by the similarity between users to suggest different methodologies [140]; an item-based approach, which analyzes the similarity between items to recommend the most relevant tools and strategies to users [132]; and a hybrid approach, which combines the aforementioned methods through a weighting system [7]. The motivation for using a hybrid model arises from the distinct differences between user-based and item-based methods. The user-based approach generates recommendations by identifying similar users and suggesting items that those users have liked. In contrast, the item-based approach focuses on the similarities between items, using user ratings to calculate these similarities. The differences between these two methods are illustrated in Figure 2.6. In the user-based approach (Figure 2.6a), the system identifies that Student 1 and Student 3 have similar preferences because they have selected some of the same learning methodologies. As a result, it recommends (indicated by the dashed arrow) to Student 3 an item that was beneficial to Student 1 but that Student 3 has not yet used. On the other hand, the item- based approach (Figure 2.6b) observes that the last two items have received similar ratings from different users (Student 1 and Student 2). Since Student 3 has already shown a preference for one of these items, the system suggests the other item to Student 3. The hybrid approach was implemented by combining the user-based and item-based methods with varying weights. This involved assigning specific relevance or weight to each of the



(a) User-based collaborative filtering. (b) Item-based collaborative filtering.

Figure 2.6: The user-based approach (a) and the item-based approach (b) visually depicted

predicted ratings, using the equation provided below:

$$\widehat{r} = \alpha\widehat{r}_u + (1-\alpha)\widehat{r}_i \tag{2.12}$$

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 deriving from predicted ratings and actual ratings as discussed in [7]. The value of α has to satisfy:

$$\alpha \geq 0 \ and \ \alpha \leq 1 \tag{2.13}$$

To determine the final weights to assign to each model, a preliminary experiment was conducted. Following this, and in line with the findings discussed in [111], it was observed that assigning higher weights to the item-based method $(1-\alpha)$ led to improved outcomes. Consequently, a range of values for the weights was chosen to prioritize higher values for the item-based weight. This range began with a user-based weight (α) set at twice the item-based weight and concluded with item-based weight values that were seven times greater than α. All the considered cases are illustrated in Table 2.3.

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

Table 2.3: Configuration of weights for the hybrid approach.

Setting $\alpha = 1$ results in a fully user-based approach while setting $\alpha = 0$ yields a fully item-based approach. Therefore, by appropriately adjusting α, it becomes possible to encompass all the analyzed scenarios within the formula 2.12.

To calculate similarities among users or items, three commonly used metrics in CF systems were evaluated and compared: the Pearson correlation coefficient, the Euclidean distance, and the Cosine distance. These metrics were employed to identify the n most similar users to a given test user (in the case of user-based filtering) or the n most similarly rated items according to the ratings provided by the test user (in the case of item-based filtering). The definitions of these three metrics are as follows:

$$Pearson\ Correlation = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{N}(y_i - \bar{y})^2}} \tag{2.14}$$

$$Euclidean\ distance = \sqrt{\sum_{i=1}^{N}(x_i - y_i)^2} \tag{2.15}$$

$$Cosine\ distance = 1 - \frac{\sum_{i=1}^{N} x_i y_i}{\sqrt{\sum_{i=1}^{N} x_i^2}\sqrt{\sum_{i=1}^{N} y_i^2}} \tag{2.16}$$

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.

The Pearson coefficient was used for the direct calculation of similarities among all users or items, with the most similar neighbors identified by selecting the n most correlated entities. In contrast, the Euclidean and Cosine distances were used as distance metrics within a kNN algorithm, where the n nearest neighbors were directly obtained from the model generated. An important consideration was the number of nearest neighbors included in the similarity calculation. After conducting extensive tests with various potential values for the number of neighbors, it was found that optimal results were achieved with n values ranging from 3 to 11. Consequently, in the final experiments, the number of neighbors considered was 3, 5, 7, and 11. Algorithm 1 contains the pseudocode of the process for the similarity computation depending on the different considered metrics. The method returns the *n_neighbors* most similar users or items sorted according the computed similarity measure, 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 goal of this study was to use the RSs to predict the best learning tools and study strategies for students with dyslexia. For the user-based approach, this prediction was made by averaging the ratings given by the most similar users. Conversely, in the item-based approach, the prediction was based on the ratings of items that were most similar in terms of their scores. In the hybrid method, the prediction was derived from the sum of the user-based and item-based predictions, each weighted according to its respective importance. The process is shown in Algorithms 2 and 3, which correspond to the user-based and item-based RSs, respectively. Both algorithms produce a list of key-value pairs, known as recommendations, which included the tools and strategies to be recommended along with their respective ratings provided by the RS.

To generate these recommendations, the algorithms utilized data for similarity computation, distinguishing between different data sources. For the user-based approach, only the training data (*data train items*) and the test user's data (*text user*, the user for whom the recommendations are being made) are considered. In contrast, the item-based approach requires evaluating each test item (*data test items*) individually to compute its ratings, while treating

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
```

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
```

the remaining items as unknown to the user. The final *recommendations* were completed with the average rating values obtained for the different test items from the *n_neighbors* most similar users or objects.

In order to evaluate the accuracy of the methodologies used, the mean absolute error (MAE) between the predicted scores provided by the RS and the actual scores given by the users was computed. MAE is determined by averaging all N absolute errors of the rating pairs (p_i, q_i). Since a lower MAE indicates better accuracy, the selection of weights must be optimized to minimize this error:

$$\arg\min(\alpha)\left(\frac{\sum_{i=1}^{N} |p_i(\alpha) - q_i(\alpha)|}{N}\right) \tag{2.17}$$

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

To evaluate the algorithm's performance in a real-world scenario, the best-performing model was employed to recommend specific learning tools and strategies to both dyslexic and non-dyslexic students. The test involved 50 participants, comprising 53% male and 47% female. Of these, 40% were dyslexic, while the remaining participants were not affected by any learning disorders. The participants included university students and individuals who had completed their undergraduate studies but were pursuing further academic qualifications such as a master's degree, a doctorate, or corporate training. The test involved providing textbooks from three disciplines—political science, communication, and economics—to students enrolled in relevant degree programs, PhD programs, or master's courses. Each student was asked to study a specific portion of a book. Fifty percent of the students, evenly divided between dyslexic and non-dyslexic individuals, used the best-performing RS to receive personalized suggestions for tools and strategies aimed at improving their study efficiency. The other 50% received random recommendations rather than those generated by the RS. Following this, all students were instructed to adhere to the suggested methodologies during their study phase. University professors then assessed their knowledge of the studied disciplines on a scale from 0 to 10, with 6 being the minimum passing score. The results of students who received personalized recommendations were compared with those who received random suggestions, and differences between dyslexic and non-dyslexic students were also analyzed.

Chapter 3

The results of the VRAILEXIA project

3.0.1 Results of the exploratory analysis

As discussed in Chapter 2.0.2, in order to design, create and implement the suite of ML models to support dyslexic students data were collected and analyzed. The first step was to create a questionnaire, as reported in Table 2.2, that included both the issues experience by dyslexic students during their learning path and the learning tools and study strategies that have found useful to overcome or, at least, mitigate some of their difficulties. The analysis started by considering the socio-demographic aspects of the sample. The main features considered are the gender, year of birth, the type of student, when the diagnosis of dyslexia was performed, if the student received aid and, if yes, what type of aid, what year of university they were, if the subject has relatives with dyslexia and if there are other learning disorders associated with dyslexia. The results are shown in Table 3.1. One of the first things investigated was a comparison between the year of birth and the received support. Figure 3.1 shows this relationship.

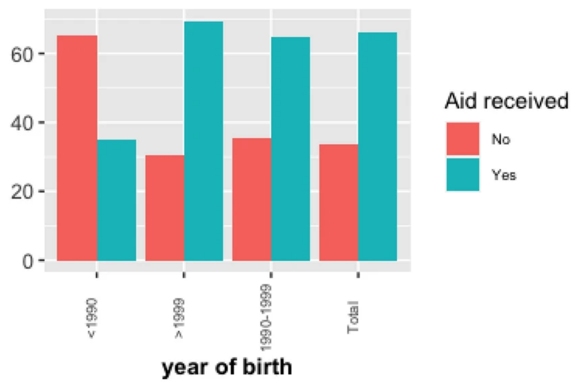


Figure 3.1: Relationship between year of birth and receive support

Gender		**Diagnosis of dyslexia**	
Male	66%	Primary school	41%
Female	24%	Secondary school	20%
Type of student		Tertiary school (1st or 2nd year)	13%
Full-time student	83%	Tertiary school (3rd to 5th year)	25%
Part-time student	17%	**Year of birth**	
Received aid		<1990	3%
No	34%	1990-1999	52%
Yes	67%	>1999	45%
Type of aid received		**Year attended**	
Private speech therapists	23%	First year	36%
Psychologist	18%	Second year	24%
Public speech therapist	16%	Third year	18%
Tutor	13%	Fourth year	4%
Parents	3%	Fifth year	3%
Teacher	1%	Out-of-study student	10%
Dyslexia association and friends	2%	Graduate student	3%
Other learning disorders		High school student	2%
No		**Relatives with dyslexia**	
Yes		No	57%
		Yes	43%

Table 3.1: Socio-demographic characteristics of the sample

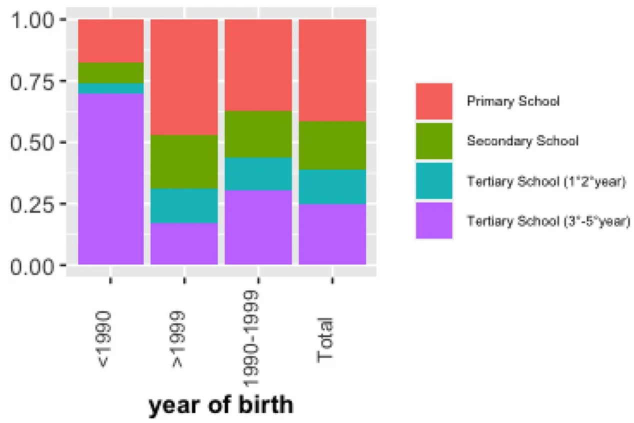


Figure 3.2: Relationship between the birth year and the time in which the diagnosis of dyslexia was performed

An interesting data is that over 60% of the students born in 1990 or earlier did not receive a specific aid after the diagnose of dyslexia. Whereas over 60% of the students born in 1999 or later, received an appropriate support. This is crucial as evidenced in Chapter 1, if the diagnosis of dyslexia is done early in life and if specific support is given, the child has higher chance to easily overcome their difficulties. The fact that people born after 1990 received more support than those born before may be partly due to increased awareness of the difficulties faced by dyslexic children. Supporting this, children born after 1999 show the highest percentage of support received compared to other groups. Indeed, in Italy the first law that recognized dyslexia, dysorthography, dysgraphia, and dyscalculia as SLDs was published in 2010 [44]. The Law 170/2010 safeguards the right to education for dyslexic children while encouraging schools to reconsider the teaching methods needed to support all students, allowing them to reach their full potential by embracing their unique qualities.

Another interesting aspect under investigation was the potential relationship between the year of birth and when, during primary, secondary and tertiary school, the diagnosis was performed. The importance of a timely diagnosis was deeply discussed in Chapter 1. Figure 3.2 shows the results of this analysis.

For the children subjects born before the 1990, 70% received the diagnosis during the final years of the tertiary school (3rd to 5th year). This datum may be in conjunction with what was presented in Figure 3.1, in which the year of diagnosis is also related on the support received. Indeed, a late diagnosis can delay or abort the activation of the necessary support systems to help dyslexics since the age of the third year of tertiary school is normally at 15 years old. By that time, it the person is supposed to have already identified some of the strategies to overcome the difficulties encountered, hence the activation of the necessary support can be wrongly perceived as non necessary. The percentage of students

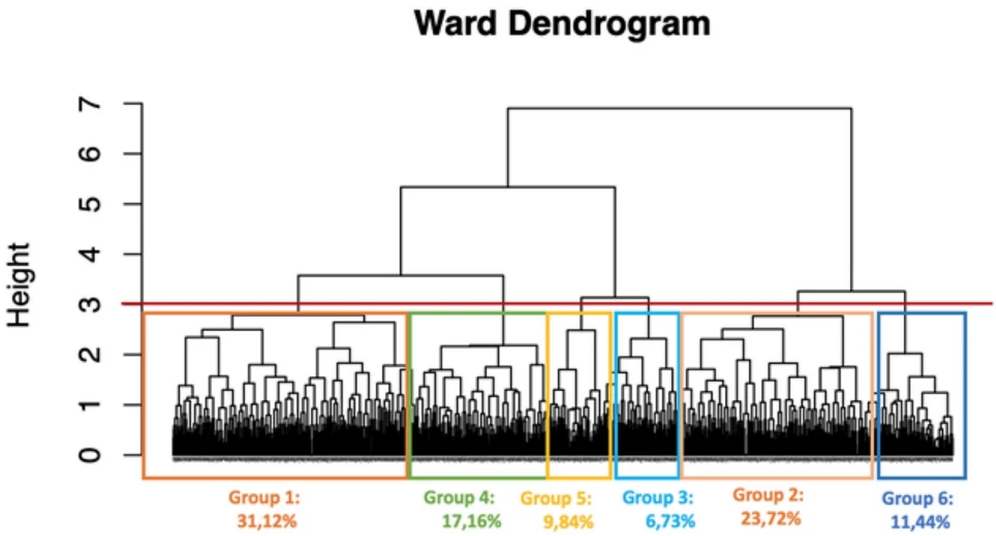


Figure 3.3: The Ward dendrogram

born after 1999 who received the diagnosis during late tertiary school (3rd to 5th year) is equal to 17%, drastically lower compared to the ones born before 1990. The last interesting datum that was found regards the relationship between the type of support given and if the student was a drop put or if the student graduated. Among graduate students, 80% received support from associations and friends, whereas among students who dropout university education, it emerges a strong association with supports from parents (50%). From the studies discussed in the Chapter 1, it was highlited how the dyslexic children tend to be more succesful when receives support in early life. The findings shown above point in this direction, that is, promoting collaborative learning is crucial. Since people have different strengths, group collaboration increases the likelihood of effective problem-solving. Group projects allow individuals to leverage their unique talents—some excel at writing, others at drawing, researching, or building models. The results shown here, underscore the positive impact of social capital on well-being within larger organizations, such as national associations, through three main mechanisms: enhanced access to vital information, stronger advocacy efforts, and connections to self-care networks. Membership in a dyslexia-focused association offers students valuable opportunities and relationships that greatly enhance their self-confidence. Recent studies on dyslexic university students highlight the critical need to build supportive communities within academic settings. Even in smaller group settings, social capital plays a vital role in improving both academic performance and boosting students' self-esteem.

The last analysis in this study was conducted using the hierarchical agglomerative method described in Chapter 2.0.2 from which it was derived a dendrogram as depicted in Figure 3.3.

	Group 6 - at risk students	**Group 3 - graduated students**
Year of birth	<1990	<1990
Type of student	Out-of-study or dropout students	5th year of university or graduated
Diagnosis of dyslexia	3rd-4th-5th year of high school	Primary school
School year repetition	Yes	No
Type of aid received	No	Parents
Relatives with dyslexia	Yes	No
Other difficulties	Yes	Yes
	Group 2 - at risk students	**Group 5 - graduated**
Year of birth	1990-1999	1990-1999
Type of student	4th or 5th year of university or out-of-study	3rd year of university or graduated
Diagnosis of dyslexia	3rd-4th-5th year of university	1st-2nd high school
School year repetition	Yes	No
Type of aid received	Parents and Tutor	Dyslexic association and friends
Relatives with dyslexia	Yes	No
Other difficulties	Yes	No
	Group 1 - at risk students	**Group 4**
Year of birth	>1999	>1999
Type of student	1st-2nd or 4th-5th year of university	High school or 1st-2nd year of university
Diagnosis of dyslexia	Primay/secondary school	1st-2nd high school year
School year repetition	Yes	No
Type of aid received	Public and private speech therapist	Private therapists and psychologist
Relatives with dyslexia	No	No
Other difficulties	Yes	Yes

Table 3.2: Groups identification by considering socio-demographic characteristics

	Difficulties	Learning tools	Study strategies
Group 6	widespread difficulties	Coloured overlays, easy-reading font, tutorial support	Group activities, lecture support, exam assestment
Group 3	Few difficulties on concentration and memory	Audiobook	Oral exam
Group 2	Concentration and memory	Audiobook, tablets, clear layout, e-books, pictures that summarize the topic	Group activities, exam assestments
Group 5	On-line lectures, exam organization	Audiobook	Group activities, exam assestments, oral exam
Group 1	Concentration, online lectures and memory	Use ready-made maps, concept maps and summaries, tablet, clear layout, picture that summarize the topic	Group activities, lecture support
Group 4	Concentration , memory, exam organization, handwriting, expressig ideas orally	Use ready-made maps, Audiobook, keywords, summaries, e-book, video-lectures	Group activities, exam assestments

Table 3.3: Difficulties encountered by the 6 groups and the most useful learning tools and study strategies

The six groups identified with the dendrogram were clustered based on the year of birth. The results are reported in Table 3.2. The analysis has identified 6 groups of dyslexic students according to the questions showed in Table 3.1. The first important result from this table is that early and accurate diagnosis is crucial to a student's success in university. Ideally, diagnosis should occur during the early years of primary school to allow for early interventions that can help manage dyslexia more effectively. Early and targeted support is more effective in addressing dyslexia. Students who don't receive assistance until later on may struggle more with essential reading skills, leading to ongoing academic difficulties that are hard to overcome. Even though a child with severe dyslexia may always find reading challenging, they can learn techniques to improve reading and develop strategies that enhance both school performance and quality of life. Groups 3 and 6 consist mostly of students born before 1990, who began their university studies prior to the introduction of Law 170/2010 in Italy, which formally recognizes dyslexia, dysorthography, dysgraphia, and dyscalculia as SLDs. Although neither group received formal support, students in Group 3 completed their university education, whereas many in Group 6 did not pass all their exams within the expected time and often dropped out.

As shown in Table 3.3, the difference in academic success between the two groups may be related to the severity of the challenges they faced. Group 3 contains students with milder forms of dyslexia, while Group 6 is composed of students with more extensive difficulties. Groups 2 and 5 include students born between 1990 and 1999. Group 5, representing 10% of the sample, can be considered the ”success” group, as these students completed their university degrees. Despite receiving their dyslexia diagnosis relatively late (in their first or second year of university), they benefited from support from associations, friends, and psychologists. Group 2, which makes up 24% of the sample, includes students born between 1990 and 1999 who are currently in their 4th or 5th year of university or enrolled in additional years. These students were diagnosed with SLD in the last three years of high school and received support from tutors and parents. Groups 1 and 4 primarily consist of students born after 1999. Group 1, representing 31% of the sample, includes students born after 1999 who are currently enrolled in university as part-time students. They were diagnosed with SLD during elementary or secondary school and received specific assistance from public and private speech therapists as well as teachers. Group 4, which makes up 17% of the sample, is similar to Group 1 and includes students born after 1999 who are currently in high school or in their first two years of university. This group received their SLD diagnosis slightly later than Group 1 (during secondary school or early high school) and were supported by private speech therapists and psychologists. These students were diagnosed through specialist services within the Italian National Health System.

3.0.2 Results of the use of the ML classification

After the initial exploratory analysis, the next part of the project focused on the use of a suite of ML algorithms to predict the most useful learning tools and study strategies for dyslexic students. As discussed in Chapter 2.0.3, four supervised ML algorithms, namely the RF, LR, SVM and k-NN were used to analyze the most useful items reported in Table 2.2. To calculate the effectiveness of these algorithms for the task, the weighted prediction accuracy and the F1-score were calculated. Table 3.4 reports the names of the best algorithms along with their setup, accuracy and F1-score for each learning tool and study strategy. To avoid confusion, the tool number 4 was excluded from the analysis, as explained in Chapter 2.0.3. Table 3.5 instead, shows the results of the best algorithms that predict each study strategy. To have a global understanding of the reuslts, is better to watch at the average scores reported in Table 3.6, Table 3.7 and Table 3.8. The weighted accuracy in predicting both tools and strategies averages around 90%, specifically 88.7% for the former and 91.6% for the latter. Overall, a global accuracy of 90.4% is attained, with low standard deviations of 0.079 for tools, 0.088 for strategies, and 0.084 overall. This means the algorithm delivers approximately 9 correct predictions out of 10. The F1-score further supports these results, reaching 0.927 for tools, 0.945 for strategies, and 0.938 overall. The maximum accuracy recorded is 0.978 for tools and 0.994 for strategies, while the lowest is 0.725 and 0.705, respectively, showing a noticeable difference from the best cases. The vast majority of the learning tools and study strategies were predicted with an accuracy above 84%. Indeed, only the learning tools T1, T11 and T12 were predicted with an accuracy of 72%, 74% and 77% respectively. Instead for the

Learning Tool	Best performing algorithm	Algorithm setup	Accuracy (weighted)	F1-score
T1	SVM	Linear kernel, binary input (Thr = 1.5)	0.725	0.813
T2	RF	Score	0.90	0.94
T3	k-NN	k=39, numeric input	0.89	0.93
T5	SVM	Linear kernel, numeric input	0.84	0.89
T6	RF	Score	0.96	0.98
T7	SVM	RBF kernel, numeric input	0.98	0.98
T8	SVM	Linear kernel, numeric input	0.91	0.94
T9	SVM	Linear kernel, numeric input	0.91	0.94
T10	SVM	Linear kernel, numeric input	0.93	0.96
T11	SVM	RBF kernel, numeric input	0.74	0.82
T12	SVM	RBF kernel, numeric input	0.77	0.84
T13	k-NN	k=31, numeric input	0.95	0.97
T14	SVM	RBF kernel, binary input (Thr = 2.5)	0.97	0.98
T15	SVM	Linear kernel, numeric input	0.91	0.95
T16	SVM	RBF kernel, numeric input	0.99	0.94
T17	k-NN	k=31, numeric input	0.92	0.95

Table 3.4: Best-predicting algorithms and setups for each learning tool

study strategies, only S1, S19, S20 and S 21 were predicted with an accuracy of 70%, 77%, 79% and 82% respectively, Therefore, the selected ML models were able to accurately predict the best learning tools and study strategies. If such a level is deemed insufficient, it may be advisable to exclude these 5 tools/strategies and focus on the remaining 30. After removing these items, the average accuracy increased to 92.7% for the learning tools, 94.8% for the study strategies, and 94.0% overall, with standard deviations of 0.029, 0.043, and 0.039, respectively. Additionally, the average F1-score improved to 0.955 for the learning tools, 0.968 for the study strategies, and 0.966 overall, offering further evidence of the model's strong performance.

Furthermore, the SVM algorithm outperforms the others most frequently, winning in 21

Study Strategy	Best performing algorithm	Algorithm setup	Accuracy (weighted)	F1-score
S1	SVM	RBF kernel, numeric input	0.70	0.80
S2	k-NN	k=31, numeric input	0.97	0.98
S3	k-NN	k=31, numeric input	0.98	0.98
S4	RF	Score	0.97	0.98
S5	SVM	RBF kernel, binary input (Thr = 1.5)	0.98	0.97
S6	RF	Score	0.98	0.98
S7	k-NN	k=31, binary input (Thr=1.5)	0.93	0.96
S8	k-NN	k=39, numeric input	0.85	0.91
S9	SVM	RBF kernel, numeric input	0.86	0.91
S10	SVM	RBF kernel, binary input (Thr=1.5)	0.88	0.93
S11	SVM	RBF kernel, numeric input	0.93	0.96
S12	SVM	RBF kernel, numeric input	0.97	0.98
S13	RF	Score	0.98	0.99
S14	RF	Score	0.99	0.98
S15	k-NN	k=31, binary input (Thr=1.5)	0.96	0.97
S16	RF	Score	0.97	0.98
S17	k-NN	k=31, numeric input	0.93	0.96
S18	k-NN	k=31, binary input (Thr=1.5)	0.97	0.96
S19	SVM	RBF kernel, numeric input	0.77	0.84
S20	SVM	RBF kernel, numeric input	0.79	0.86
S21	SVM	RBF kernel, numeric input	0.82	0.89
S22	SVM	RBF kernel, numeric input	0.93	0.96

Table 3.5: Best-predicting algorithms and setups for each study strategy

Learning Tools	
Average prediction accuracy	0.887
Accuracy standard deviation	0.079
Maximum accuracy	0.978
Minimum accuracy	0.725
Average F1-score	0.927

Table 3.6: Average learning tools scores

Study strategies	
Average prediction accuracy	0.916
Accuracy standard deviation	0.088
Maximum accuracy	0.994
Minimum accuracy	0.705
Average F1-score	0.945

Table 3.7: Average study strategies scores

Global	
Average prediction accuracy	0.904
Accuracy standard deviation	0.084
Maximum accuracy	0.994
Minimum accuracy	0.705
Average F1-score	0.938

Table 3.8: Average global scores

	Useful items (as stated by students)	**Useless items (as stated by students)**
Predicted as useful (by the algorithm)	Learning tools: 90.3%	Learning tools: 9.7%
	Study strategies: 94%	Study strategies: 5.9%
	Global: 92.4%	Global: 7.6%
Predicted as useless (by the algorithm)	Learning tools: 13.4%	Learning tools: 86.6%
	Study strategies: 8.7%	Study strategies: 91.3%
	Global: 10.7%	Global: 89.3%

Table 3.9: Prediction accuracy of the proposed algorithm, calculated on the tested real case

out of 38 cases, particularly when the input is treated as numeric and the RBF kernel is applied. Following SVM, k-NN performs best in 10 out of 38 cases, with k set to 31 in 8 instances and 39 in 2, also typically using numeric input. RF comes in third, outperforming the others in 7 out of 38 instances, consistently when the input is treated as a score. LR, however, does not surpass the other algorithms in any scenario. After selecting and implementing the most effective prediction algorithm, it was tested in a real-world scenario. The test involved comparing the support tools and strategies that 43 dyslexic students found useful or ineffective, based on their own experience, with the predictions generated by the algorithm using the challenges these students encountered throughout their studies. As shown in Table 3.9, the results confirmed the algorithm's high accuracy. Over 92% of the methodologies (both tools and strategies) predicted to be useful were indeed helpful, while nearly 90% of those predicted to be ineffective were actually found to be so. Similar outcomes were observed when tools and strategies were analyzed individually. These findings demonstrate that the algorithm can effectively predict the most beneficial support methodologies for dyslexic students.

In addition, this study shows that different learning tools and study strategies are best predicted with different models and with specific hyperparameters configuration. This is an interesting aspect that will be further investigated in the future.

3.0.3 Results of the recommendation system

The last part of the VRAILEXIA project focused on the creation of a recommendation model capable of suggesting the best learning tools and study strategies to dyslexic students. As discussed in Chapter 2, three types of RS models were compared: item-based, user-based and hybrid RSs (which mixes the other two with a weight system). Each of the RSs was analyzed using three different metrics, namely the Euclidean distance, the Cosine distance and the Pearson correlation. The first step of the study was to compared the different weight

similarity	n	MAE_0	MAE_1/8	MAE_1/7	MAE_1/6	MAE_1/5	MAE_1/4	MAE_1/3	MAE_1/2	MAE_2/3	MAE_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

Table 3.10: Experimentation results considering the different similarity measures, number of neighbors and weights for the hybrid implementation. The best result (highlighted in the table) has been obtained by the hybrid method with an α value equal to 1/4, using Pearson as similarity measure and 3 neighbors.

configurations for the hybrid RS. In addition,the optimal number of neighbors to consider was determined. Table 3.10 presents all the results from the different configurations of the system, where n represents the number of neighbors used for similarity calculation, and MAE_x refers to the MAE obtained using the hybrid model with an α value set to x.

Table 3.10 shows that the hybrid model, with an α value of 1/4 and a Pearson correlation with 3 neighbors, obtained the most favourable outcome compared to the other cases analyzed. The final MAE was 0.8093. To have a comparable measure, the relative error was calculated as:

$$\varepsilon_r = \frac{1}{N} \sum_{i,j} \left(\frac{|p_{i,j} - q_{i,j}|}{q_{i,j}} \right) \tag{3.1}$$

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%. Currently, there is no system in place that offers recommendations for this specific type of tools and study methodologies, or anything closely related. However, the error rates obtained in the evaluation suggest that employing a hybrid RS to suggest the most effective support methodologies for dyslexic students is a viable approach. The system achieved an error of less than one point on the 5-point rating scale used for evaluating the recommendations. This means that, for example, if the RS suggests a methodology with a rating of 1 (indicating very limited usefulness), the actual usefulness would fall within a range of 0.2 (not useful at all) to 1.8 (somewhat useful), which would still make it a valid recommendation. Similarly, if the RS recommends a methodology with a rating of 4 (indicating high usefulness), the actual rating would likely be between 3.2 (useful) and 4.8 (very useful), offering a reasonably accurate prediction. These results demonstrate that even with some margin of error, the system can provide acceptable and useful recommendations to support dyslexic students in their studies. In addition, Table 3.10 shows that the optimal number of neighbors is 3, with an average MAE of 1.1816. Higher numbers led to worse performances in most of the cases reported. A smaller number of neighbors, such as 3, allows for the suggestion of less popular items, avoiding the spread of misinformative items [45].

The next step of the study was to investigate the best configuration for every single weight. Each of the considered variants were subjected to individual analysis to identify the optimal configuration and the MAE. The results are summarized in Table 3.11.

alpha	**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

Table 3.11: Best configurations and MAEs obtained for the different weights in the hybrid model.

An interesting insight from Table 3.11 is that the Pearson metric consistently delivers the best performance in most cases. For each weight configuration, Pearson outperforms other metrics, with the exception of the purely user-based filter, where the best results are obtained using the Euclidean distance. In this specific case, the optimal number of neighbors is 7, as opposed to 3 in the other configurations. Despite these differences, the variations in performance across the different metrics are not particularly significant, with the results ranging from 0.8734 to 0.8093. This difference becomes even less pronounced when focusing on the hybrid models that emphasize the user-based methodology, where the MAE lies within a narrow range of 0.8093 to 0.8217. Another key observation is that an alpha value of 1/4 marks the turning point at which the system's performance starts to degrade, with a more noticeable decline as the alpha value increases beyond this point. This suggests that balancing the weight between user-based and item-based methods is critical for maintaining optimal system performance. The differences between the results of the optimal configurations of each weight are shown in Figure 3.4.

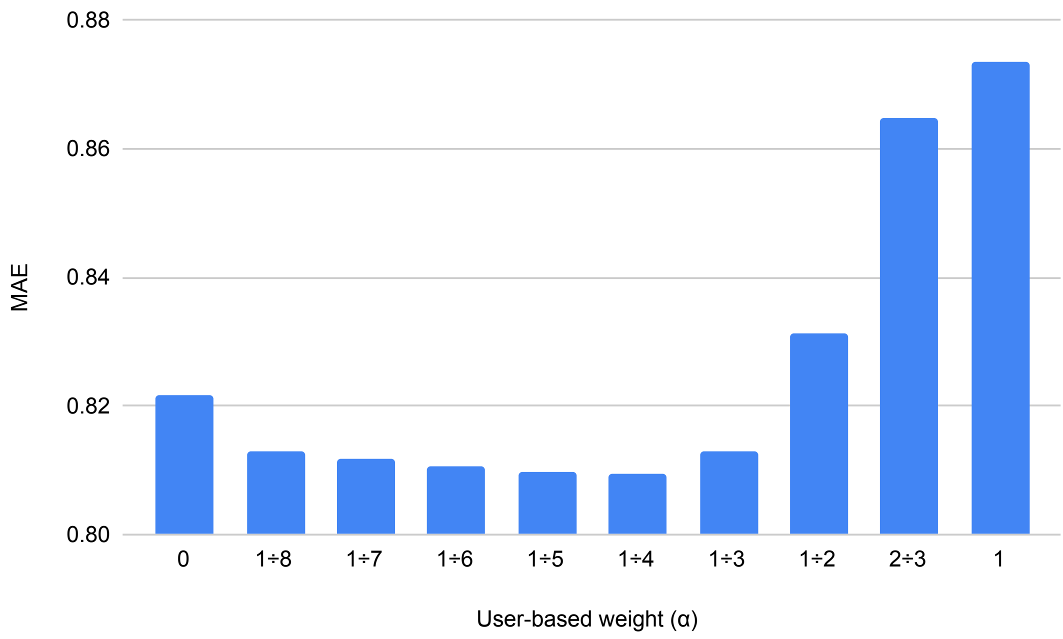


Figure 3.4: Best MAE for the different hybrid RS weight configurations.

The differences in performance across the various similarity metrics become more apparent in Figure 3.5. This figure highlights the results for each similarity measure using the selected weights, focusing on the best performance achieved by each metric. Of the metrics tested, the Cosine distance had the highest average MAE (1.1432) across all experiments, indicating relatively poor performance. The Euclidean distance performed similarly to the Cosine distance, with an average MAE of 1.0723, suggesting it may not be the best fit for our system. However, as previously mentioned, Euclidean distance does perform better when used within a user-based filter context. In contrast, Pearson correlation consistently yielded lower MAE values, making it the top-performing metric overall. Another noteworthy observation is how the metrics respond to changes in the parameter α. As α increases, both Euclidean and Cosine similarities experience a decline in performance, while Pearson correlation remains relatively stable. It only starts to show a rise in MAE when the system shifts towards a fully user-based algorithm. This stability highlights the robustness of the Pearson metric, particularly in hybrid models where it continues to perform well across varying configurations.

Since the hybrid model with an $\alpha = 1/4$, using Pearson's correlation and 3 neighbors for similarity calculations, achieved the lowest MAE, it was selected as the optimal system for recommending learning strategies and support tools for dyslexic students. To further validate the effectiveness of this recommendation model, it was also evaluated using precision and

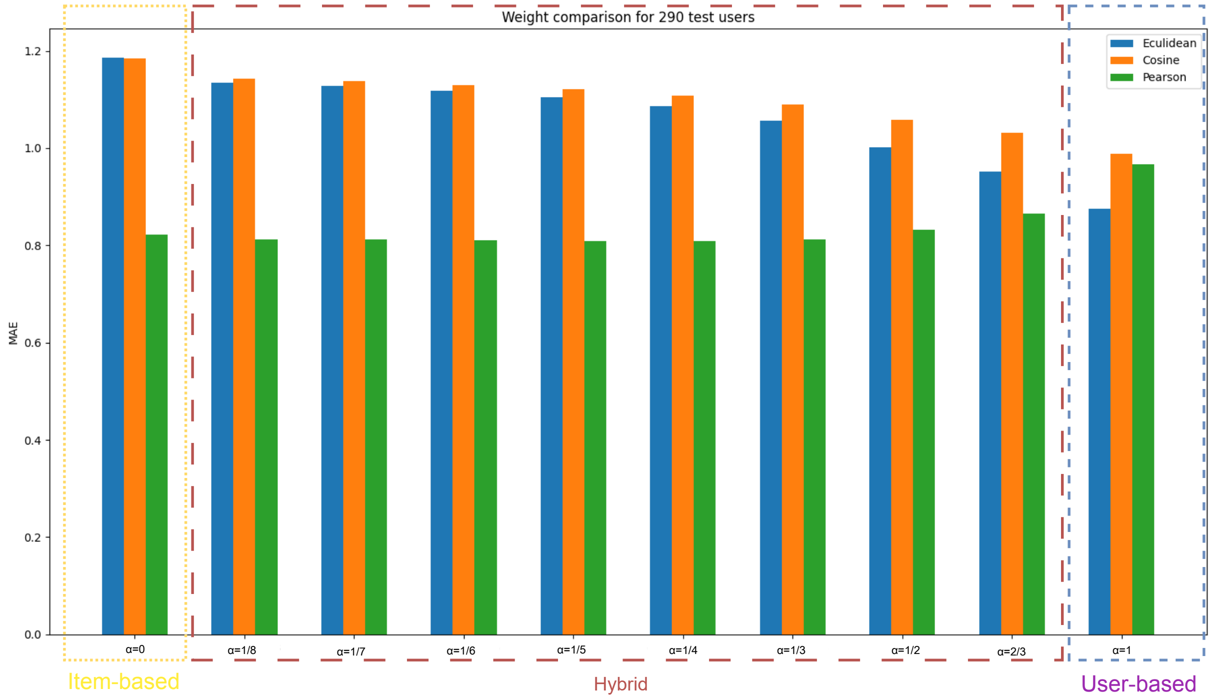


Figure 3.5: Comparison among different weight-pairs of the hybrid approach according MAE.

recall at k metrics [109]. In this evaluation, a rating threshold of 3 on the Likert scale was used to classify a tool or strategy as relevant. This threshold was determined by a panel of experts in dyslexia support methodologies and is a common reference point in the literature when using Likert-scale ratings from 0 to 5 [61]. The precision and recall 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:

$$Precision@k = \frac{V@k}{R@k} \tag{3.2}$$

  where $V@k$ is the number of recommended items at k that are relevant for an 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:

$$Recall@k = \frac{V@k}{T} \tag{3.3}$$

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

Similar to the MAE calculation, precision@k and recall@k were computed for the 290 users

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

Table 3.12: Score received by dyslexic and non-dyslexic students that adopted or not the RS system suggestions

in the test set. The proposed hybrid recommendation system achieved an average precision of 0.8524 and an average recall of 0.8278. This means that, based on precision, 85% of the methodologies recommended to a specific student are relevant support tools or strategies. Additionally, the recall indicates that approximately 83% of all relevant tools for each student were captured by the recommendations. These findings corroborate the results from the MAE analysis, further affirming the effectiveness of the proposed recommendation system. Once the utility of the hybrid recommendation model was confirmed, its optimal configuration was employed to evaluate the algorithm's impact on the learning experiences of students in a real-world setting. The experiment outlined in Section 2.0.4 was conducted, yielding results presented in Table 3.12. This table shows the average scores obtained by four groups: (i) non-dyslexic students who received suggestions from the RS, (ii) non-dyslexic students who did not receive suggestions, (iii) dyslexic students who received suggestions, and (iv) dyslexic students who did not receive suggestions. This comparative analysis aims to assess the effectiveness of the recommendation system in enhancing the learning outcomes of both dyslexic and non-dyslexic students.

The results clearly demonstrate that the adoption of the support tools and strategies recommended by the implemented RS significantly enhances the scores of dyslexic students, with an increase of over 1 point. This confirms that the proposed approach can effectively aid their learning experience. Additionally, non-dyslexic students also experienced an improvement in their average scores, increasing by 0.4 points. This finding opens up intriguing avenues for future research into the broader effectiveness of ML-suggested support methodologies. One particularly noteworthy outcome is that dyslexic students can achieve performance levels comparable to those of their non-dyslexic peers, marking a meaningful step toward genuine inclusivity in educational settings. This suggests that well-designed recommendation systems can bridge the gap in learning experiences, enabling all students to access the support they need to succeed.

Chapter 4

Discussions and future perspectives

Dyslexia is a specific learning disorder that typically manifests during early childhood and has a significant impact on various cognitive abilities, including reading, memorization, and concentration. Children with dyslexia often experience difficulties in recognizing and processing written words, which can hinder their academic progress and affect their self-esteem. Over the years, numerous researchers have tried to understand the underlying cognitive causes of this complex disorder. Some theories suggest that dyslexia stems from a phonological impairment, which means that individuals struggle to process the sounds of language. This impairment makes it challenging for them to map sounds onto letters and words, a crucial skill for reading. Other theories emphasize deficits in processing visual or auditory information, proposing that difficulties in perceiving and integrating sensory inputs contribute to the reading challenges faced by those with dyslexia. Despite the diversity of theories, there is no consensus on a single cause of dyslexia. Instead, it is increasingly recognized as a multifaceted condition that likely arises from an intricate interplay of genetic, neurological, and environmental factors. The complexity of dyslexia is further underscored by its high comorbidity with other neurodevelopmental disorders such as autism spectrum disorder and attention-deficit/hyperactivity disorder. This overlap of conditions can exacerbate the challenges faced by individuals, making it even more difficult for them to succeed in academic and social environments. For instance, a child with both dyslexia and ADHD may struggle not only with reading but also with maintaining attention and managing impulsive behaviors, creating a compounded barrier to learning and social integration. Such challenges can negatively impact their psychological well-being, leading to frustration, anxiety, and a lack of confidence. Given these complexities, early diagnosis of dyslexia is crucial. Identifying the disorder at an early stage allows for the timely implementation of support tools and interventions that can help the child cope with their difficulties. One of the most widely used methods for diagnosing dyslexia involves cognitive tests that assess a child's abilities in various domains, including reading, phonological processing, and visual and auditory processing. These tests are designed to identify specific areas of weakness and provide a comprehensive understanding of the child's cognitive profile. However, traditional diagnostic settings can sometimes be intimidating for children, potentially affecting their performance and the accuracy of the diagnosis.

To address these limitations, modern technology has introduced innovative solutions that make the diagnostic and support processes more accessible and engaging. Digital tools such as computers, smartphones, tablets, and virtual reality devices are now widely used to support children with dyslexia. These technologies offer several advantages over conventional methods. For one, they are easily accessible and familiar to most children, making them more likely to engage with the tools. Additionally, they provide a more interactive and enjoyable environment compared to the clinical settings where traditional tests are usually conducted. For example, diagnostic assessments can be embedded within mini-games that evaluate cognitive skills in a playful and non-threatening manner. This approach not only reduces anxiety but also allows for more accurate assessments, as children are likely to perform better when they are relaxed and engaged. Moreover, technology-based tools are invaluable for ongoing support and rehabilitation. Educational apps and games can be tailored to address specific areas of difficulty, such as phonological processing or visual tracking, providing personalized and adaptive learning experiences. Virtual reality environments can simulate real-life scenarios in which children practice reading and comprehension skills in a dynamic and immersive way. These tools can help children develop strategies to compensate for their deficits, ultimately enhancing their academic performance and self-confidence.

Among the various modern technologies currently being explored, one stands out as particularly promising: the implementation of artificial intelligence and machine learning algorithms. These are sophisticated mathematical models designed to process and analyze vast amounts of diverse data, revealing hidden patterns, classifying information, and predicting future outcomes. The application of these models is rapidly expanding across nearly every human-related domain, and the field of education is certainly no exception. Notably, an increasing number of studies are focusing on harnessing these models to detect dyslexia early and to develop tools that can alleviate the challenges faced by individuals with dyslexia. This is of paramount importance because if dyslexia goes undiagnosed or if diagnostic efforts fall short, the implementation of effective support systems becomes even more crucial to assist students with dyslexia. Additionally, machine learning offers the valuable advantage of enabling the creation of personalized tools tailored to meet the unique needs of each user. By learning and adapting over time, these algorithms are capable of providing targeted assistance designed to ease the specific challenges faced by different students. Unfortunately, much of the current research primarily centers on children and adolescents with dyslexia, while relatively little attention has been directed toward university students with the condition. However, focusing on higher education students presents significant reasons that should not be overlooked. For instance, the cognitive demands and level of effort required in primary education differ greatly from those encountered at the university level. Furthermore, the intensity of study and the complexity of the material increase substantially, making it reasonable to assume that university students with dyslexia may require distinct support tools compared to those used for younger students in primary education.

In light of this, we have created VRAILEXIA, a framework that combines artificial intelligence and virtual reality to create personalized support tools for dyslexic university students. This project aims to leverage on the collaboration of several European Universities and private companies to create an ensemble of tools capable of offering a personalized help to dyslexic students. The *"IN THE BOX"* unit is focused on creating virtual reality assessments for dyslexics while the *"BE SPECIAL"* unit is focused on creating artificial intelligence models to support dyslexic users during their learning path. The VRAILEXIA project aims not only to create tools that directly assist dyslexic students but also to serve as a comprehensive reference point for educators who seek to deepen their understanding of dyslexia and explore the most effective teaching practices for dyslexic learners. By offering access to an online repository, the project equips teachers with specialized materials that can be integrated into their lessons to enhance the educational experience of students with dyslexia. Furthermore, a key goal of the VRAILEXIA initiative is to foster collaboration among European universities, creating a network for sharing valuable insights and developing innovative approaches to teaching that promote the inclusion of dyslexic students.

One of the central components of the VRAILEXIA project currently under development is its artificial intelligence segment, which has been the primary focus of this dissertation. The research began with an exploratory analysis that involved 1,261 dyslexic participants. These participants were asked to complete a detailed questionnaire, which gathered various pieces of information, including demographic data, specific challenges they faced in their learning journeys, and the learning tools and study strategies they found most effective in overcoming or mitigating some of these difficulties. The findings of this research revealed a significant generational difference in the level of support received by dyslexic students. More than half of the participants born before 1990 reported that they had not received adequate support for their dyslexia. In contrast, those born after 1990 were more likely to have received appropriate aid. This discrepancy is likely due to the gradual improvement in our understanding of dyslexia over time, coupled with a growing recognition that early intervention is critical in addressing the challenges posed by the disorder. Another datum that support these claims is the percentage of dyslexic students that received their diagnose based on the year they were born. Indeed, 70% of the people born in or before the 1990, received their diagnosis later in life, during the final years of the tertiary school while 53% of the people born between 1990 and 1999. Lastly, 68% of the students born in or after the 1999, received their diagnosis during primary or secondary school. This datum is in line with the hypothesis that during the years, a greater understanding and a growing recognition of the importance of a timely intervention, developed.

Thanks to the data collected, an agglomerative cluster analysis was performed, which identified six distinct groups of students, organized by their year of birth. Of these six groups, three were categorized as at risk of not completing their studies, while the other three had either successfully graduated or were on track to graduate. This classification enabled a deeper exploration into the specific challenges each group faced, as well as the most effective learning tools and strategies they employed. A key insight from the analysis was the importance of social engagement in academic success. Interestingly, all six groups highlighted group activities as one of the most effective study strategies. This finding underscores the critical role that social inclusion and collaboration play throughout the academic journey, fostering not only academic achievement but also a sense of belonging among students. By working together, students were able to better grasp complex topics and share insights, benefiting from diverse perspectives within their study groups. Another study strategy widely deemed as beneficial across the groups was the incorporation of regular exam assessments. These assessments not only helped students become familiar with the format and structure of exams but also provided valuable opportunities for them to evaluate their understanding of key concepts presented during lectures. Receiving intermediate feedback throughout the course allowed students to identify areas of weakness and take corrective action well before the final exam, ensuring a more comprehensive understanding of the material. In terms of learning tools, the analysis revealed that two technological resources were particularly favored by the groups: audiobooks and tablets. These tools proved to be highly effective for students with and without specific learning disorders, further validating the growing role of technology in modern education. Audiobooks facilitated learning on the go, while tablets offered versatility in accessing course materials, enabling students to study in various locations and environments. In addition to digital tools, more traditional methods such as concept maps, summaries, and visual aids were also cited as extremely useful. These tools helped simplify complex subjects by organizing information in a clear, concise manner, making it easier for students to retain key points. Notably, the flexibility of modern devices allowed for the integration of these tools, giving students the freedom to access and engage with their study materials whenever and wherever they chose to study.

After the exploratory analysis, four machine learning algorithms were used to detect the most useful learning tools and study strategies for each student. The goal was twofold, on one hand was to check if it was possible to use mathematical models to predict the best learning tools and study strategies for each student, on the other hand, was to identify the best possible parameters for each model for this task. The accuracy obtained by the models for the learning tools ranged from 72,5% to 97,8%, with an average of of 88,7%. The support vector machine model emerged as the most effective choice for the majority of learning tools, outperforming other models in 11 out of 16 instances. Following support vector machine, k-Nearest Neighbors was the best model in 3 out of 16 cases, while the random forest model was most successful in 2 out of 16. A similar pattern was observed within the study strategy set: the support vector machine model led in performance for 10 out of 22 study strategies, with k-Nearest Neighbors excelling in 7 out of 22, and random forest being the top model for 5 out of 22 strategies. The models demonstrated a wide range in accuracy across study strategies, from a minimum of 70.5% to a peak of 99.4%. Beyond illustrating the benefits of machine learning in this field, these findings highlight that specific algorithms may be better suited for particular tasks, indicating that a combination of models could offer a more effective solution than relying on any one model subset. Furthermore, using tailored machine learning models to recommend the most appropriate learning tools and study strategies supports our objective of creating personalized assistance tools for students, with this customization mirrored in the selection of models deployed.

The final phase of the VRAILEXIA project involved creating a recommendation system designed specifically to identify and suggest optimal learning tools and study strategies for dyslexic students. The primary objective of this experiment was to evaluate the performance of a tailored recommendation model in comparison to other established machine learning algorithms. Among various types of recommendation systems, we selected collaborative filtering, a method focused on suggesting the most suitable items based on ratings given by similar users. Collaborative filtering comprises several approaches, notably the user-based, item-based, and hybrid models. In the user-based approach, recommendations are generated based on similarities between users. This method operates on the idea that users who share similar tastes or preferences will also likely benefit from similar tools or strategies. By identifying users with comparable learning needs or challenges, the system can recommend items that these similar users have found helpful. The item-based approach, in contrast, centers on identifying similarities between items rather than users. Instead of analyzing user preferences, it compares items directly, recommending tools or strategies similar to those the user has already liked or engaged with. This approach is particularly effective for users who may not have much interaction data available, as it relies on the characteristics of the items themselves rather than user histories. The hybrid approach combines both user-based and item-based filtering methods, assigning varying weights to each to optimize recommendations. By leveraging the strengths of both approaches, the hybrid model enhances accuracy and provides more personalized recommendations, accommodating the diverse and specific needs of dyslexic students. In addition to exploring different collaborative filtering approaches, we also tested three similarity metrics to measure the closeness between users or items. The metrics examined were Euclidean distance, Pearson correlation, and Cosine similarity, each offering unique insights into user or item relationships. After conducting multiple analyses that paired the different collaborative filtering approaches with these similarity metrics, we found that the hybrid model, combined with Pearson correlation, delivered the highest accuracy in recommending effective learning tools and study strategies.

To validate these findings further, we organized an experiment involving both dyslexic and non-dyslexic students. This experiment aimed to assess the effectiveness of the recommendation model in a real-world learning environment. Participants were divided into four groups: dyslexic and non-dyslexic students who followed the study suggestions generated by the recommendation model, and dyslexic and non-dyslexic students who used their own preferred study methods. Each group was tasked with studying specific books, and their comprehension and retention were evaluated by experienced university professors. The results were compelling. Both dyslexic and non-dyslexic students who utilized the recommendation model's suggestions achieved higher scores than their peers who relied on their usual study methods. This outcome strongly supports the effectiveness of the recommendation model and underscores its potential as a valuable tool for improving academic outcomes for university students, particularly those with dyslexia. These findings emphasize the utility of a personalized recommendation system in providing targeted, effective support, potentially transforming the way students with diverse learning needs approach their studies.

The VRAILEXIA project has generated a range of interesting results across multiple experiments, offering valuable insights into the development of tailored learning tools and study strategies for dyslexic students. These findings provide a promising foundation for further investigation, potentially paving the way for more refined and widely applicable educational support systems. However, this project also has certain limitations that merit attention and discussion in this section.

The primary limitation of the project relates to the number of students who participated in the study. While involving over 1,200 dyslexic students offers a substantial starting point for preliminary analysis, an even larger and more diverse sample size would likely increase the statistical power and robustness of the findings. A higher number of participants would allow for more sophisticated statistical analyses, enabling the detection of subtler trends and variations that a smaller dataset might overlook. This could also lead to a more comprehensive understanding of how different factors—such as age, academic level, or learning context—impact the effectiveness of recommended tools and strategies for dyslexic students. Furthermore, expanding the sample size would improve the generalizability of the results, making it easier to apply the insights gained to a broader population of dyslexic students. Given the diversity in learning profiles among individuals with dyslexia, a larger sample could capture a wider array of learning needs, preferences, and challenges. This would enable the recommendation system to be fine-tuned to better accommodate the diverse cognitive and educational requirements of dyslexic learners. Additionally, increasing the number of participants, particularly from varied geographical, linguistic, and cultural backgrounds, could help highlight whether the recommendation model performs consistently across different educational systems and cultural contexts, offering a truly global perspective. Another consideration is the benefit of longitudinal data. With a larger pool of students, it would be possible to track learning outcomes over an extended period, assessing not only immediate improvements but also long-term retention and academic progress. This would add another layer to the analysis, helping to establish the enduring impact of the VRAILEXIA recommendations on dyslexic students' academic success and study habits.

Another key limitation lies in the need to validate the recommendation system's results against outputs generated by a range of machine learning algorithms. While certain machine learning models may outperform the recommendation model on accuracy metrics alone, these metrics don't always capture the practical effectiveness of the outputs in real-world settings. A higher accuracy rate in predictive modeling doesn't necessarily equate to better support for dyslexic students. To confirm true efficacy, machine learning outputs should be tested with real users who can provide qualitative feedback on their usability and relevance to individual learning needs. This feedback is essential for evaluating whether the most accurate model from a technical standpoint also delivers tangible benefits in practice. Additionally, the sample size of students tested using the recommendation model should be expanded. Increasing the number of participants would not only allow for a more robust comparison across various machine learning models but also provide a more reliable basis for statistical analysis. A larger sample size improves the generalizability of the findings and increases the statistical power, allowing for greater confidence in the observed differences in model performance. Furthermore, with a larger dataset, it may be possible to tailor recommendations more precisely, potentially leading to an iterative improvement in the recommendation model itself. Ultimately, to develop a recommendation system that provides consistent, real-world value, the study should integrate quantitative performance metrics with qualitative user feedback and expand the dataset to capture a broader range of user experiences. This approach will help ensure that the recommendations align not only with theoretical accuracy but also with practical effectiveness.

Another important limitation of this project is the specific selection of learning tools and study strategies included. The items and strategies evaluated were those that dyslexic students, through their own experiences, found to be the most helpful along their learning journeys. Many of these tools are technology-based, including audiobooks, e-books, tablets, and similar resources. However, as technology continues to evolve, new devices, software, and digital platforms are constantly being introduced and embraced by new generations of students. These emerging technologies offer both new opportunities and challenges for enhancing learning experiences.

For example, artificial intelligence driven tools are rapidly gaining popularity among students as they facilitate personalized and interactive learning. artificial intelligence-based systems now allow students to engage in a real-time, question-and-answer format with the technology, enabling them to request explanations, examples, or even detailed breakdowns of complex topics. This personalized interaction contrasts with the limitations of traditional educational settings, where professors are generally available only during lectures or scheduled office hours. AI tools, on the other hand, are available 24/7, offering students an on-demand resource that adapts to their schedules and learning needs, which is especially valuable for students with learning differences who may require extra time or alternative explanations for specific concepts. As artificial intelligence and other technology-based learning tools become more sophisticated, they have the potential to address several challenges that dyslexic and other students face in conventional learning environments. For instance, artificial intelligence can assist in breaking down complex information into more manageable parts, provide audio-visual explanations, and deliver text in dyslexia-friendly formats, all of which can significantly enhance comprehension and retention for students who struggle with traditional text-heavy materials. Looking forward, it is essential that this project keeps pace with these technological advancements to offer relevant and effective recommendations. This will involve periodically revisiting and updating the study's scope to include emerging tools and technologies, ensuring that students receive the most current and effective support for their learning needs. Future iterations of this project could explore not only artificial intelligence based tools but also virtual reality for immersive learning, augmented reality for interactive textbook overlays, and adaptive learning platforms that respond to each student's progress in real time. Integrating these innovations can provide a richer, more comprehensive set of recommendations, ultimately supporting students in overcoming the unique challenges they face in traditional academic settings.

Aside from the technological limitations of the project, another key limitation arises from the geographic and educational context of the participants. This study's participants are dyslexic students exclusively from Italian universities, which impacts the generalizability of the findings. Since all analyses are based on the responses provided by this specific group, it may be challenging to apply these insights broadly, especially across different educational systems internationally. Educational structures and expectations vary significantly by country, including variations in university organization, lecture styles, and exam formats. For example, some countries may emphasize written exams, while others prioritize oral assessments. These structural differences can greatly influence the learning tools and study strategies that dyslexic students find most effective in overcoming their challenges. In educational systems that rely more heavily on written exams, students may develop strategies focused on reading and writing efficiency, while those in systems favoring oral exams might prioritize verbal communication skills and memory aids. Consequently, the study methods and tools developed based on Italian students' needs might not fully apply to dyslexic students in other countries who are exposed to different instructional styles and evaluation methods. To capture these potential differences, it would be essential to replicate similar studies in diverse countries with varied educational systems. By doing so, researchers could detect cross-national differences in learning styles and tailor more universally applicable learning tools and strategies that address the unique challenges posed by each educational organization. This approach would enhance the global relevance and applicability of the findings, supporting dyslexic students in a broader range of educational settings.

All of the limitations discussed in this chapter also represent valuable opportunities for enhancing the reliability and applicability of the results obtained in this study. By addressing these limitations in future research, there is significant potential to refine the model and expand its usefulness. The VRAILEXIA project has already yielded promising results and laid essential groundwork for creating support tools that can be customized to meet the specific needs of students. One of the most exciting possibilities for future directions is the adaptability of these mathematical models over time. As students progress through their education, their learning needs often evolve—study loads become more demanding, course complexity increases, and the knowledge required becomes more advanced. For students with dyslexia, these shifting demands can pose additional challenges that may require updated or newly tailored learning strategies and tools. An adaptive recommendation system that evolves in response to these changing needs would be an invaluable support, enabling both dyslexic and non-dyslexic students to receive personalized assistance throughout their educational journey.

Furthermore, such adaptability allows the system to remain relevant and effective as educational tools and strategies evolve. By dynamically adjusting to the user's needs, this system could provide ongoing, personalized support that enhances learning efficiency and engagement, potentially improving outcomes for a broad spectrum of learners. This adaptive aspect thus not only addresses current limitations but also represents a forward-looking approach that aligns with the goal of creating a supportive, flexible learning environment for all students.

Bibliography

[1] Wadee Alhalabi. Virtual reality systems enhance students' achievements in engineering education. *Behaviour & Information Technology*, 35(11):919–925, 2016.

[2] DSMTF American Psychiatric Association, DS American Psychiatric Association, et al. *Diagnostic and statistical manual of mental disorders: DSM-5*, volume 5. American psychiatric association Washington, DC, 2013.

[3] John R Anderson, Mark V Albert, and Jon M Fincham. Tracing problem solving in real time: fmri analysis of the subject-paced tower of hanoi. *Journal of cognitive neuroscience*, 17(8):1261–1274, 2005.

[4] Martijn Arns, Sylvia Peters, Rien Breteler, and Ludo Verhoeven. Different brain activation patterns in dyslexic children: evidence from eeg power and coherence patterns for the double-deficit theory of dyslexia. *Journal of integrative neuroscience*, 6(01):175–190, 2007.

[5] Marie Arsalidou, Matthew Pawliw-Levac, Mahsa Sadeghi, and Juan Pascual-Leone. Brain areas associated with numbers and calculations in children: Meta-analyses of fmri studies. *Developmental cognitive neuroscience*, 30:239–250, 2018.

[6] Isuru Avishka, Kalana Kumarawadu, Akalanka Kudagama, Mihiran Weerathunga, and Samantha Thelijjagoda. Mobile app to support people with dyslexia and dysgraphia. In *2018 IEEE International Conference on Information and Automation for Sustainability (ICIAfS)*, pages 1–6. IEEE, 2018.

[7] Gilbert Badaro, Hazem Hajj, Wassim El-Hajj, and Lama Nachman. A hybrid approach with collaborative filtering for recommender systems. In *2013 9th International wireless communications and mobile computing conference (IWCMC)*, pages 349–354. IEEE, 2013.

[8] Stéphanie Bellocchi, Mathilde Muneaux, Mireille Bastien-Toniazzo, and Stéphanie Ducrot. I can read it in your eyes: What eye movements tell us about visuo-attentional

processes in developmental dyslexia. *Research in developmental disabilities*, 34(1):452–460, 2013.

[9] Ilaria Benedetti, Marcella Barone, Valentina Panetti, Juri Taborri, Tony Urbani, Andrea Zingoni, and Giuseppe Calabrò. Clustering analysis of factors affecting academic career of university students with dyslexia in italy. *Scientific reports*, 12(1):9010, 2022.

[10] Harald Beneventi, Finn Egil Tønnessen, Lars Ersland, and Kenneth Hugdahl. Working memory deficit in dyslexia: behavioral and fmri evidence. *International Journal of Neuroscience*, 120(1):51–59, 2010.

[11] Fatimaezzahra Benmarrakchi, Nihal Ouherrou, Oussama Elhammoumi, and Jamal El Kafi. An innovative approach to involve students with learning disabilities in intelligent learning systems. In *International Conference on Advanced Intelligent Systems for Sustainable Development*, pages 39–50. Springer, 2018.

[12] Dorothy VM Bishop. The interface between genetics and psychology: lessons from developmental dyslexia. *Proceedings of the Royal Society B: Biological Sciences*, 282(1806):20143139, 2015.

[13] Teresa Bittencourt, João Savino, Helena Fernandes, and Luiza Helena Boueri Rebello. Mobile device development and its contribution to the treatment of young dyslexic brazilian children. In *Advances in Design for Inclusion: Proceedings of the AHFE 2016 International Conference on Design for Inclusion, July 27-31, 2016, Walt Disney World®, Florida, USA*, pages 339–349. Springer, 2016.

[14] Giuseppe Bonaccorso. *Machine Learning Algorithms: Popular algorithms for data science and machine learning*. Packt Publishing Ltd, 2018.

[15] Marcelo C Borba, Petek Askar, Johann Engelbrecht, George Gadanidis, Salvador Llinares, and Mario Sánchez Aguilar. Blended learning, e-learning and mobile learning in mathematics education. *ZDM*, 48:589–610, 2016.

[16] Katarzyna Brimo, Lisa Dinkler, Christopher Gillberg, Paul Lichtenstein, Sebastian Lundström, and Jakob Åsberg Johnels. The co-occurrence of neurodevelopmental problems in dyslexia. *Dyslexia*, 27(3):277–293, 2021.

[17] WE Brown, S Eliez, V Menon, JM Rumsey, CD White, and AL Reiss. Preliminary evidence of widespread morphological variations of the brain in dyslexia. *Neurology*, 56(6):781–783, 2001.

[18] N Brunswick, E McCrory, CJ Price, CD Frith, and U Frith. Explicit and implicit processing of words and pseudowords by adult developmental dyslexics: A search for wernicke's wortschatz? *Brain*, 122(10):1901–1917, 1999.

[19] Robin Burke. Hybrid recommender systems: Survey and experiments. *User modeling and user-adapted interaction*, 12(4):331–370, 2002.

[20] Elisa Cainelli, Luca Vedovelli, Barbara Carretti, and Patrizia Bisiacchi. Eeg correlates of developmental dyslexia: a systematic review. *Annals of Dyslexia*, pages 1–30, 2022.

[21] Francesco Calì, Francesco Domenico Di Blasi, Emanuela Avola, Mirella Vinci, Antonino Musumeci, Angelo Gloria, Donatella Greco, Daniela Rita Raciti, Alessandro Zagami, Biagio Rizzo, et al. Specific learning disorders: variation analysis of 15 candidate genes in 9 multiplex families. *Medicina*, 59(8):1503, 2023.

[22] Claudia Cappa, Sara Giulivi, Antonino Schilirò, Luca Bastiani, Carlo Muzio, and Fabrizio Meloni. A screening on specific learning disorders in an italian speaking high genetic homogeneity area. *Research in developmental disabilities*, 45:329–342, 2015.

[23] Walter Carrer-Neto, María Luisa Hernández-Alcaraz, Rafael Valencia-García, and Francisco García-Sánchez. Social knowledge-based recommender system. application to the movies domain. *Expert Systems with applications*, 39(12):10990–11000, 2012.

[24] Manuel F Casanova, Julio Araque, Jay Giedd, and Judith M Rumsey. Reduced brain size and gyrification in the brains of dyslexic patients. *Journal of Child Neurology*, 19(4):275–281, 2004.

[25] M Ciuffo, D Angelini, C Barletta Rodolfi, A Gagliano, E Ghidoni, and G Stella. Bda 16-30. *Batteria Dislessia Adulti, Giuntu Psychometrics*, 2019.

[26] C Cornoldi and L Montesano. Nuova batteria per studenti universitari e adulti lsc-sua. 2020.

[27] Jennifer T Coull. fmri studies of temporal attention: allocating attention within, or towards, time. *Cognitive Brain Research*, 21(2):216–226, 2004.

[28] Helen Crompton. Understanding angle and angle measure: A design-based research study using context aware ubiquitous learning. *International Journal for Technology in Mathematics Education*, 22(1):19–30, 2015.

[29] Daniel Dancsa, Iveta Štempel'ová, Ondrej Takáč, and Norbert Annuš. Digital tools in education. *Journal of Advanced Natural Sciences and Engineering Researches*, 7(4):289–294, 2023.

[30] Carolien GF De Kovel, Barbara Franke, Frans A Hol, Jérémie JP Lebrec, Ben Maassen, Han Brunner, George W Padberg, Jill Platko, and David Pauls. Confirmation of dyslexia susceptibility loci on chromosomes 1p and 2p, but not 6p in a dutch sib-pair collection. *American Journal of Medical Genetics Part B: Neuropsychiatric Genetics*, 147(3):294–300, 2008.

[31] Maria De Luca, Marta Borrelli, Anna Judica, Donatella Spinelli, and Pierluigi Zoccolotti. Reading words and pseudowords: An eye movement study of developmental dyslexia. *Brain and language*, 80(3):617–626, 2002.

[32] Marc Peter Deisenroth, A Aldo Faisal, and Cheng Soon Ong. *Mathematics for machine learning*. Cambridge University Press, 2020.

[33] Valentina Di Giusto, Giulia Purpura, Carla Fulvia Zorzi, Rosanna Blonda, Elena Brazzoli, Paolo Meriggi, Tarjn Reina, Silvia Rezzonico, Roberta Sala, Ivana Olivieri, et al. Virtual reality rehabilitation program on executive functions of children with specific learning disorders: a pilot study. *Frontiers in Psychology*, 14, 2023.

[34] Rebeca Diaz, Nils M Kronenberg, Angela Martinelli, Philipp Liehm, Andrew C Riches, Malte C Gather, and Silvia Paracchini. Kiaa0319 influences cilia length, cell migration and mechanical cell–substrate interaction. *Scientific Reports*, 12(1):722, 2022.

[35] Mirela Duranovic, Smajlagic Senka, and Branka Babic-Gavric. Influence of increased letter spacing and font type on the reading ability of dyslexic children. *Annals of Dyslexia*, 68:218–228, 2018.

[36] Mark D'Esposito, Bradley R Postle, and Bart Rypma. Prefrontal cortical contributions to working memory: evidence from event-related fmri studies. *Executive control and the frontal lobe: Current issues*, pages 3–11, 2000.

[37] John D Eicher and Jeffrey R Gruen. Language impairment and dyslexia genes influence language skills in children with autism spectrum disorders. *Autism Research*, 8(2):229–234, 2015.

[38] Tanya M Evans, D Lynn Flowers, Eileen M Napoliello, and Guinevere F Eden. Sex-specific gray matter volume differences in females with developmental dyslexia. *Brain Structure and Function*, 219:1041–1054, 2014.

[39] Andrea Facoetti, Pierluigi Paganoni, Massimo Turatto, Valentina Marzola, and Gian Gastone Mascetti. Visual-spatial attention in developmental dyslexia. *Cortex*, 36(1):109–123, 2000.

[40] Jannat Falah, Soheeb Khan, Tasneem Alfalah, Salsabeel FM Alfalah, Warren Chan, David K Harrison, and Vassilis Charissis. Virtual reality medical training system for anatomy education. In *2014 Science and information conference*, pages 752–758. IEEE, 2014.

[41] Angela Fawcett and RI Nicholson. *The dyslexia adult screening test (DAST)*. Pearson London, 1998.

[42] Angela J Fawcett and Roderick I Nicolson. The dyslexia early screening test. *The Irish Journal of Psychology*, 16(3):248–259, 1995.

[43] Angela J Fawcett, Roderick I Nicolson, and Paul Dean. Impaired performance of children with dyslexia on a range of cerebellar tasks. *Annals of Dyslexia*, 46:259–283, 1996.

[44] A Feola, V Marino, A Masullo, M Trabucco Aurilio, LT Marsella, et al. The protection of individuals affected with specific learning disorders in the italian legislation. *Clin. Ter*, 166:177–181, 2015.

[45] Miriam Fernández, Alejandro Bellogín, and Iván Cantador. Analysing the effect of recommendation algorithms on the amplification of misinformation. *arXiv preprint arXiv:2103.14748*, 2021.

[46] Léon Franzen, Zoey Stark, and Aaron Johnson. Ab004. the dyslexia font opendyslexic facilitates visual processing of text and improves reading comprehension in adult dyslexia. *Annals of Eye Science*, 4:AB004–AB004, 2019.

[47] Nadine Gaab, JDE Gabrieli, GK Deutsch, P Tallal, and E Temple. Neural correlates of rapid auditory processing are disrupted in children with developmental dyslexia and ameliorated with training: an fmri study. *Restorative neurology and neuroscience*, 25(3-4):295–310, 2007.

[48] José-Antonio García-Martínez, Francisco-César Rosa-Napal, Isabel Romero-Tabeayo, Sara López-Calvo, and Eduardo-José Fuentes-Abeledo. Digital tools and personal learning environments: An analysis in higher education. *Sustainability*, 12(19):8180, 2020.

[49] Marianthi Georgitsi, Iasonas Dermitzakis, Evgenia Soumelidou, and Eleni Bonti. The polygenic nature and complex genetic architecture of specific learning disorder. *Brain sciences*, 11(5):631, 2021.

[50] Eva Germanò, Antonella Gagliano, and Paolo Curatolo. Comorbidity of adhd and dyslexia. *Developmental neuropsychology*, 35(5):475–493, 2010.

[51] John C Gower. A general coefficient of similarity and some of its properties. *Biometrics*, pages 857–871, 1971.

[52] C Grünling, M Ligges, R Huonker, M Klingert, H-J Mentzel, R Rzanny, WA Kaiser, H Witte, and B Blanz. Dyslexia: the possible benefit of multimodal integration of fmri-and eeg-data. *Journal of Neural Transmission*, 111:951–969, 2004.

[53] J Hair. Multivariate data analysis. *Exploratory factor analysis*, 2009.

[54] Constance Hammen. Stress and depression. *Annu. Rev. Clin. Psychol.*, 1:293–319, 2005.

[55] Riitta Hari and Hanna Renvall. Impaired processing of rapid stimulus sequences in dyslexia. *Trends in cognitive sciences*, 5(12):525–532, 2001.

[56] John Haugeland. *Artificial intelligence: The very idea.* MIT press, 1989.

[57] Jon Herlocker, Joseph Konstan, Loren Terveen, John C.s Lui, and T. Riedl. Evaluating collaborative filtering recommender systems. *ACM Transactions on Information Systems*, 22:5–53, 01 2004.

[58] Natasa Hoic-Bozic, Martina Holenko Dlab, and Vedran Mornar. Recommender system and web 2.0 tools to enhance a blended learning model. *IEEE Transactions on education*, 59(1):39–44, 2015.

[59] Maria Joseph Israel. Effectiveness of integrating moocs in traditional classrooms for undergraduate students. *International Review of Research in Open and Distributed Learning*, 16(5):102–118, 2015.

[60] ER John, L Prichep, H Ahn, P Easton, J Fridman, and H Kaye. Neurometric evaluation of cognitive dysfunctions and neurological disorders in children. *Progress in neurobiology*, 21(4):239–290, 1983.

[61] Nima Joorabloo, Mahdi Jalili, and Yongli Ren. A probabilistic graph-based method to solve precision-diversity dilemma in recommender systems. *Expert Systems with Applications*, 184:115485, 2021.

[62] Michael I Jordan and Tom M Mitchell. Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245):255–260, 2015.

[63] Nancy Just and Lauren B Alloy. The response styles theory of depression: tests and an extension of the theory. *Journal of abnormal psychology*, 106(2):221, 1997.

[64] Katerina Kalyvioti and Tassos A Mikropoulos. Memory performance of dyslexic adults in virtual environments. *Procedia Computer Science*, 14:410–418, 2012.

[65] Zoï Kapoula, Rebecca Ganem, Sarah Poncet, Daunys Gintautas, Thomas Eggert, Dominique Brémond-Gignac, and Maria Pia Bucci. Free exploration of painting uncovers particularly loose yoking of saccades in dyslexics. *Dyslexia*, 15(3):243–259, 2009.

[66] Gagandeep Kaur, Sonia Goyal, and Harpreet Kaur. Brief review of various machine learning algorithms. In *Proceedings of the International Conference on Innovative Computing & Communication (ICICC)*, 2021.

[67] Timo Kirschstein and Rüdiger Köhling. What is the source of the eeg? *Clinical EEG and neuroscience*, 40(3):146–149, 2009.

[68] Yanika Kowitlawakul, Moon Fai Chan, Sharon Swee Lin Tan, Alan Swee Kit Soong, and Sally Wai Chi Chan. Development of an e-learning research module using multimedia instruction approach. *CIN: Computers, Informatics, Nursing*, 35(3):158–168, 2017.

[69] Jeremy M Law, Jan Wouters, and Pol Ghesquière. Morphological awareness and its role in compensation in adults with dyslexia. *Dyslexia*, 21(3):254–272, 2015.

[70] Guylaine Le Jan, Régine Le Bouquin-Jeannès, Nathalie Costet, Nolwenn Trolès, Pascal Scalart, Dominique Pichancourt, Gérard Faucon, and Jean-Emile Gombert. Multivariate predictive model for dyslexia diagnosis. *Annals of dyslexia*, 61:1–20, 2011.

[71] Katia Lehongre, Benjamin Morillon, Anne-Lise Giraud, and Franck Ramus. Impaired auditory sampling in dyslexia: further evidence from combined fmri and eeg. *Frontiers in human neuroscience*, 7:454, 2013.

[72] Nikos K Logothetis. What we can do and what we cannot do with fmri. *Nature*, 453(7197):869–878, 2008.

[73] Aoife Lonergan, Caoilainn Doyle, Clare Cassidy, Shane MacSweeney Mahon, Richard AP Roche, Lorraine Boran, and Jessica Bramham. A meta-analysis of executive functioning in dyslexia with consideration of the impact of comorbid adhd. *Journal of Cognitive Psychology*, 31(7):725–749, 2019.

[74] Maureen W Lovett, Jan C Frijters, Maryanne Wolf, Karen A Steinbach, Rose A Sevcik, and Robin D Morris. Early intervention for children at risk for reading disabilities: The impact of grade at intervention and individual differences on intervention outcomes. *Journal of Educational Psychology*, 109(7):889, 2017.

[75] Martin Macaš, Lenka Lhotská, and Daniel Novák. Hidden markov models for analysis of eye movements of dyslexic children. In *2013 18th international conference on digital signal processing (DSP)*, pages 1–5. IEEE, 2013.

[76] Spyros Makridakis. The forthcoming artificial intelligence (ai) revolution: Its impact on society and firms. *Futures*, 90:46–60, 2017.

[77] Irene C Mammarella, Marta Ghisi, Monica Bomba, Gioia Bottesi, Sara Caviola, Fiorenza Broggi, and Renata Nacinovich. Anxiety and depression in children with nonverbal learning disabilities, reading disabilities, or typical development. *Journal of learning disabilities*, 49(2):130–139, 2016.

[78] Fernanda Tostes Marana, Renato da Silva Fernandes, Jorge Luis Bazán Guzmán, André Carlos Ponce de Leon Ferreira, Mariana 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*, page 122981, 2023.

[79] Giuseppa Maresca, Simona Leonardi, Maria Cristina De Cola, Silvia Giliberto, Marcella Di Cara, Francesco Corallo, Angelo Quartarone, and Alessandra Pidalà. Use of virtual reality in children with dyslexia. *Children*, 9(11):1621, 2022.

[80] Eva Marinus, Michelle Mostard, Eliane Segers, Teresa M Schubert, Alison Madelaine, and Kevin Wheldall. A special font for people with dyslexia: Does it work and, if so, why? *Dyslexia*, 22(3):233–244, 2016.

[81] Ewan W McDonald, Jessica L Boulton, and Jacqueline L Davis. E-learning and nursing assessment skills and knowledge–an integrative review. *Nurse education today*, 66:166–174, 2018.

[82] Vinod Menon and Sonia Crottaz-Herbette. Combined eeg and fmri studies of human brain function. *Int Rev Neurobiol*, 66(05):291–321, 2005.

[83] Tassos A Mikropoulos and Vassilis Strouboulis. Factors that influence presence in educational virtual environments. *CyberPsychology & Behavior*, 7(5):582–591, 2004.

[84] TR Miles, TJ Wheeler, and MN Haslum. The existence of dyslexia without severe literacy problems. *Annals of Dyslexia*, 53:340–354, 2003.

[85] S Mohamad, W Mansor, and Khuan Y Lee. Review of neurological techniques of diagnosing dyslexia in children. In *2013 IEEE 3rd international conference on system engineering and technology*, pages 389–393. IEEE, 2013.

[86] Kristina Moll, Sarah Kunze, Nina Neuhoff, Jennifer Bruder, and Gerd Schulte-Körne. Specific learning disorder: Prevalence and gender differences. *PLoS one*, 9(7):e103537, 2014.

[87] Gianluca Morciano, José Manuel Alcalde Llergo, Andrea Zingoni, Enrique Yeguas Bolívar, Juri Taborri, and Giuseppe Calabrò. Use of recommendation models to provide support to dyslexic students. *Expert Systems with Applications*, 249:123738, 2024.

[88] Daniel Mpia Ndombo, Sunday Ojo, and Isaac O. Osunmakinde. An intelligent integrative assistive system for dyslexic learners. *Journal of Assistive Technologies*, 7(3):172–187, 2013.

[89] Daniele Mugnaini, Stefano Lassi, Giampaolo La Malfa, and Giorgio Albertini. Internalizing correlates of dyslexia. *World Journal of Pediatrics*, 5:255–264, 2009.

[90] J Fraser Mustard. Early child development and the brain-the base for health, learning, and behavior throughout life. *From early child development to human development*, 3(10):23–62, 2002.

[91] Roderick I Nicolson and Angela J Fawcett. Procedural learning difficulties: reuniting the developmental disorders? *TRENDS in Neurosciences*, 30(4):135–141, 2007.

[92] Shally Novita. Secondary symptoms of dyslexia: A comparison of self-esteem and anxiety profiles of children with and without dyslexia. *European journal of special needs education*, 31(2):279–288, 2016.

[93] Szczepan Paszkiel and Piotr Szpulak. Methods of acquisition, archiving and biomedical data analysis of brain functioning. In *Biomedical Engineering and Neuroscience: Proceedings of the 3rd International Scientific Conference on Brain-Computer Interfaces, BCI 2018, March 13-14, Opole, Poland*, pages 158–171. Springer, 2018.

[94] GH Payne, TR Miles, and TJ Wheeler. Does the ddat programme provide a cure for dyslexia? results from the bangor dyslexia test. *Dyslexia Review*, 19(1):7, 2007.

[95] Elisa Pedroli, Patrizia Padula, Andrea Guala, Maria Teresa Meardi, Giuseppe Riva, and Giovanni Albani. A psychometric tool for a virtual reality rehabilitation approach for dyslexia. *Computational and mathematical methods in medicine*, 2017, 2017.

[96] Barbara Penolazzi, Chiara Spironelli, and Alessandro Angrilli. Delta eeg activity as a marker of dysfunctional linguistic processing in developmental dyslexia. *Psychophysiology*, 45(6):1025–1033, 2008.

[97] Conrad Perry, Marco Zorzi, and Johannes C Ziegler. Understanding dyslexia through personalized large-scale computational models. *Psychological science*, 30(3):386–395, 2019.

[98] Davide Piffer, Davide Ponzi, Paola Sapienza, Luigi Zingales, and Dario Maestripieri. Morningness–eveningness and intelligence among high-achieving us students: Night owls have higher gmat scores than early morning types in a top-ranked mba program. *Intelligence*, 47:107–112, 2014.

[99] Zainab Pirani and M Sasikumar. Assistive e-learning system for the learning disabled. *Procedia Computer Science*, 45:718–727, 2015.

[100] Daniëlle Posthuma, Eco JC De Geus, Wim FC Baaré, Hilleke E Hulshoff Pol, René S Kahn, and Dorret I Boomsma. The association between brain volume and intelligence is of genetic origin. *Nature neuroscience*, 5(2):83–84, 2002.

[101] Emmanuel M Pothos and Jane Kirk. Investigating learning deficits associated with dyslexia. *Dyslexia*, 10(1):61–76, 2004.

[102] Sampath Rajapakse, Dasuni Polwattage, Umesha Guruge, Isuru Jayathilaka, Tharindu Edirisinghe, and Samantha Thelijjagoda. Alexza: A mobile application for dyslexics utilizing artificial intelligence and machine learning concepts. In *2018 3rd International Conference on Information Technology Research (ICITR)*, pages 1–6. IEEE, 2018.

[103] Franck Ramus. Outstanding questions about phonological processing in dyslexia. *Dyslexia*, 7(4):197–216, 2001.

[104] Franck Ramus. Developmental dyslexia: specific phonological deficit or general sensorimotor dysfunction? *Current opinion in neurobiology*, 13(2):212–218, 2003.

[105] Franck Ramus, Stuart Rosen, Steven C Dakin, Brian L Day, Juan M Castellote, Sarah White, and Uta Frith. Theories of developmental dyslexia: insights from a multiple case study of dyslexic adults. *Brain*, 126(4):841–865, 2003.

[106] Maud Rasamimanana, Mylène Barbaroux, Pascale Colé, and Mireille Besson. Semantic compensation and novel word learning in university students with dyslexia. *Neuropsychologia*, 139:107358, 2020.

[107] Todd L Richards and Virginia W Berninger. Abnormal fmri connectivity in children with dyslexia during a phoneme task: Before but not after treatment. *Journal of neurolinguistics*, 21(4):294–304, 2008.

[108] Paula A Rodríguez, Demetrio A Ovalle, and Néstor D Duque. A student-centered hybrid recommender system to provide relevant learning objects from repositories. In *International Conference on Learning and Collaboration Technologies*, pages 291–300. Springer, 2015.

[109] Alan Said, Alejandro Bellogín Kouki, and Arjen de Vries. A top-n recommender system evaluation protocol inspired by deployed systems. In *2013 ACM RecSys Workshop on Large-Scale Recommender Systems*, October 2013.

[110] Giuseppe Sartori, Christopher Barry, and Remo Job. Phonological dyslexia: A review. *Dyslexia: A global issue*, pages 339–356, 1984.

[111] Badrul Sarwar, George Karypis, Joseph Konstan, and John Riedl. Item-based collaborative filtering recommendation algorithms. In *Proceedings of the 10th international conference on World Wide Web*, pages 285–295, 2001.

[112] Gerd Schulte-Körne. The prevention, diagnosis, and treatment of dyslexia. *Deutsches Ärzteblatt International*, 107(41):718, 2010.

[113] Zohreh Sharafi, Zéphyrin Soh, and Yann-Gaël Guéhéneuc. A systematic literature review on the usage of eye-tracking in software engineering. *Information and Software Technology*, 67:79–107, 2015.

[114] Sally E Shaywitz, Bennett A Shaywitz, Kenneth R Pugh, Robert K Fulbright, R Todd Constable, W Einar Mencl, Donald P Shankweiler, Alvin M Liberman, Pawel Skudlarski, Jack M Fletcher, et al. Functional disruption in the organization of the brain for reading in dyslexia. *Proceedings of the National Academy of Sciences*, 95(5):2636–2641, 1998.

[115] Sally E Shaywitz, Jonathan E Shaywitz, and Bennett A Shaywitz. Dyslexia in the 21st century. *Current opinion in psychiatry*, 34(2):80–86, 2021.

[116] Pramila P Shinde and Seema Shah. A review of machine learning and deep learning applications. In *2018 Fourth international conference on computing communication control and automation (ICCUBEA)*, pages 1–6. IEEE, 2018.

[117] Roxani Skiada, Eva Soroniati, Anna Gardeli, and Dimitrios Zissis. Easylexia: A mobile application for children with learning difficulties. *Procedia Computer Science*, 27:218–228, 2014.

[118] Margaret Snowling. Dyslexia as a phonological deficit: Evidence and implications. *Child Psychology and Psychiatry Review*, 3(1):4–11, 1998.

[119] Margaret J Snowling. Phonemic deficits in developmental dyslexia. *Psychological research*, 43(2):219–234, 1981.

[120] Phauk Sokkhey and Takeo Okazaki. Hybrid machine learning algorithms for predicting academic performance. *Int. J. Adv. Comput. Sci. Appl*, 11(1):32–41, 2020.

[121] John Stein. The magnocellular theory of developmental dyslexia. *Reading and dyslexia: From basic functions to higher order cognition*, pages 103–134, 2018.

[122] Paula Tallal. Auditory temporal perception, phonics, and reading disabilities in children. *Brain and language*, 9(2):182–198, 1980.

[123] Paula Tallal, Steve Miller, Roslyn Holly Fitch, et al. Neurobiological basis of speech: a case for the preeminence of temporal processing. *Annals-New York Academy of Sciences*, 682:27–27, 1993.

[124] Elise Temple, Russell A Poldrack, Joanna Salidis, Gayle K Deutsch, Paula Tallal, Michael M Merzenich, and John DE Gabrieli. Disrupted neural responses to phonological and orthographic processing in dyslexic children: an fmri study. *Neuroreport*, 12(2):299–307, 2001.

[125] Michal Teplan et al. Fundamentals of eeg measurement. *Measurement science review*, 2(2):1–11, 2002.

[126] Samantha Thelijjagoda, Mithila Chandrasiri, Dilan Hewathudalla, Pasindu Ranasinghe, and Isuru 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)*, pages 808–813. IEEE, 2019.

[127] Joseph K Torgesen. Individual differences in response to early interventions in reading: The lingering problem of treatment resisters. *Learning disabilities research & practice*, 15(1):55–64, 2000.

[128] Sylviane Valdois, Marie-Line Bosse, Bernard Ans, Serge Carbonnel, Michel Zorman, Danielle David, and Jacques Pellat. Phonological and visual processing deficits can dissociate in developmental dyslexia: Evidence from two case studies. *Reading and Writing*, 16:541–572, 2003.

[129] Sanne van der Mark, Peter Klaver, Kerstin Bucher, Urs Maurer, Enrico Schulz, Silvia Brem, Ernst Martin, and Daniel Brandeis. The left occipitotemporal system in reading: disruption of focal fmri connectivity to left inferior frontal and inferior parietal language areas in children with dyslexia. *Neuroimage*, 54(3):2426–2436, 2011.

[130] Sharon Vaughn, Paul T Cirino, Jeanne Wanzek, Jade Wexler, Jack M Fletcher, Carolyn D Denton, Amy Barth, Melissa Romain, and David J Francis. Response to intervention for middle school students with reading difficulties: Effects of a primary and secondary intervention. *School psychology review*, 39(1):3–21, 2010.

[131] Richard K Wagner, Fotena A Zirps, Ashley A Edwards, Sarah G Wood, Rachel E Joyner, Betsy J Becker, Guangyun Liu, and Bethany Beal. The prevalence of dyslexia: A new approach to its estimation. *Journal of learning disabilities*, 53(5):354–365, 2020.

[132] Jun Wang, Arjen P De Vries, and Marcel JT 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*, pages 501–508, 2006.

[133] Runzhou Wang and Hong-Yan Bi. A predictive model for chinese children with developmental dyslexia—based on a genetic algorithm optimized back-propagation neural network. *Expert Systems with Applications*, 187:115949, 2022.

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

[135] Jessica J Wery and Jennifer A Diliberto. The effect of a specialized dyslexia font, opendyslexic, on reading rate and accuracy. *Annals of dyslexia*, 67:114–127, 2017.

[136] Monica Wijers, Vincent Jonker, and Paul Drijvers. Mobilemath: exploring mathematics outside the classroom. *ZDM*, 42:789–799, 2010.

[137] Maryanne Wolf. Proust and the squid: The story and science of the reading brain. *New York*, 2007.

[138] Zhichao Xia, Fumiko Hoeft, Linjun Zhang, and Hua Shu. Neuroanatomical anomalies of dyslexia: Disambiguating the effects of disorder, performance, and maturation. *Neuropsychologia*, 81:68–78, 2016.

[139] Pratheepan Yogarajah and Braj Bhushan. Deep learning approach to automated detection of dyslexia-dysgraphia. In *The 25th IEEE International Conference on Pattern Recognition*, 2020.

[140] Zhi-Dan Zhao and Ming-Sheng Shang. User-based collaborative-filtering recommendation algorithms on hadoop. In *2010 third international conference on knowledge discovery and data mining*, pages 478–481. IEEE, 2010.

[141] Andrea Zingoni, Juri Taborri, and Giuseppe Calabrò. A machine learning-based classification model to support university students with dyslexia with personalized tools and strategies. *Scientific Reports*, 14(1):273, 2024.