*applied sciences*

MDPI

*Article*

# Investigating Issues and Needs of Dyslexic Students at University: Proof of Concept of an Artificial Intelligence and Virtual Reality-Based Supporting Platform and Preliminary Results

**Andrea Zingoni [1,*], Juri Taborri [1], Valentina Panetti [1], Simone Bonechi [2], Pilar Aparicio-Martínez [3], Sara Pinzi [4] and Giuseppe Calabrò [1]**

[1] Department of Economics, Engineering, Society and Business Organization (DEIM), University of Tuscia, 01100 Viterbo, Italy; juri.taborri@unitus.it (J.T.); valentina.panetti@unitus.it (V.P.); giuseppe.calabro@unitus.it (G.C.)
[2] Department of Computer Science, University of Pisa, 56100 Pisa, Italy; simone.bonechi@unitus.it
[3] Department of Nursing, Physiotherapy and Pharmacology, University of Córdoba, 14001 Córdoba, Spain; n32apmap@uco.es
[4] Department of Chemistry, Physics and Applied Thermodynamic, University of Córdoba, 14001 Córdoba, Spain; sara.pinzi@uco.es
* Correspondence: andrea.zingoni@unitus.it

check for updates

**Citation:** Zingoni, A.; Taborri, J.; Panetti, V.; Bonechi, S.; Aparicio-Martínez, P.; Pinzi, S.; Calabrò, G. Investigating Issues and Needs of Dyslexic Students at University: Proof of Concept of an Artificial Intelligence and Virtual Reality-Based Supporting Platform and Preliminary Results. *Appl. Sci.* **2021**, *11*, 4624. https://doi.org/10.3390/app11104624

Academic Editors: João M. F. Rodrigues, Pedro J. S. Cardoso and Marta Chinnici

Received: 20 April 2021
Accepted: 14 May 2021
Published: 19 May 2021



**Featured Application: The outcomes of this work can represent a turning point toward a more and more inclusive university environment for dyslexic students, at the same time showing the full potential of artificial intelligence and virtual reality in dealing with issues related to education.**

**Abstract:** Specific learning disorders affect a significant portion of the population. A total of 80% of its instances are dyslexia, which causes significant difficulties in learning skills related to reading, memorizing and the exposition of concepts. Whereas great efforts have been made to diagnose dyslexia and to mitigate its effects at primary and secondary school, little has been done at the university level. This has resulted in a sensibly high rate of abandonment or even of failures to enroll. The VRAIlexia project was created to face this problem by creating and popularizing an innovative method of teaching that is inclusive for dyslexic students. The core of the project is BESPECIAL, a software platform based on artificial intelligence and virtual reality that is capable of understanding the main issues experienced by dyslexic students and to provide them with ad hoc digital support methodologies in order to ease the difficulties they face in their academic studies. The aim of this paper is to present the conceptual design of BESPECIAL, highlighting the role of each module that composes it and the potential of the whole platform to fulfil the aims of VRAIlexia. Preliminary results obtained from a sample of about 700 dyslexic students are also reported, which clearly show the main issues and needs that dyslexic students experience and these will be used as guidelines for the final implementation of BESPECIAL.

**Keywords:** specific learning disorders; dyslexia; artificial intelligence; virtual reality; adaptive learning; inclusive teaching

## 1. Introduction

According to the classification of the World Health Organization (WHO) [1], specific learning disorders (SLDs) are neurodevelopmental disorders characterized by significant and persistent difficulties in learning skills, which may include reading, writing and performing calculations. This leads to an incomplete automation of such processes, which is likely to affect scholarly and academic life significantly and even generate forms of psychological distress, especially when the problem is not detected early enough [2,3]. Nevertheless, following the work of [1], SLDs can be grouped into four categories, depending on the impaired learning skills: dyslexia, which affects skills related to reading; dysgraphia, which affects skills related to writing; dyscalculia, which affects skills related to arithmetic; and a fourth group including all those disorders that affect other skills. Among them, dyslexia is absolutely the most common [4]. The difficulties associated with it involve not only word reading accuracy and reading fluency but also, as a consequence, comprehension, memorization, concepts exposition [1] and the ability to take notes, compose text and organize the study activity [5]. It is straightforward to understand that the learning process of a dyslexic student is very likely to be compromised.

Over the years, a lot has been done to diagnose dyslexia. Diagnosis has usually relied on some specific tests that aim to quantify reading difficulties, jointly with clinical tools that measure cognitive abilities. Dyslexia is diagnosed for reading performances that, in terms of speed and accuracy, are below the fifth percentile or below two standard deviations with respect to the mean, in the presence of normal cognitive abilities. The focus of such tests has been especially on primary school students. In the past few years, however, tools that are also targeted to secondary school and university students have been created, including the LSC-SUA test [6] and the Adult Dyslexia Battery (BDA) [7]. Classical and widely used diagnostic tests consist of reading aloud meaningful and meaningless words. More novel approaches, however, are based on silent reading, fused passages (namely, reporting when spaces between words are missing) and dys-words (namely, reading words that contain numerous spelling errors but are still recognizable as if they were spelled correctly) [6].

The advent and the wide spread of information technology (IT) has also positively impacted the problem of dyslexia diagnosis and novel and interesting approaches exploiting digital technologies have been proposed. These can be broadly grouped into two categories [8]: The first one comprises those approaches based on neurological data analysis, which aim at spotting the differences in brain anatomy, organization and functioning that correlate with the presence of the typical symptoms caused by dyslexia [9,10] by employing modern screening techniques and novel algorithms to enhance their output. Significant evidence of anomalies in dyslexic people's cerebral morphology and operative processes has been found through the analysis of 3D scans of the brain obtained with magnetic resonance imaging (MRI) [11–15] and functional magnetic resonance imaging (fMRI) [16–19], respectively. In addition, different behaviors between dyslexic and non-dyslexic subjects have been observed in the frequency [20], entropy [21] and spatial activation patterns [22,23] of electroencephalogram (EEG), a widely used technique to assess human concentration [24]. Interesting results have also been obtained with the tracking of the movements of the eye during the act of reading (easily and cheaply performable at the state-of-the art level thanks to the progress in the design and production of eye-trackers [25] and tracking techniques [26–28]), which have demonstrated that the saccades of the readers differ in number and amplitude, depending on if they have dyslexia or not [29–32]. The second category consists of those approaches that revise and improve classical testing methodologies, using the potential offered by IT. These, in turn, can be divided into three groups, on the basis of the aspects they aim at improving: administration of the tests, choice of the most predictive ones and analysis of the results. The first group is focused on presenting the most consolidated tests for dyslexia diagnosis by means of platforms or digital tools that allow the facilitation and speeding up of the collection of the necessary data [33–36]. These platforms/tools can also provide specialists with real-time information and help them monitor the specific objectives step by step, in order to constantly provide the chance to compare results and revise previous evaluations, increasing the probability of a correct final diagnosis [33]. In addition, their capability to gather and store data can also be exploited for research purposes [35]. This kind of approach is particularly useful for the assessment of dyslexia during childhood, since it allows the administration of tests as a set of serious games that are appealing to the children and hide the sensation of being under evaluation [33–35]. In light of its peculiar features, virtual reality (VR) has proven to be a powerful tool to achieve this goal and, in fact, its use in this area is increasing [36,37]. VR also provides a control environment that submerges the user in a controlled but relaxed structure, making it possible to carry out screening tests and decreasing emotional distress [38]. The second group aims at selecting the best tests among the available ones [39,40]. To do this, fuzzy logic, artificial intelligence (AI) and genetic algorithms are generally employed to reach a more significant joint interpretation of the scores of the typical dyslexia screening tasks [39] and to exclude the less predictive ones [40]. The third group is instead focused on jointly analyzing several dyslexia assessment tests, in order to build an automatic predictor of the presence/absence of the disorder. Again, AI perfectly suits this purpose, both for the large amount of data provided by the tests and considering the capability of machine learning (ML) algorithms to find significant relationships between the tested features and obtained results. Numerous promising works have used AI profitably; for example, in [41], the results of the Gibson test of brain skills were used to train an artificial neural network (ANN) and an accuracy predictor of almost 90% was implemented. A similar approach was followed in the works of [42,43], but instead relying, respectively, on human–computer interaction measures and on a self-evaluation questionnaire about difficulties in speaking, reading, spelling and writing. In the works of [44,45], instead, state-of-the-art ML algorithms were trained on a wide battery of tests, exceeding 90% accuracy.

It is not surprising that a much has been done to improve the diagnosis of dyslexia, since it is universally acknowledged that recognizing it early, especially before the beginning of the school, is crucial to help affected people fill their learning gap [46–48]. However, we are still far from having a rigorous, systematic and widespread methodology to spot it at pre-school age [49]; therefore, the development of supporting strategies and tools for dyslexic people whose condition is found late is of paramount importance. With this in mind, several methodologies have been developed to improve reading skills in terms of both accuracy and speed. For example, in the work of [50], a training method based on phonetic instructions was presented and defined as the only statistically effective method. In the work of [51], a combination of the cognitive training of executive functions with a phonological-based treatment has proven a significant method for the rehabilitation of dyslexic subjects. Other approaches, instead, focused on using a rhythmic background [52] or even music [53] for a sublexical training. It is interesting to point out that the vast majority of these studies agree that providing support to dyslexic people also helps them in building a personal and creative study method that follows their own learning styles, thus being even more effective. Although the efforts in this direction are multiplying year after year, not enough has been done yet. One of the largest gaps is the integration of IT, which seems particularly suitable for the purpose but has not yet been fully exploited.

## 2. Related Works

As mentioned, IT solutions have not yet reached their great potential in supporting students with dyslexia, even if the efforts in this direction are gradually increasing. The works of [54,55] raise the problem of proposing an ontology to facilitate the development of e-learning tools aligned with the needs of dyslexic students, but no practical supporting solutions are introduced. In the works of [56,57], instead, the readability of websites for dyslexic people is analyzed and improved, but this can be considered only as a first step toward their full inclusion in the learning system. A second step is performed in [58], where web applications are also taken into account, but only the preliminary phase of a dyslexia-friendly collaborative learning system is presented. A further advance has been made with the introduction of specific and sophisticated tools aimed at increasing the impaired skills. For example, in the work of [59], using a computer platform equipped with speech synthesis and eye tracking was a great boost to the comprehension of a text by dyslexic subjects. Several works have explored the use of AI, demonstrating that it is likely to be one of the most effective instruments to face the problem. The ability of AI to predict future situations by learning from available data makes it a powerful tool to analyze a great amount of information. Further, its improvement over the years has led to very effective techniques capable of dealing with a lot of different data at the same time. Nowadays, multivariate, quantitative, qualitative and ranked data can be used together to train AI algorithms that can automatically find hidden relationships among them, leading to a deeper understanding of the examined phenomenon. It appears clear how AI can be used to support people affected by dyslexia. In the work of [60], a supervised ANN is used to model the reading ability of dyslexic primary school students, in order to give specific support to each one. Network training is performed on the data about the main deficits caused by dyslexia and the results demonstrate that only personalized models can correctly profile dyslexic students and be helpful for them. In the work of [61], a hidden Markov model predicts the difficulties in learning the Malay language in primary school students affected by dyslexia by tracking their mistakes in solving phonology, spelling, reading and writing exercises. The results are not reported but, again, the need for individual support interventions is pointed out. A similar approach is adopted in the work of [62] but, in this case, students' behavior is also considered in training the model. A computer-assisted learning system is developed on the basis of the output predictions and a 60% improving of dyslexics' skills with respect to classical supporting tools was achieved. The aim of the works of [63,64] is to implement an assistive learning platform for primary and secondary school students. The former is focused on helping the process of reading. First, optical character recognition (OCR) is employed to capture the text; then, an ANN identifies two classes of words: easy and difficult ones; finally, the second ones are highlighted, spelled, pronounced or accompanied by images and synonyms in order to make their comprehension easier. ML techniques are used to decide which kind of support is better, depending on the words encountered. The latter, instead, is focused on both reading and writing abilities. A support vector machine (SVM) predictor is constantly trained on the basis of the dyslexic students' scores in serious games and exercises, whose types and difficulty levels are adaptively changed, depending on the obtained performance. Improvements of students' skills and engagement in learning—along with parents' and therapists' capabilities of monitoring progress—are reported. As previously mentioned, a powerful IT tool in the education field is VR [65], thanks to the opportunity it provides to present totally customizable and appealing contents (study material, activities to be performed, tests, etc.), which can be received by the users in an immersive environment—typically created by means of wearable helmets, provided of near-eye displays (NED) and headphones—, increasing their engagement and, thus, their attention. In addition, it allows monitoring easily progresses and obstacles encountered during the learning process. Virtual environments have been included in education since the beginning of the century, especially to reproduce real-life situations [66]. More recently, they have been employed also for training purposes [67]. Previous works have investigated their application in several learning tasks, like improving linguistic abilities and assess the attention of the reader, by also relying on eye-trackers included in VR helmets [68]. In addition, the results of the study of [69] have indicated that VR can improve memory and audio–visual abilities. Its application has also been prompted by the advances in the dedicated hardware technology, which have led to the development of cheap but effective devices. Several works have thus explored the use of VR to increase dyslexic students' memory performance [70] and reading abilities [69], obtaining better performance than using classical or less immersive training methods. It is worth nothing that the vast majority of the works related to supporting dyslexic learners are targeted to pre-school, primary and secondary school age. Methodologies and tools to help them at university level are almost totally missing or provide just a partial aid [71]. However, as discussed in depth in the next chapter, dyslexic university students often experience the typical problems given by this disorder and see their academic career slowed down or even spoiled.

The project VRAIlexia (virtual reality and artificial intelligence for dyslexia) has been launched to face this problem. Starting from the necessity to untap dyslexic students' potential and enhance their strengths, it aims to develop learning tools and services for to ensure to them equal access and opportunity of success during their career and their lifelong learning experience. Among the several activities provided for by VRAIlexia project, the main one consists of the design and implementation of the software platform BESPECIAL, the role of which is to provide dyslexic students at university with digital supporting tools that are specific for each of them and, thus, much more effective, in order to decisively reduce the problems they usually encounter and facilitate their academic career. To do this, BESPECIAL will be trained right on the individual issues and needs of the students, exploiting the powerful means of AI—to learn which are the best tools for each and deliver them automatically—and VR— to administer evaluation test and, at the same time, monitor progress and weak points and provide a constant feedback to the AI.

In this paper, the conceptual design of BESPECIAL will be presented, focusing on the background situations of dyslexic students, which have suggested the necessary intervention of VRAIlexia project and the design choices of the software platform (Section 3); the role of each module of the platform (Section 4); the preliminary results that will be used as a guideline for the future implementations (Section 5). Section 6 concludes and discusses the next steps.

## 3. Background, Motivation and Purpose of the VRAIlexia Project

The decision to develop the VRAIlexia project and implement the BESPECIAL platform was born from a case study (referred as "Tuscia case study") conducted at the University of Tuscia (an Italian academic institution, whose headquarters are located in Viterbo, Italy) concerning the number, distribution and academic outcomes of students with SLDs. The results, considered jointly with the global statistics about the topic, pointed out some crucial issues about the academic opportunities of such students.

According to the works of [4,72], between 6.25% and 12.50% of the world population experiences SLDs, which means around 875 million people worldwide. However, the datum is likely to be underestimated, since some evidence [73] makes the percentage increase to up to 21.25%, that is, around 1.6 billion people. Such numbers give an idea of the scale of this phenomenon. Among them, about 80% are dyslexic, though the remaining 20% suffer from other SLDs [4]. It is also important to note that two or more disorders may occur together. However, dyslexia alone is the most common learning disorder, with a percentage of between 35% and 50% of SLD cases [74].

An investigation by Italian Ministry of Education and Ministry of University and Research that was carried out in 2019 [75] reported a similar distribution of the SLD typologies within the students of national primary and secondary schools; of all the students with SLDs, 34% are affected only by dyslexia (Figure 1).

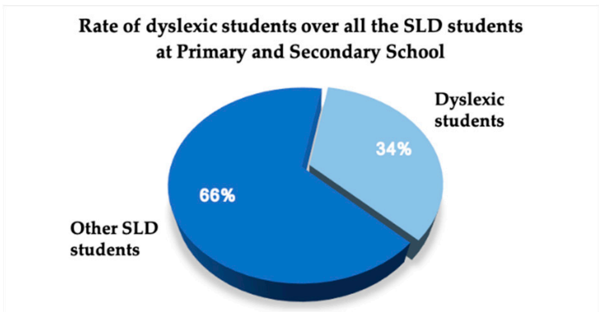
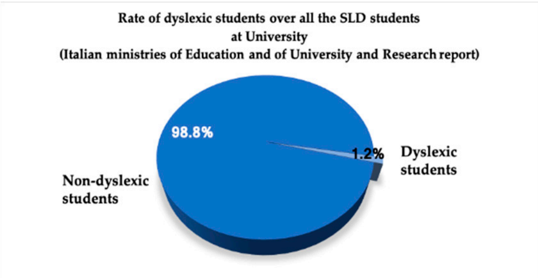
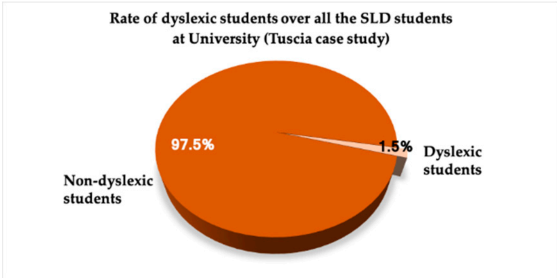



**Figure 1.** Rate of dyslexic students over all the SLD students attending Italian primary and secondary school, according to the 2019 report of Ministry of Education and Ministry of University and Research [75].

The report also showed that students with SLDs constitute 3.2% of the total students at primary and secondary school, whereas at university, they constitute only 1.2% (Figure 2a). This drastic decrease clearly highlights how university can become an insurmountable wall for them and how some actions in this regard are necessary to mitigate the main problems they experience during academic life. According to the Tuscia case study, the percentage of university students with SLDs is slightly higher (Figure 2b), but consistent with [75].




(**a**)




(**b**)

**Figure 2.** Rate of dyslexic students attending university according to the 2019 report of Ministry of Education and Ministry of University and Research [75] (**a**) and to Tuscia case study (**b**).

The rate of dyslexic students over all the students with SLDs is also in line with both primary/secondary school datum and the statistic at global level, showing that this disorder affects 39% of academic population (Figure 3) and is the most frequent one.

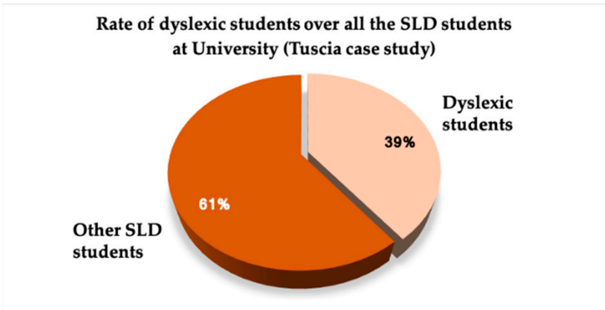



**Figure 3.** Rate of dyslexic students over all the SLD students attending university, according to the Tuscia case study.

Another interesting fact is that dyslexic students attending a degree course in the sciences constitute 44.3% of the total number of students with SLDs. Instead, they constitute only 25.8% in degree courses in humanities (Figure 4). This matches with the typical problems that dyslexics experience, which have an adverse impact on tasks that are more commonly required in the second branch, like reading, memorizing, exposing concepts aloud, etc. The conspicuous presence of such tasks is likely to discourage the enrolment in humanities courses or leads to their abandonment. Further evidence comes from the graph in Figure 5, which shows the average number of university credits in the European Credit Transfer and Accumulation System (ECTS) achieved per year by dyslexic and non-dyslexic students, both globally and specifically for sciences and humanities. The global data show that dyslexic people accumulate, on average, six ECTS less, which correspond, approximately, to one exam per year lost compared to non-dyslexics. This illustrates a situation of hardship for dyslexic students that must be faced thoroughly, in order to guarantee equal opportunities to them. The specific data for sciences and humanities confirm the above regarding the greater difficulties encountered by dyslexic students in the second branch. The difference in the achieved ECTS rises up to 6.7 for humanities, compared to 4.6 for sciences.

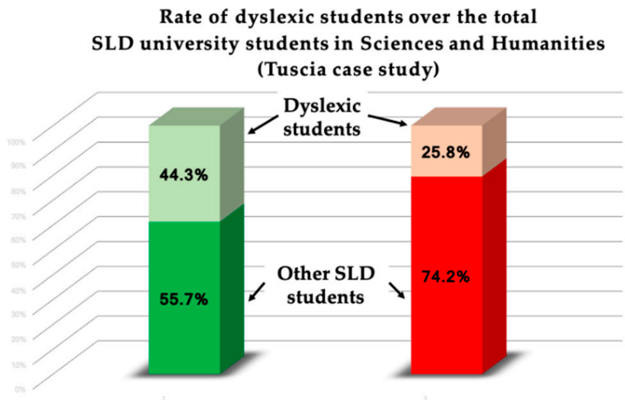



**Figure 4.** Rate of dyslexic students over the total number of SLD university students in sciences and humanities, according to the Tuscia case study.

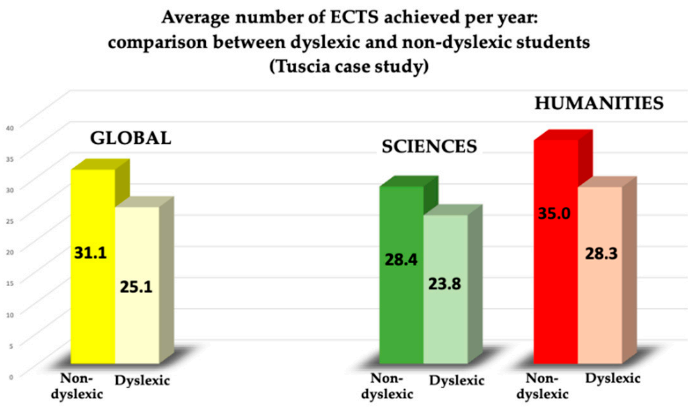



**Figure 5.** Average number of ECTS achieved per year: comparison between dyslexic and non-dyslexic students globally and specifically for sciences and humanities, according to the Tuscia case study.

Summarizing the statistics shown above, four main facts stand out: (i) people with SLDs are a significant percentage of the global population; (ii) the vast majority of them experience dyslexia; (iii) the presence of this disorder affects the academic career in terms of both graduation time dilation and abandonments; (iv) this problem strikes mainly degree courses in humanities.

The VRAIlexia project starts from these assumptions and, within the first three years of the project, intends to achieve five tangible outcomes to overcome all the main difficulties encountered by dyslexic students at university and eliminate, or at least reduce, the gap with respect to non-dyslexic students. More specifically, in addition to the software platform BESPECIAL, which represents both the core of the project and the focus of this paper, the other four outcomes are the ones listed below.

1. A battery of tests in VR to assess the skills of dyslexic students, which will allow teachers to better and more easily understand the issues of them.
2. An online shared repository containing all the digital modules, resources, tools and any other kind of material that can be useful to implement innovative teaching and learning methods.
3. A training path consisting in two events, the first one addressed to the improvement of dyslexia awareness from teachers and the second one addressed to dyslexic students to enhance their self-entrepreneurial mindsets. Both events will be organized by experts of various disciplines, according to the Universal Design Learning methodology [76].
4. A memorandum of understanding for the creation of common inclusion strategies among European higher education institutions.

It is easy to understand how these outcomes have the potentiality to represent a valid opportunity to eliminate or at least mitigate significantly the above-reported issues, related to the enrolment of dyslexic students in university. In addition, they will allow to define a standardized approach, which is likely to increase students' motivation to complete their career and to move the first steps in the work market. The high level of intricacy of the SLDs spectrum requires not dealing with all the disorders at the same time, but focusing on each singularly. Since dyslexia is absolutely the prevailing SLD among the world population, VRAIlexia will focus on it. In addition, the intrinsic diversity in teaching/learning different disciplines [77] suggests thinking of specific methodologies for each of them. Humanities being the disciplines more challenging for dyslexic students, only them will be considered within VRAIlexia. An extension to the other SLD types and to scientific disciplines has been already projected and is likely to be performed at a later time.

The previously listed assumptions, jointly with the information obtained from the literature analysis, have also been taken into account in the design of BESPECIAL that, as mentioned, is in charge of providing dyslexic students with ad hoc strategies and tools to support them during university, so as to try to mitigate the career slowdown and abandonments phenomenon. In order to produce specific material for each student (a fundamental factor to achieve the goal [60,61]), the platform will be implemented starting from the individual issues they experience and according to their precise needs. Given the focus on humanities, the produced material and methodologies will cover the typical problems related to the main tasks of these disciplines. In addition, the BESPECIAL output is not meant to be delivered only to students in the form of digital tools, but also to teachers and university institutions in the form of strategies and best practice, which will simplify the academic path for dyslexics, making it really inclusive for everyone.

## 4. Conceptual Design of BESPECIAL

To deal with the complexity of the task BESPECIAL must perform, it is advisable to develop it in two stages.

### 4.1. First Development Stage

In the first stage, the basics of BESPECIAL will be implemented, so as to build the backbone of the platform. The kernel consists of an AI-based module that will be employed to assess the dyslexia status of the users, starting from both their clinical reports and a questionnaire about the problems they feel while studying, plus the solutions they deem to be helpful. From the results of the assessment, the best supporting tools and strategies will be predicted. Then, the former will be used to digitalize the study material and provided directly to the users, whereas the latter will be passed to the teachers and, in general, to the university institutions to enable them to help students in the best way by implementing standardized guidelines. The training of the AI module will be performed from a large database of clinical reports of dyslexic students and from their answers to the above-mentioned questionnaire. This allows simultaneous consideration of both the evaluation made by the experts and the self-evaluation of dyslexic subjects. At this level, the provided material will not yet be specific for each one of the students singularly, but still they will be divided in some broad categories created on the basis of the relations between their issues and their needs, which will have been spotted by the AI. The group of tools and strategies that best fits those students belonging to a specific category will be assigned to them. This preliminary classification also allows the simplifying the work of the AI assessment module of the second stage, which will have to switch from being category-specific to be student-specific.

The block diagram of the first development stage of BESPECIAL is depicted in Figure 6, whereas its modules and steps are described in detail in the following subsections.

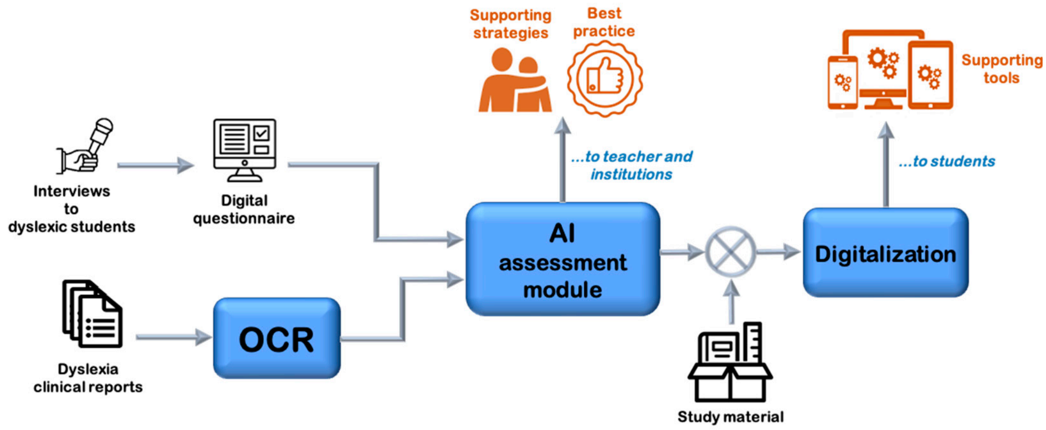


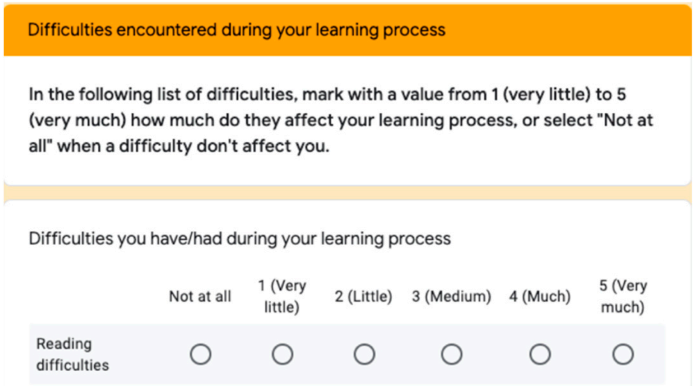

**Figure 6.** Block diagram of BESPECIAL at its first stage.

#### 4.1.1. Interviews to Dyslexic Students

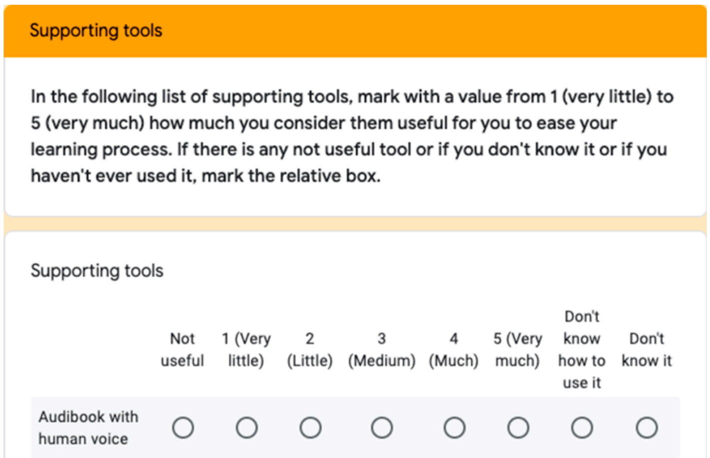
The very first step for the development of BESPECIAL consists of carrying out semi-structured interviews with dyslexic students with the aim of investigating aspects concerning metacognition and learning methods, which will be used to build a self-assessment questionnaire that will allow students to describe their study issues and the supporting strategies and tools that each one finds most useful. A sample of 20 dyslexic university students will thus be interviewed on a voluntary basis. The distribution between male and female subjects will be random. Students will be asked to answer to a group of questions concerning their study method, the main difficulties they experienced in their university learning path and the tools and strategies they have applied and found helpful. Finally, the answers will be analyzed, in order to create a list of typical issues and needs of dyslexic university students, which will be then used to design the questionnaire. The obtained data will not be aggregated at this step, so as to maintain a wider analysis capability. Possible aggregations can be done later.

#### 4.1.2. Digital Questionnaire

On the basis of the information gathered from the interviews, a questionnaire will be created and then digitalized and hosted online, so as to significantly speed up the collection of the data about the self-evaluation of issues and needs of dyslexic students. The questionnaire will be organized as follows. After a few demographical questions (age, gender, etc.), information about the high school and university career and about the dyslexia status and history will be asked. The answers will be useful mostly for the objectives of VRAIlexia other than BESPECIAL implementation. The software platform, however, could also benefit from this information by finding unexpected relations between it and dyslexic students' problematics and needs, which could be interesting additional outcomes of the project. Then, three groups of questions will be asked: (i) which have been the main issues experienced during the last years of the learning path; (ii) which have been the most useful supporting tools; (iii) which have been the most useful supporting strategies. Each group will be organized in multiple choice questions, each of which concerning one of the issues/tools/strategies that emerged from the interviews to dyslexic students. The choice consists of a score from 1 (very little) to 5 (very much), depending on the severity of the issue or on the utility of the supporting methodology, plus the option "not experienced" (for the issues) or "not useful" (for the tools and strategies). In addition, the groups of questions about supporting methodologies will also present the options "never tried" and "don't know". This will allow the AI to distinguish the reason why a certain methodology is not regarded as helpful. In Figure 7, two pictures showing two of the above-mentioned inquiries from the questionnaire are reported by way of an example.




(**a**)




(**b**)

**Figure 7.** Example of two inquiries of the questionnaire, about the issues experienced (**a**) and the supporting methodologies considered as useful (**b**) by dyslexic students.

The answers to these three groups of questions will be the main input of BESPECIAL. A large amount of them will, indeed, be used initially to train the AI assessment module and build the predictor of the most suitable supporting methodologies, given the issues experienced by dyslexic students. Later, instead, the answers of each student will be read to formulate the prediction.

#### 4.1.3. Application of Optical Character Recognition to the Dyslexia Clinical Report of the Students

The clinical reports of dyslexic students are the second input to BESPECIAL. From them, the information given by the experts about the status of the disorder for each student will be collected. In order to automate the extraction of this information, an algorithm based on optical character recognition (OCR) will be devised. Medical reports are generally not released in a digital format, requiring to be photographed to be passed to a computer, or, however, their format does not permit easy modifications (like pdf). The platform must, thus, be able to take files in different formats as input and interpret them. The system will then use the OCR algorithm provided by Google Vision API to recognize and extract the text of the medical reports from such files. After that, the three typical steps of text pre-processing will be applied to the text extracted with OCR. These are: removing stop words, tokenization and stemming. The first one aims at removing commonly used words that are not useful to characterize the content of the document, such as articles and conjunctions. The second one, instead, splits the text into single words (tokens), so as to ease the content analysis. Finally, the third one aims at reducing each word to its root, allowing inflected forms of the same word to be grouped and then treated as a single element. Once the clinical reports will be processed by the OCR module, useful information can be extracted from them. For example, it may be possible to understand the type of dyslexia of each subject or their specific needs.

#### 4.1.4. AI Assessment Module

The input coming from the questionnaire and the clinical reports will be passed to the AI assessment module, first to train it and then, after the training will be completed, to provide those pieces of information about BESPECIAL users that allow predicting the most suitable supporting material for each of them. To develop the module, ML techniques will be used. At this stage, indeed, it is not advisable to rely on deep learning (DL), since the input (namely, the issues experienced by dyslexic students) and the output (the supporting tools and strategies) variables are not a huge number. Using DL is, thus, likely to result in data overfitting. At the second stage, instead, when a much higher number of variables will have to be processed, the possibility to switch to DL techniques will be taken into account. The good practice of testing several ML algorithms will be followed. In particular, supervised algorithms will be considered, since the questionnaire and the clinical reports provide labeled output variables, for which the label is given by the supporting tools and strategies. The typical and state-of-the-art set of ML algorithms will be used. It comprises naïve Bayes, logistic regression, k-nearest neighbors, random forest, gradient boosting tree, SVM and ANN [78]. After training them and build a predictor for each, cross-validation will be carried out, so as to choose the best performing one. Accuracy and precision metrics (like AUC, F-measure, etc. [79]) will be taken into account as performance criteria. To take account of the possible presence of highly variable data, the algorithms testing will be run on different database setups, namely, rearranging data in different ways. For example, a different ranking scales for the answers to the questionnaire could be adopted, like scores from 1 to 3 (obtained by opportunely aggregating the original scores from 1 to 5), or the questions could be considered as "yes/no" ones (by collapsing the original 1 to 5 scores into "yes" and keeping the "no" answer). Similarly, different ways to aggregate and rank the information gained from the clinical reports will be considered. Furthermore, protocols to manage possible missing data will be developed. This step is necessary for two reasons. The main one is that clinical reports are compiled by human beings and guidelines on how to do it correctly are still lacking. This results in documents that are often and considerably incomplete. The other reason is that the questionnaire features the option "never tried" and "don't know" among the answers about the most useful supporting methodologies. Obviously, these answers cannot be considered the same as "not useful" and, thus, they must be treated as missing data. All the typical strategies to address this issue will be applied, like simple deletion, imputation and prediction and the techniques that will give the best result will be implemented. Once the AI module will have made its prediction, the results will be split into two parts. The most suitable tools for the user will be passed to the digitalization module, whereas the most suitable strategies will be one of the final output of BESPECIAL platform, which will be provided to the institutions and the teachers to orient their interventions in favor of the students.

#### 4.1.5. Digitalization of the Supporting Tools

As previously mentioned, the tools that best fit the students' needs, according to the AI module prediction, will be passed to another module that is in charge of their digitalization. This operation will allow full exploitation of the benefits offered by the modern IT devices (PCs, tablets, smartphones, e-books, etc.), by creating supporting material that is not only easy-to-use and appealing for the users, but also customizable and portable. The digitalization will involve the study material of the university courses, which will also be passed as input to the module and which the tools will be applied to. To define the techniques to be employed to achieve the goal, it is of course necessary to know which supporting tools must be implemented. Nevertheless, some steps will almost certainly be required in any case, given the nature of the typical study material of humanities branch.

The first one is the transformation of the texts into ASCII format, which is a necessary initial operation, in order to have the possibility to treat them digitally. Again, OCR will be used for this purpose. Then, the ASCII strings will be passed to a language detection algorithm. This will allow improvement of the accuracy of the OCR output, by inferring the specific feature of the detected language. Once a text is readable by a computer, the possibility for the user to modify some display settings will be implemented, following the suggestions in [80]. In particular, they will be able to specify style, size and spacing of the font and to communicate which syllables and words cause reading or understanding difficulties, so as to have them highlighted in different colors. The selected syllables/words will be identified within the text by means of regular expressions, which are sequences of characters that specifies patterns of search, thus finding all the repetitions of the targeted string. The audio reproduction of the documents will also be implemented by relying on speech synthesis algorithms based on DL models. The detection of the language that has been obtained previously will also be useful to this end. To meet the user's needs better, the possibility to set preferences on how the audio should be played will be given. These will include the choice of the speaking voice and the audio speed. The digitalized tools applied to the study material constitute the second final output of BESPECIAL. It will be provided to the students in order to support them during their academic career.

### 4.2. Second Development Stage

In the second stage, the features developed in the first one will be enhanced, leading to the final version of BESPECIAL platform, which is shown in Figure 8.

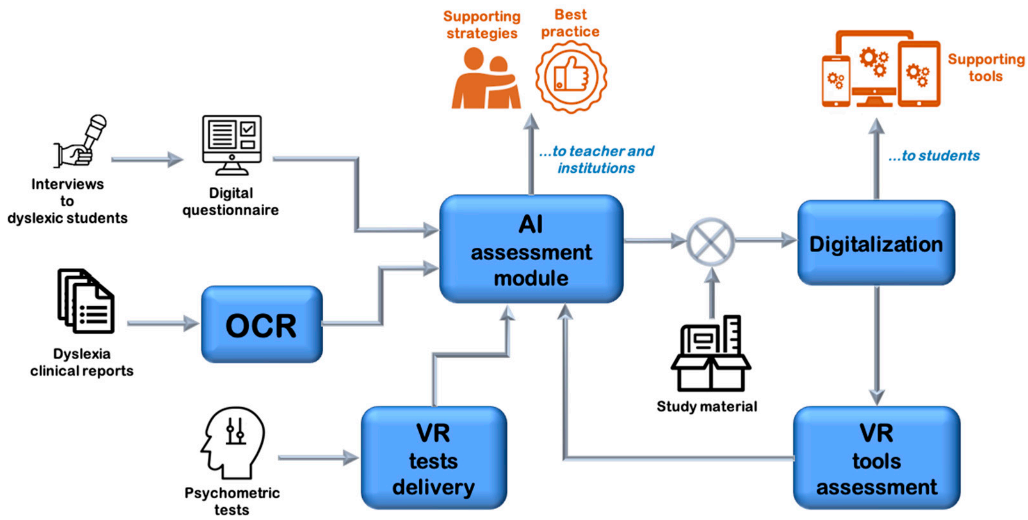



**Figure 8.** Block diagram of the final implementation of BESPECIAL.

In particular, two aspects will be improved, namely, the input data collection and the level of specificity of the provided supporting material for each student. Concerning the former, a new input source will be introduced, namely, the results of a battery of psychometric tests, which will be delivered using VR to ease their accessibility and improve students' engagement. Concerning the latter, a further assessment module will be added, which will evaluate the response of the users to the digital supporting tools and will give a feedback about their usefulness to the AI module, in order to guide its prediction towards the creation of an increasingly customized material for each one. This step will allow us to switch from category-specific to student-specific supporting tools, which should give a decisive contribution to facilitate the career of dyslexic students. Again, VR will be exploited, given the possibility it offers to easily and quickly monitor users' progress, skills and weak points.

An in-depth description of the new features introduced in this second and last implementation stage is presented in detail in the next subsections.

#### 4.2.1. Psychometric Tests and Their Delivery via VR

As previously mentioned, a new input from dyslexic students will be collected in the final version of BESPECIALBESPECIAL, that is, the information coming from a battery of psychometric tests. The introduction of psychometric tests has been deemed necessary in order to have also an objective initial profile of the users, allowing comparison of different people in a unitary manner. In addition, the tests will enable the progress of dyslexic students to be tracked by monitoring the obtained scores over time. It is worth noting that not only learning performance, but also psychological aspects related to the learning process, such as anxiety, self-esteem, self-efficacy, strategies and motivations for studying will be assessed. Psychometric tests will be divided into five batteries. The first one is the previously mentioned BDA. It is targeted at 16 to 30 years old dyslexics and consists of 11 unpublished tests that evaluate three kinds of skills, namely, reading, writing and texts comprehension. In particular, BDA investigates the flexibility of the process of reading aloud and in silent mode, providing specific tasks to assess the degree of automation when writing and introduces a culture free, multiple choice answer-free reading comprehension trial. Its results allow the creation of detailed operating profiles of the assessed skills. The second battery is the State-Anxiety Inventory (STAI-Y), devised in the middle of the 1960s and revised in the early 1980s [81]. It is split into two scales (Y1 and Y2), which evaluate state anxiety and trait anxiety, respectively. The assessment of the former is performed through questions related to how the subject feels at the time of administering the questionnaire, whereas the assessment of the latter relies on questions that investigate how the subject feels habitually. For the purpose of BESPECIAL, only Y1 will be performed. The third battery measures the General Self-Efficacy Scale [82] and consists of 10 items aimed at explaining various cognitive and motivational aspects related to learning, including the impact of positive experiences and successes, perseverance in commitment, optimism and the development of interests in specific cultural and professional fields. The fourth battery is the Questionnaire on Learning Processes [83], in the D version (QPA-D), which is the one targeted at university students. It uses three scales that investigate the following aspects.

1. Intrinsic motivation for learning (MI), in which those who are engaged in learning regularly perform their school duties and progress harmoniously in all disciplines obtain high scores.
2. Metacognition and self-regulated learning (MA), in which those who are aware of their cognitive processes and, hence, manage their learning process effectively obtain high scores.
3. Learning strategies (SA), in which those that are capable to adopt good and effective strategies to process contents and information obtain high scores.

The fifth battery is the Rosenberg Self-Esteem Scale (R-SES) [84], which is aimed at measuring self-esteem and consists of 10 items related to overall feelings of self-worth or self-acceptance. The items are answered on a four-point scale ranging from strongly agree to strongly disagree.

An intrinsic problem of the introduced psychometric tests lies in their format, which tends to be too formal and repetitive. Moreover, such tests require a lot of time to be completed. This causes people to get bored easily and, thus, to lose concentration and perform them without commitment. This issue is even more severe for dyslexics, whose problems affect exactly concentration and understanding. To overcome this, psychometric tests will be delivered by relying on VR. Its characteristics, indeed, allow recreating an interactive environment with high fidelity, thus presenting any material in a playful and appealing way, which is likely to improve engagement and attention [38]. In addition, tests performing time will be reduced and the obtained results will be collected and stored more easily and in a convenient way for their use in the AI module. Two main approaches can be followed to deliver contents via VR, depending on the type of devices used, namely, immersive virtual reality (IVR) and desktop virtual reality (DVR). IVR is capable of offering a complete immersion of the user in the virtual environments by using specific hardware known as a VR headset, which consists of a helmet provided with two head-mounted displays and headphones. The displays allow for 3D vision and isolate the user's sight from the real world, as well as headphones for the user's hearing. Coherence between the user's and virtual images movements are ensured by inertial sensors equipped on the helmet. Hand controllers are also provided often, in order to improve the interaction with the virtual world. The result is the projection of multiple images that configure a room-size venue for experiencing VR and creating a flow through the scenario, thus generating the full immersion experience. Unfortunately, IVR suffer a major limitation due to the high costs and the low accessibility of the needed devices. Conversely, DVR does not need complex and expensive hardware to be played, since it runs on common devices, like personal computers, tablets and smartphones, which are more sustainable for higher education institutions [85]. As a counterpart, it can provide only a static and less interactive experience, making the sense of complete immersion be lost. Some cheap helmets, into which a smartphone can be inserted, however, can partially render it affordable. The majority of the previous studies are based on IVR [86]. Nevertheless, some novel works are focused on DVR environments [85]. Inspired by the second ones, BESPECIAL VR psychometric tests will be created by relying on DVR. They will thus, be suitable for ubiquitous devices, like smartphones and tablets, allowing for a wider and quicker spread. JSON and PhoneGap framework will be used to develop the VR module, including PHP and HTML, combined with MySQL, CSS, JavaScript and JQuery, as complementary base languages. The created VR environment will present the tests in a calming background, made of soft colors and arcade game elements. Cheap cardboard helmets for common smartphones to be inserted into will be used to reduce the field of view of the user, in order to enhance the degree of immersion perceived. The results of psychometric tests will then be passed to the AI assessment module and used jointly with the results of the questionnaire and the information extracted from the clinical reports, first to train the AI and, then, to predict which is the best supporting material for each user.

#### 4.2.2. VR Tools Assessment Module

The second module based on VR will have in charge to assess the response of each dyslexic student to the provided digital supporting tools. The assessment result will then be passed to the AI module, which will combine it with the BESPECIAL input data, so as to create completely ad hoc tools to be exploited during their academic career. Analogously to the previous subsection concerning psychometric tests, in this case, the evaluation process can also be long and boring for the users. Using VR can, thus, make it less heavy, ensuring a much higher level of engagement and, therefore, a more accurate assessment. In addition, VR itself can become an interesting supporting tool, enhancing the interest of the students, promoting autonomy and increasing self-esteem. A further application is that it can create a virtual environment where the main difficulties and the emotional distress of dyslexic students is simulated, enabling teachers and students without learning disorders to experience it, in order to improve understanding of the dyslexia and teacher-to-student empathy. This can provide useful strategies to enrich the BESPECIAL outcome of the best practice. In this phase, the IVR approach will be preferred to DVR one, since tools assessment will last much longer than psychometric tests and, thus, an increased level of engagement is required. Furthermore, fewer students will participate in the training phase; therefore, the higher cost of the needed devices will be compensated by the low number. VR will also be particularly useful in this phase because of its capability to collect and store data quickly. A comparison between the use of DVR and IVR in the two different phases is shown in Table 1, jointly with the main advantages and drawbacks.

**Table 1.** Use of the two VR approaches (DVR and IVR) within BESPECIAL.

| VR Approach | Devices Needed | Targeted Users | Aim | Pros | Cons |
|---|---|---|---|---|---|
| DVR | Smartphone + Cardboard headset | Dyslexic Students | Psychometric tests delivering | Accessible hardware<br>Low cost devices | Lack of immersivity |
| IVR | VR specific headset | Dyslexic and non dyslexic students | Supporting tools assessment | Completely immersive experience | Complex hardware required |
| | | Teachers | Creation of an emphatic experience of dyslexia | Improved capability of data collection | Expensive devices |

#### 4.2.3. New Version of the AI Assessment Module

In this second stage of BESPECIAL, not only the input data from clinical reports, questionnaire and psychometric tests, but also the feedback from the VR tools assessment module will be used to predict the best supporting tools for each dyslexic student. The AI assessment module will thus have to be modified accordingly. Even if it is not possible to design the new version of the module before knowing which these tools are and, thus, how the VR module will evaluate them, the amount of data on which the AI will be trained is expected to be great. Big data and DL techniques will therefore be likely to be employed, to manage it and to build the predictor.

## 5. Results

At present, the interviews of dyslexic students have been carried out and the questionnaire has been created and released online. The following tables report the three groups of questions that will be passed as input to BESPECIALBESPECIAL, that is, those concerning the issues of dyslexic students (Table 2) and those concerning the tools (Table 3) and the strategies (Table 4) considered helpful. Note that they are derived directly from the information gathered through the interviews and that they will be presented to the users in the form shown in Figure 7. To date, more than 800 answers to the questionnaire in Italian have been collected. An analogous collection will be made in other languages, namely, Spanish, English, French, Portuguese, Greek and Dutch, since the partners of the VRAIlexia project are from countries where these languages are spoken. An extension to further languages will be evaluated after the end of the project. Initially, the data will be considered separately for each language. It has been shown, indeed, that the issues related to dyslexia can change considerably from a language to another [87]. Nevertheless, possible analogies will be investigated.

In addition to the answers to the questionnaire, a large number of clinical reports has been collected and OCR has been applied to each, in order to extract useful data for the AI module. By analyzing the reports, however, it was realized that, unfortunately, only a few contain the necessary information about the issues and needs of people affected by dyslexia. The vast majority are limited to a coarse division into wide categories like "impairment in writing" or "impairment in reading", etc., or even to a simple statement about the presence or the absence of the disorder. Thus, it was decided to only use report information to: (i) verify automatically if a subject is affected by dyslexia and, therefore, if their answers to the questionnaire can be inserted in the AI training; (ii) make an initial sketch of the categories in which AI will group dyslexic people together to provide them ad hoc supporting material. These categories will then be refined by using the data from the questionnaire and, later, also from the psychometric tests.

**Table 2.** List of the questions about dyslexic students' issues, asked within the BESPECIAL questionnaire.

| **Have You Ever Experienced One or More of These Issues during Your Academic Career?** | | |
|---|---|---|
| Reading difficulties | Text comprehension difficulties | Uncommon words understanding |
| Concentration difficulty while studying | Concentration difficulty during in-class lessons | Concentration difficulty during online lessons |
| Verbal short-term memory impairment | Verbal long-term memory impairment (memory loss during exams) | Study scheduling |
| Note-taking difficulties | Lack of time to prepare exams | |

**Table 3.** List of the questions about the most useful supporting tools for dyslexic students, asked within the BESPECIAL questionnaire.

| **Are One or More of These Tools Useful to Support You with Dyslexia Related Issues?** | | |
|---|---|---|
| Audiobook with human voice | Audiobook with artificial voice | Words in different colors |
| Clear layout of the study material | Highlighted keywords | Digital concept maps |
| Digital schemes | Summaries | Digital Tutor |
| Use of images for words memorization and understanding | Use of images for concepts memorization | Audio recording of the lessons |
| Video lessons | Integrating study material using internet | |

**Table 4.** List of the questions about the most useful supporting strategies for dyslexic students, asked within the BESPECIAL questionnaire.

| **Are One or More of These Strategies Useful to Support You with Dyslexia Related Issues?** | | |
|---|---|---|
| Someone that reads the study material | Repeating studied material | Study groups |
| Tutor | Participating or creating students' associations to exchange information | On-line lessons availability |
| Pauses during lessons | Lessons slides availability | Recording lessons |
| Early availability of courses programme | Dividing exams in multiple shorter modules | Only written exams |
| Only oral exams | | |

A preliminary analysis was made on the collected data. A total of 807 students with SLDs sent their clinical reports. Using the above-described approach with OCR, 114 of them were discarded, since dyslexia did not appear among their disorders. The remaining 693 students completed the questionnaire, providing information about their difficulties related to dyslexia (see Table 2) and the supporting tools and strategies they find useful (see Tables 3 and 4). Figure A1 (hosted in Appendix A for better clarity) shows the results about the importance given by the students to each issue they have encountered during their university career. The first detachable fact is that low scores (less importance) are less frequent than high scores (more importance). This demonstrates how dyslexic people, on average, still experience a lot of difficulties in higher education and, thus, how supporting them is of paramount importance. Further evidence comes from the number of answers affirming that a specific issue is not present, which is always less than all the other answers for all the assessed issues. To better understand which are the most affecting issues, the average score from 1 (very little experienced issues) to 5 (very much experienced issues) was calculated for each issue and reported in Table 5 jointly with the percentage of students that had not experience that issue.

**Table 5.** Average score of the experiencing of dyslexia-related issues, given by the students in the questionnaire, from 1 (very little experienced) to 5 (very much experienced) and percentage of students that has not experience them.

| Issue | Average Score | Not Experienced by (%) |
|---|---|---|
| Reading difficulties | 3.18 | 8.9% |
| Text comprehension difficulties | 3.18 | 6.5% |
| Uncommon words understanding | 3.30 | 7.2% |
| Concentration difficulty while studying | 3.76 | 2.6% |
| Concentration difficulty during in-class lessons | 3.07 | 7.5% |
| Concentration difficulty during online lessons | 3.76 | 5.8% |
| Verbal short-term memory impairment | 3.46 | 3.2% |
| Verbal long-term memory impairment | 3.35 | 4.0% |
| Study scheduling | 3.37 | 11.1% |
| Note-taking difficulties | 3.32 | 7.2% |
| Lack of time to prepare exams | 3.57 | 3.5% |

It turns out that concentration is the most strongly striking difficulty, but only when the students are alone, that is, while studying and during online lessons. The problem is indeed less felt during lessons in the classroom. Verbal memory impairments also strike quite strongly, especially in the short-term, as well as scheduling problems, which prompt students to ask for more time to prepare the exams. Reading and text comprehension difficulties are present, but weigh less significantly. This is probably because the majority of the students have already found compensative learning strategies by university age.

In Figure A2 (see Appendix A), the results of the students' self-assessment about the most useful supporting tools within the list of Table 3 are reported. The average score for each tool and the percentage of students that have not found it suitable for their need are shown in Table 6. Highlighted keywords and a clear layout of the study material are the supporting tools that best fit dyslexic students' needs, followed by the use of images, summaries, concept maps and schemes. This points out that classical study material, generally consisting of books with long and visually monotonous texts, is likely to be a considerable obstacle in presence of dyslexia, even at university age. A more straight-to-the-point material, in which the basic concepts and their relations are summed up and emphasized in a simple and clear way, alternative to large verbal explanations, should thus be provided. Audio recording lessons have also been indicated as a useful supporting tool, confirming that the auditory channel can be preferred to the visual one, as shown in [52,53]. Despite all of this, in this case, a monotonous presentation is not helpful, as the low score of audiobooks (which are generally less lively than the speech of a teacher during a lesson) demonstrate. In particular, the use of audiobooks read by an artificial voice obtained the lowest score and more than half of the students that participated in the questionnaire have found it useless. This pairs with the 25.4% of unfavorable opinions by the digital tutor in giving a clear indication of how interacting with machines instead of human beings should be avoided when teaching people affected by dyslexia. It is worth noting that using different colors for the words of a text, which is strongly recommended in childhood [55,56], is still a helpful supporting tool at university age for almost 9 out of 10 people, but is less important compared to other tools.

**Table 6.** Average score given by dyslexic students in the questionnaire to the usefulness of each supporting tool, from 1 (very little useful) to 5 (very much useful) and percentage of students that found it useless.

| Supporting Tool | Average Score | Not Useful for (%) |
|---|---|---|
| Audiobook with human voice | 3.25 | 26.8% |
| Audiobook with artificial voice | 2.28 | 51.7% |
| Words in different colors | 3.61 | 10.2% |
| Clear layout of the study material | 4.02 | 4.6% |
| Highlighted keywords | 4.24 | 2.5% |
| Digital concept maps | 3.80 | 7.9% |
| Digital schemes | 3.80 | 8.0% |
| Summaries | 3.94 | 6.1% |
| Digital Tutor | 3.34 | 25.4% |
| Use of images for words memorization and understanding | 3.90 | 7.1% |
| Use of images for concepts memorization | 4.00 | 4.8% |
| Audio recording of the lessons | 3.82 | 6.2% |
| Video lessons | 3.67 | 9.2% |
| Integrating study material using internet | 3.65 | 7.8% |

The same analysis made for the supporting tools was also carried out for the supporting strategies listed in Table 4. Results are reported in Figure A3 (see Appendix A) and in Table 7.

**Table 7.** Average score given by dyslexic students in the questionnaire to the usefulness of each supporting strategies, from 1 (very little useful) to 5 (very much useful) and percentage of students that found it useless.

| Supporting Tool | Average Score | Not Useful for (%) |
|---|---|---|
| Someone that reads the study material | 4.05 | 3.3% |
| Repeating studied material | 4.16 | 2.7% |
| Study groups | 3.39 | 11.0% |
| Tutor | 3.56 | 10.4% |
| Participating or creating students' associations to exchange information | 3.86 | 5.8% |
| On-line lessons availability | 4.22 | 1.4% |
| Pauses during lessons | 4.49 | 1.0% |
| Lessons slides availability | 4.14 | 3.3% |
| Recording lessons | 4.04 | 3.8% |
| Early availability of courses programme | 4.15 | 2.5% |
| Dividing exams in multiple shorter modules | 3.27 | 19.0% |
| Only written exams | 3.17 | 15.3% |
| Only oral exams | 3.69 | 13.3% |

The very first observation that deserves to be made is that, on average, the score achieved by supporting strategies is higher than the one achieved by supporting tools. This fact highlights the necessity to combine both supporting methodologies in order to be capable of helping dyslexic students during their academic career. Conversely, the vast majority of approaches proposed until now [56–65] have only taken into account digital tools, neglecting to also create, in parallel, a list of the best practices to be followed to provide support to dyslexic students. The supporting strategies that obtained the highest scores are taking pauses during lessons, hosting lessons online, repeating the studied material and making the program and the slides of the course available, which are considered useful by about 96 to 99% of the participants in the questionnaire. Having someone read the study material and recording the lessons also achieved high scores. This, again, underlines the importance of the auditory channel in the learning process of dyslexic students. A lower score was obtained by tutors and study groups, even if about 9 of every

10 students recognize a certain utility in such supporting strategies. Finally, oral exams are preferred to written ones (3.69 points against 3.17) and dividing them into shorter modules is not considered as fundamental (19% of the students thinks it is useless, a high percentage compared to the other strategies).

## 6. Conclusions and Next Steps

In this paper, the conceptual design of a supporting software platform (BESPECIAL) to help dyslexic students during their academic career has been presented jointly with preliminary results. The functioning of BESPECIAL and its role within the wider project (VRAIlexia), aimed at mitigating the difficulties encountered by dyslexic students at university, have been addressed in detail, in order to show a proof of concept of the overall methodology that will lead to its final implementation.

The platform takes as input the clinical reports of dyslexia, the answers to a self-assessment questionnaire and the results of a battery of psychometric tests to extract useful information about the issues and needs of dyslexic students at university. By relying on AI, it will be capable of predicting automatically which of the supporting methodologies are most suitable for each student, in terms of both best practices to be followed by teachers and institutions and digital tools to make the study material more accessible, given the difficulties they encountered during their academic career. A two-stage implementation of the platform is planned. In the first stage, AI will be trained with a significant number of the above-mentioned input data, so as to create a preliminary version of the predictor that can be considered category-specific, since it will be based on statistical data. In the second stage, each student will test the digital supporting tools and their reactions, improvements and residual difficulties will be evaluated. The results of the evaluation will feed back the AI, so as to improve the predictor by transforming it from category- to student-specific, as strongly recommended by experts to most usefully support people with dyslexia. The evaluation modules will be implemented in VR, given its capability to deliver material in a more engaging way and, at the same time, to easily gather the required information. This should help avoid problems such as reading impairments and lack of concentration, which often strike people with dyslexia. VR will also be used to simulate the difficulties encountered by them, in order to make teachers more conscious about the phenomenon and allow them intervene in order to mitigate it.

At present, data from about 700 dyslexic students have been collected. A preliminary analysis has been carried out and first results about the most severe difficulties and the most helpful supporting tools and strategies have been obtained. In particular, concentration when alone is the issue that most affects dyslexic students, followed by memory impairments, especially in short-term and scheduling problems. Moreover, in general, all the presented issues significantly affect (average score higher than 3 out of 5 for all of them) the majority of dyslexic students (at least more than 88.9% of the students experience each issues), highlighting that providing them with proper support is fundamental. Concerning the supporting methodologies, highlighted keywords, a clear layout of the study material and use of images, summaries, concept maps and schemes have been proven to be the most useful tools, with an average score equal or higher than 3.8 out of 5. Conversely, audiobooks read by artificial voices and digital tutors are considered useless by about 1 in every 2 and 1 in every 4 students, respectively, underlining that interacting with machines instead of human beings should be avoided. Taking pauses during lessons, hosting lessons online, repeating the studied material and making the program and the slides of the course available, instead are considered the most suitable supporting strategies (average score higher than 4 out of 5) and should, thus, be taken into account as the best practices to follow. Furthermore, the auditory channel should be exploited more, by automatically or manually recording lessons, using audiobooks with a human voice, having someone read aloud the study material and preferring oral exams to written ones. Finally, it is worth noting that supporting strategies obtained, on average, a higher score than supporting tools. This should prompt us to overcome the numerous approaches that have relied exclusively on digital tools and have not proposed any best practices to be shared with institutions and teachers. Such results will be exploited as useful guidelines to improve the conceptual and technical choices that will be made for the final implementation of BESPECIAL.

The next implementation step will be the training of the AI module responsible for the automatic prediction of the most useful tools and strategies, which will be performed once further data are available. The tools will be digitalized in the meantime. Then, the development of the second and last stage will begin by adding the VR functionalities to deliver psychometric tests and assess the digital tools.

Future work will concern the extension of the platform to several languages and to scientific disciplines and the support to other SLDs, aiming at reaching a full inclusion of all students in academic life. In addition, the data collected through the questionnaire about demographical characteristics and dyslexia history of the students will be exploited both to create social statistics to be widespread, in order to raise awareness on dyslexia phenomenon, and to perform further analysis that may improve the AI predictor.

**Author Contributions:** Conceptualization, A.Z., J.T. and G.C.; methodology, A.Z., J.T., V.P., S.B., P.A.-M., S.P. and G.C.; design of the software, A.Z., J.T, S.B., P.A.-M. and S.P.; formal analysis, A.Z. and J.T.; investigation, A.Z., J.T., V.P. and G.C.; writing—original draft preparation, A.Z.; writing—review and editing, A.Z., J.T., V.P., S.B., P.A.-M., S.P. and G.C.; supervision A.Z., J.T. and G.C.; funding acquisition, G.C. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was co-funded by European Union Committee within the Erasmus+ Programme 2014–2020—Key Action 2: Strategic Partnership Project (Agreement n. 2020-1-IT02-K203-080006—P.I.: Prof. Giuseppe Calabrò).

**Institutional Review Board Statement:** Ethical review and approval were waived for this study, since no experimentation has been carried out on human beings. The involvement of humans has been limited to the completion of a questionnaire, for which informed consent has been regularly obtained.

**Informed Consent Statement:** Informed consent was obtained from all subjects involved in the study.

**Acknowledgments:** The VRAIlexia project has received funding from the European Committee and the authors would like to acknowledge them for the financial support to this study. In addition, the authors want to acknowledge Estro s.r.l. for its support in the design of BESPECIAL and, in particular, of the tools digitalization module.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Appendix A

This appendix hosts some of the figures mentioned in Section 5, which are quite large. They have been thus reported here for the sake of clarity.

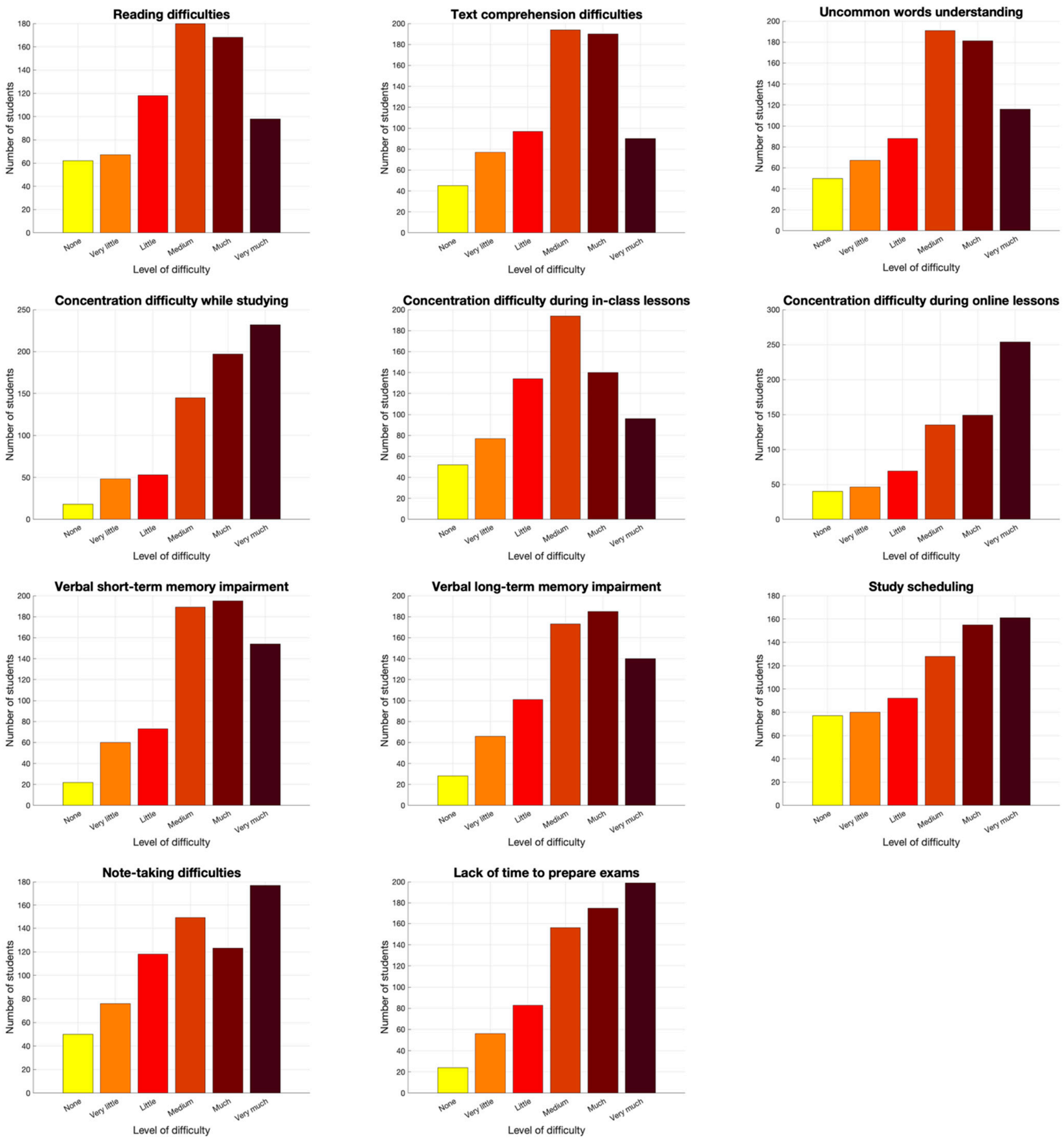



**Figure A1.** Histograms of the scores given by dyslexic students to the importance of each issue present in the questionnaire.

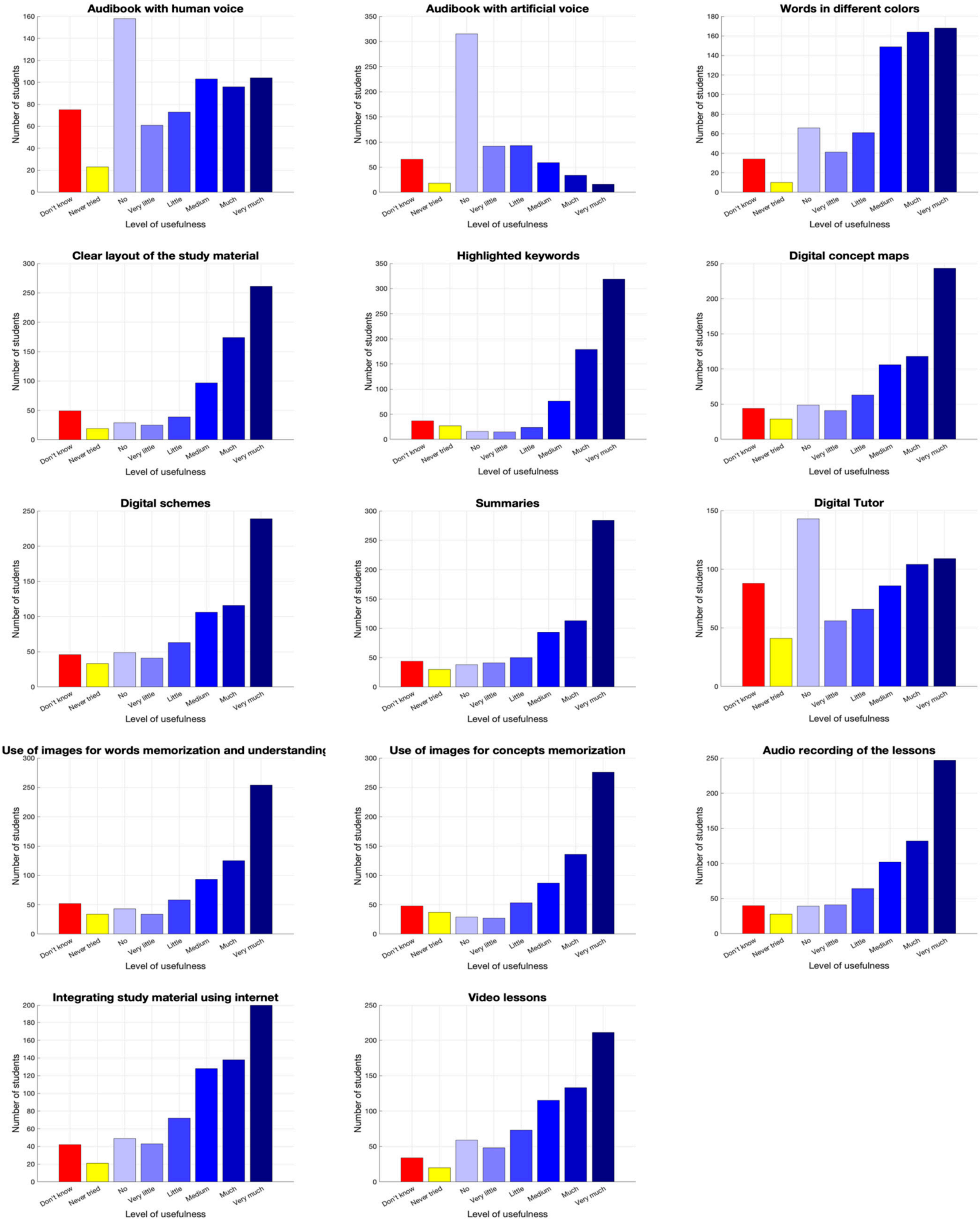



**Figure A2.** Histograms of the scores given by dyslexic students to the usefulness of each supporting tool present in the questionnaire.

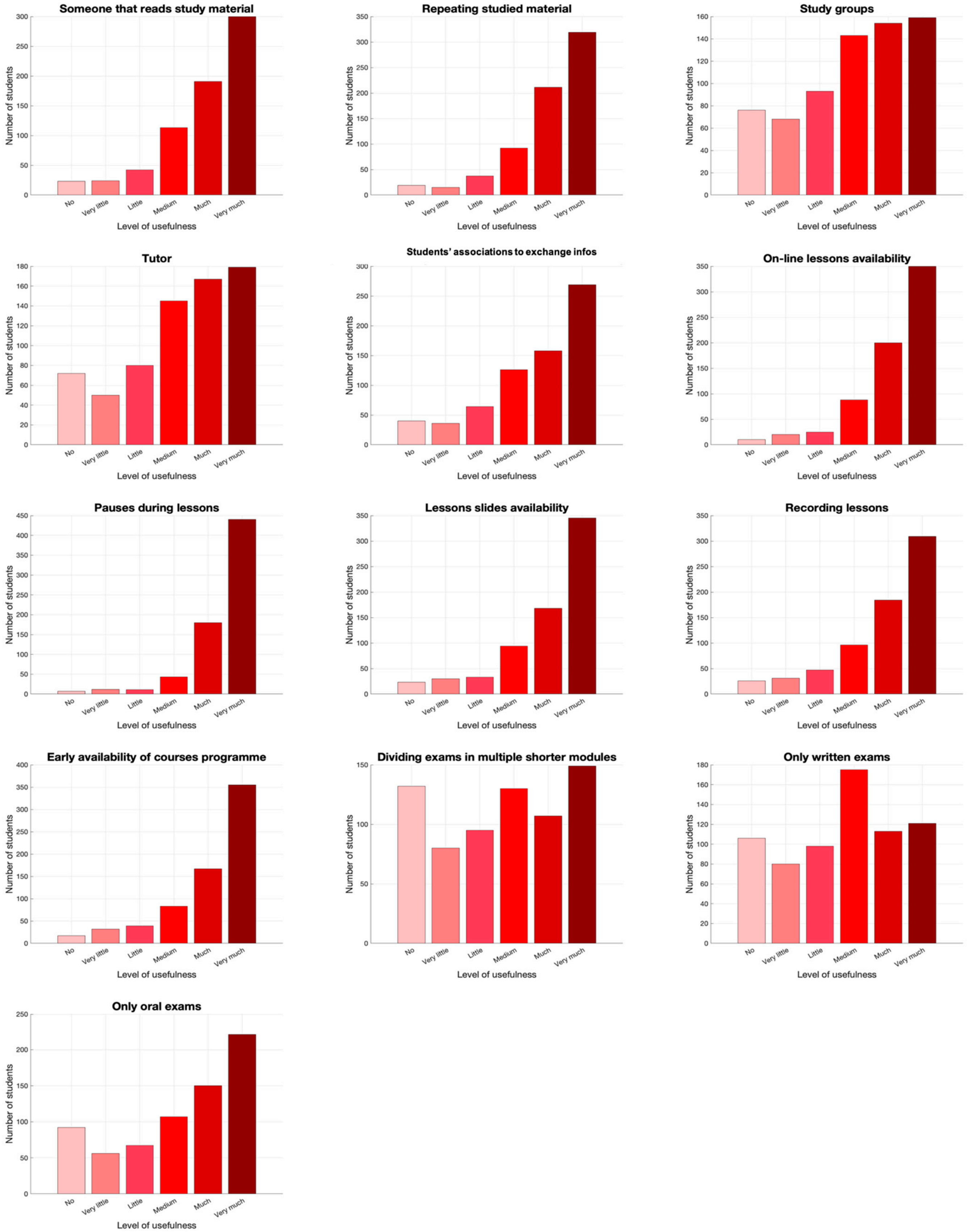



**Figure A3.** Histograms of the scores given by dyslexic students to the usefulness of each supporting strategy present in the questionnaire.

## References


1. World Health Organization. 6A03-Developmental Learning Disorder. In *International Classification of Diseases and Related Health Problems (ICD-11)*, 11th ed.; World Health Organization: Geneva, Switzerland, 2005; Available online: https://icd.who.int/browse11/l-m/en#/http://id.who.int/icd/entity/2099676649 (accessed on 14 February 2021).
2. Carawan, L.W.; Nalavany, B.A.; Jenkins, C. Emotional experience with dyslexia and self-esteem: The protective role of perceived family support in late adulthood. *Aging Ment. Health* **2016**, *20*, 284–294. [CrossRef]
3. Ghisi, M.; Bottesi, G.; Re, A.M.; Cerea, S.; Mammarella, I.C. Socioemotional Features and Resilience in Italian University Students with and without Dyslexia. *Front. Psychol.* **2016**, *7*, 478. [CrossRef]
4. Kohli, A.; Sharma, S.; Padhy, S.K. Specific Learning Disabilities: Issues that Remain Unanswered. *Indian J. Psychol. Med.* **2018**, *40*, 399–405. [CrossRef]
5. Mortimore, T.; Crozier, R. Dyslexia and difficulties with study skills in higher education. *Stud. High. Educ.* **2006**, *31*, 235–251. [CrossRef]
6. Cornoldi, C. La dislessia evolutiva. In *I Disturbi Dell'Apprendimento*; Il Mulino: Bologna, Italy, 2019; pp. 109–111, 126–131.
7. Cassandro, C.; Manassero, A.; Scarpa, A.; Landi, V.; Aschero, G.; Lovallo, S.; Velardo, P.; de Luca, P.; Albera, A.; Albera, P.; et al. Auditory-Verbal Processing Disorder and Dyslexia in Adulthood. *Transl. Med. UniSa* **2019**, *20*, 28–31.
8. Perera, H.; Shiratuddin, M.F.; Wong, K.W. Review of the Role of Modern Computational Technologies in the Detection of Dyslexia. *Inf. Sci. Appl. (ICISA)* **2016**, *376*, 1465–1475. [CrossRef]
9. Mohamad, S.; Mansor, W.; Lee, K.Y. Review of neurological techniques of diagnosing dyslexia in children. In Proceedings of the 2013 IEEE 3rd International Conference on System Engineering and Technology, Shah Alam, Malaysia, 19–20 August 2013; pp. 389–393. [CrossRef]
10. Paszkiel, S.; Szpulak, P. Methods of Acquisition, Archiving and Biomedical Data Analysis of Brain Functioning. In Proceedings of the 3rd International Scientific Conference on Brain-Computer Interfaces, Opole, Poland, 13–14 March 2018; pp. 158–171. [CrossRef]
11. El-Baz, A.; Casanova, M.; Gimel'farb, G.; Mott, M.; Switala, A. An MRI-based diagnostic framework for early diagnosis of dyslexia. *Int. J. Comput. Assist. Radiol. Surg.* **2008**, *3*. [CrossRef]
12. Brown, W.E.; Eliez, S.; Menon, V.; Rumsey, J.M.; White, C.D.; Reiss, A.L. Preliminary evidence of widespread morphological variations of the brain in dyslexia. *Neurology* **2001**, *56*, 781–783. [CrossRef] [PubMed]
13. Steinbrink, C.; Vogt, K.; Kastrup, A.; Müller, H.P.; Juengling, F.D.; Kassubek, J.; Riecker, A. The contribution of white and gray matter differences to developmental dyslexia: Insights from DTI and VBM at 3.0 T. *Neuropsychologia* **2008**, *46*, 3170–3178. [CrossRef]
14. Kronbichler, M.; Wimmer, H.; Staffen, W.; Hutzler, F.; Mair, A.; Ladurner, G. Developmental dyslexia: Gray matter abnormalities in the occipitotemporal cortex. *Hum. Brain Mapp.* **2008**, *29*, 613–625. [CrossRef] [PubMed]
15. Elnakib, A.; Casanova, M.; Gimelrfarb, G.; Switala, A.E.; El-Baz, A. Dyslexia Diagnostics by 3-D Shape Analysis of the Corpus Callosum. *IEEE Trans. Inf. Technol. Biomed.* **2012**, *4*, 700–708. [CrossRef]
16. Temple, E.; Poldrack, R.A.; Protopapas, A.; Nagarajan, S.; Salz, T.; Tallal, P.; Merzenich, M.M.; Gabrieli, J.D.E. Disruption of the neural response to rapid acoustic stimuli in dyslexia: Evidence from functional MRI. *Proc. Natl. Acad. Sci. USA* **2000**, *97*, 13907–13912. [CrossRef]
17. Pugh, K.R.; Mencl, W.E.; Jenner, A.R.; Katz, L.; Frost, S.J.; Lee, J.R.; Shaywitz, S.E.; Shaywitz, B.A. Functional neuroimaging studies of reading and reading disability (developmental dyslexia). *Ment. Retard. Dev. Disabil. Res. Rev.* **2000**, *6*, 207–213. [CrossRef]
18. Soo-Yeon, J.; Najarian, K. A modified maximum correlation modeling method for fMRI brain mapping; application for detecting dyslexia. In Proceedings of the IEEE International Conference on Bioinformatics and Biomeidcine Workshops, Philadelphia, PA, USA, 3–5 November 2008; pp. 64–69. [CrossRef]
19. Berninger, V.W.; Richards, T.L.; Abbott, R.D. Differential diagnosis of dysgraphia, dyslexia, and OWL LD: Behavioral and neuroimaging evidence. *Read. Writ.* **2015**, *28*, 1119–1153. [CrossRef] [PubMed]
20. Fadzal, C.W.; Mansor, W.; Lee, K.Y.; Mohamad, S.; Amirin, S. Frequency analysis of EEG signal generated from dyslexic children. In Proceedings of the 2012 International Symposium on Computer Applications and Industrial Electronics (ISCAIE), Kota Kinabalu, Malaysia, 3–4 December 2012; pp. 202–204. [CrossRef]
21. Andreadis, I.; Giannakakis, G.; Papageorgiou, C.; Nikita, K. Detecting Complexity Abnormalities in Dyslexia Measuring Approximate Entropy of Electroencephalographic Signals. In Proceedings of the 2009 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Minneapolis, MN, USA, 3–6 September 2009; pp. 6292–6295. [CrossRef]
22. Arns, M.; Peters, S.; Bretler, R.; Verhoeven, L. Different brain activation patterns in dyslexic children: Evidence from EEG power and coherence patterns for the double-deficit theory of dyslexia. *J. Integr. Neurosci.* **2007**, *6*, 175–190. [CrossRef] [PubMed]
23. Perera, H.; Shiratuddin, M.F.; Wong, K.W.; Fullarton, K. EEG signal analysis of passage reading and rapid automatized naming between adults with dyslexia and normal controls. In Proceedings of the 2017 IEEE 8th International Conference on Software Engineering and Service Science (ICSESS), Beijing, China, 24–26 November 2017; pp. 104–108. [CrossRef]
24. Paszkiel, S.; Hunek, W.; Shylenko, A. Project and Simulation of a Portable Device for Measuring Bioelectrical Signals from the Brain for States Consciousness Verification with Visualization on LEDs. In *Challenges in Automation, Robotics and Measurement Techniques*; Springer: Cham, Switzerland, 2016; Volume 440. [CrossRef]

25. Sharafi, Z.; Soh, Z.; Guéhéneuc, Y. A systematic literature review on the usage of eye-tracking in software engineering. *Inf. Softw. Technol.* **2015**, *67*, 79–107. [CrossRef]
26. Zingoni, A.; Diani, M.; Corsini, G. A Flexible Algorithm for Detecting Challenging Moving Objects in Real-Time within IR Video Sequences. *Remote Sens.* **2017**, *9*, 1128. [CrossRef]
27. Zingoni, A.; Diani, M.; Corsini, G. Real-time moving objects detection and tracking from airborne infrared camera. In Proceedings of the SPIE Security + Defence, Warsaw, Poland, 5 October 2017; p. 10434. [CrossRef]
28. Zingoni, A.; Diani, M.; Corsini, G. Tutorial: Dealing with rotation matrices and translation vectors in image-based applications: A tutorial. *IEEE Aerosp. Electron. Syst. Mag.* **2019**, *34*, 38–53. [CrossRef]
29. De Luca, M.; Borrelli, M.; Judica, A.; Spinelli, D.; Zoccolotti, P. Reading Words and Pseudowords: An Eye Movement Study of Developmental Dyslexia. *Brain Lang.* **2002**, *80*, 617–626. [CrossRef]
30. Bellocchi, S.; Muneaux, M.; Bastien-Toniazzo, M.; Ducrot, S. I can read it in your eyes: What eye movements tell us about visuo-attentional processes in developmental dyslexia. *Res. Dev. Disabil.* **2013**, *34*, 452–460. [CrossRef]
31. Macaš, M.; Lhotská, L.; Novák, D. Hidden Markov models for analysis of eye movements of dyslexic children. In Proceedings of the 18th International Conference on Digital Signal Processing (DSP), Fira, Greece, 1–3 July 2013; pp. 1–5. [CrossRef]
32. Rello, L.; Ballesteros, M. Detecting readers with dyslexia using machine learning with eye tracking measures. In Proceedings of the 12th Web for All Conference (W4A'15), Florence Italy, 18–20 May 2015; pp. 1–8. [CrossRef]
33. Bartolomé, N.A.; Zorrilla, A.M.; Zapirain, B.G. Dyslexia diagnosis in reading stage though the use of games at school. In Proceedings of the 2012 17th International Conference on Computer Games (CGAMES), Louisville, KY, USA, 30 July–1 August 2012; pp. 12–17. [CrossRef]
34. Gaggi, O.; Palazzi, C.E.; Ciman, M.; Galiazzo, G.; Franceschini, S.; Ruffino, M.; Gori, S.; Facoetti, A. Serious Games for Early Identification of Developmental Dyslexia. *Comput. Entertain.* **2017**, *15*. [CrossRef]
35. Lyytinen, H.; Erskine, J.; Hämäläinen, J.; Torppa, M.; Ronimus, M. Dyslexia—Early Identification and Prevention: Highlights from the Jyväskylä Longitudinal Study of Dyslexia. *Curr. Dev. Disord. Rep.* **2015**, *2*, 330–338. [CrossRef] [PubMed]
36. Kalyvioti, K.; Mikropoulos, T.A. Virtual Environments and Dyslexia: A Literature Review. *Procedia Comput. Sci.* **2014**, *27*, 138–147. [CrossRef]
37. Rizzo, A.; Parsons, T.D.; Kenny, P.; Buckwalter, J.G. Using Virtual Reality for Clinical Assessment and Intervention. In *Handbook of Technology in Psychology, Psychiatry, and Neurology: Theory, Research, and Practice*; L'Abate, P., Ed.; Nova Science Publishers: Hauppage, NY, USA, 2012.
38. Jivraj, B.A.; Schaeffer, E.; Bone, J.N.; Stunden, C.; Habib, E.; Jacob, J.; Mulpuri, K. The Use of Virtual Reality in Reducing Anxiety during Cast Removal: A Randomized Controlled Trial. *J. Child. Orthop.* **2020**, *14*, 574–580. [CrossRef] [PubMed]
39. Palacios, A.M.; Sánchez, L.; Couso, I. Diagnosis of dyslexia with low quality data with genetic fuzzy systems. *Int. J. Approx. Reason.* **2010**, *8*, 993–1009. [CrossRef]
40. Le Jan, G.; Le Bouquin-Jeannès, R.; Costet, N.; Trolès, N.; Scalart, P.; Pichancourt, D.; Faucon, G.; Gombert, J.E. Multivariate predictive model for dyslexia diagnosis. *Ann. Dyslexia* **2011**, *61*, 1–20. [CrossRef] [PubMed]
41. Al-Barhamtoshy, H.M.; Motaweh, D.M. Diagnosis of Dyslexia using computation analysis. In Proceedings of the 2017 International Conference on Informatics, Health & Technology (ICIHT), Riyadh, Saudi Arabia, 21–23 February 2017; pp. 1–7. [CrossRef]
42. Rello, L.; Romero, E.; Rauschenberger, M.; Ali, A.; Williams, K.; Bigham, J.P.; Cushen White, N. Screening Dyslexia for English Using HCI Measures and Machine Learning. In Proceedings of the 2018 International Conference on Digital Health (DH'18), Lyon, France, 23–26 April 2018; pp. 80–84. [CrossRef]
43. Maitrei, K.; Prasad, T.V. Identifying Dyslexic Students by Using Artificial Neural Networks. In Proceedings of the 2010 World Congress on Engineering (WCE 2010), London, UK, 30 June–2 July 2010; Volume 1.
44. Varol, H.A.; Mani, S.; Compton, D.L.; Fuchs, L.S.; Fuchs, D. Early prediction of reading disability using machine learning. In Proceedings of the AMIA Annual Symposium, San Francisco, CA, USA, 14 November 2009; pp. 667–671.
45. Palacios, A.; Sánchez, L.; Couso, I.; Destercke, S. An extension of the FURIA classification algorithm to low quality data through fuzzy rankings and its application to the early diagnosis of dyslexia. *Neurocomputing* **2016**, *176*, 60–71. [CrossRef]
46. Glazzard, J. The impact of dyslexia on pupils′ self-esteem. *Supporting Learn.* **2010**, *25*, 63–69. [CrossRef]
47. Battistutta, L.; Commissaire, E.; Steffgen, G. Impact of the Time of Diagnosis on the Perceived Competence of Adolescents with Dyslexia. *Learn. Disabil. Q.* **2018**, *41*. [CrossRef]
48. Sanfilippo, J.; Ness, M.; Petscher, Y.; Rappaport, L.; Zuckerman, B.; Gaab, N. Reintroducing Dyslexia: Early Identification and Implications for Pediatric Practice. *Pediatrics* **2020**, *146*, e20193046. [CrossRef]
49. Barbiero, C.; Lonciari, I.; Montico, M.; Monasta, L.; Penge, R.; Vio, C.; Tressoldi, P.E.; Ferluga, V.; Bigoni, A.; Tullio, A.; et al. The submerged dyslexia iceberg: How many school children are not diagnosed? Results from an Italian study. *PLoS ONE* **2012**, *7*, e48082. [CrossRef] [PubMed]
50. Galuschka, K.; Use, E.; Krick, K.; Schulte-Körne, G. Effectiveness of Treatment Approaches for Children and Adolescents with Reading Disabilities: A Meta-Analysis of Randomized Controlled Trials. *PLoS ONE* **2014**, *9*, e89900. [CrossRef]
51. Pasqualotto, A.; Venuti, P. A Multifactorial Model of Dyslexia: Evidence from Executive Functions and Phonological-based Treatments. *Learn. Disabil. Res. Pract.* **2020**, *35*, 150–164. [CrossRef]
52. Bonacina, S.; Cancer, A.; Lanzi, P.L.; Lorusso, M.L.; Antonietti, A. Improving reading skills in students with dyslexia: The efficacy of a sublexical training with rhythmic background. *Front. Psychol.* **2015**, *6*, 1510. [CrossRef]

53. Cogo-Moreira, H.; Andriolo, R.B.; Yazigi, L.; Ploubidis, G.B.; Brandão de Ávila, C.R.; Mari, J.J. Music education for improving reading skills in children and adolescents with dyslexia. *Cochrane Database Syst. Rev.* **2012**. [CrossRef]
54. Wang, R.; Chen, L.; Solheim, I.; Schulz, T.; Ayesh, A. Conceptual Motivation Modeling for Students with Dyslexia for Enhanced Assistive Learning. In Proceedings of the 2017 ACM Workshop on Intelligent Interfaces for Ubiquitous and Smart Learning (SmartLearn'17), Limassol, Cyprus, 13 March 2017; pp. 11–18. [CrossRef]
55. Yaquob Alsobhi, A.; Khan, N.; Rahanu, H. Personalised Learning Materials Based on Dyslexia Types: Ontological Approach. *Procedia Comput. Sci.* **2015**, *60*, 113–121. [CrossRef]
56. Pang, L.; Jen, C.C. Inclusive dyslexia-friendly collaborative online learning environment: Malaysia case study. *Educ. Inf. Technol.* **2018**, *23*, 1023–1042. [CrossRef]
57. Saidah Sarpudin, S.N.; Zambri, S. Web readability for students with Dyslexia: Malaysian case study. In Proceedings of the 2014 3rd International Conference on User Science and Engineering (i-USEr), Shah Alam, Malaysia, 2–5 September 2014; pp. 192–197. [CrossRef]
58. Alhabashneh, M.; Abu-Salih, B.; Knight, S. Impact of Web 2.0 Technology on Students with Learning Difficulties: A State-of-the-Art and Future Challenges. In Proceedings of the 2018 32nd International Conference on Advanced Information Networking and Applications Workshops (WAINA), Krakow, Poland, 16–18 May 2018; pp. 693–697. [CrossRef]
59. Schiavo, G.; Mana, N.; Mich, O.; Zancanaro, M.; Job, R. Attention-driven read-aloud technology increases reading comprehension in children with reading disabilities. *J. Comput. Assist. Learn.* **2021**. [CrossRef]
60. Perry, C.; Zorzi, M.; Ziegler, J.C. Understanding Dyslexia through Personalized Large-Scale Computational Models. *Psychol. Sci.* **2019**, *30*, 386–395. [CrossRef]
61. Siti Suhaila, A.H.; Admodisastro, A.N.; Abd Ghani, A.A. Computer-based learning model to improve learning of the malay language amongst dyslexic primary school students. In Proceedings of the Asia Pacific HCI and UX Design Symposium, Melbourne, Vic, Australia, 7 December 2015. [CrossRef]
62. Ndombo, D.M.; Ojo, S.; Osunmakinde, I.O. An intelligent integrative assistive system for dyslexic learners. *J. Assist. Technol.* **2013**, *7*. [CrossRef]
63. Rajapakse, S.; Polwattage, D.; Guruge, U.; Jayathilaka, I.; Edirisinghe, T.; Thelijjagoda, S. ALEXZA: A Mobile Application For Dyslexics Utilizing Artificial Intelligence And Machine Learning Concepts. In Proceedings of the 2018 3rd International Conference on Information Technology Research (ICITR), Moratuwa, Sri Lanka, 5–7 December 2018; pp. 1–6. [CrossRef]
64. Thelijjagoda, S.; Chandrasiri, M.; Hewathudalla, D.; Ranasinghe, P.; Wickramanayake, I. The Hope: An Interactive Mobile Solution to Overcome the Writing, Reading and Speaking Weaknesses of Dyslexia. In Proceedings of the 2019 14th International Conference on Computer Science & Education (ICCSE), Toronto, ON, Canada, 19–21 August 2019; pp. 808–813. [CrossRef]
65. Brooks, B.M.; Rose, F.D.; Attree, E.A.; Elliot-Square, A. An evaluation of the efficacy of training people with learning disabilities in a virtual environment. *Disabil. Rehabil.* **2002**, *24*, 622–626. [CrossRef]
66. Redel-Macías, M.D.; Pinzi, S.; Martínez-Jiménez, M.P.; Dorado, G.; Dorado, M.P. Virtual Laboratory on Biomass for Energy Generation. *J. Clean. Prod.* **2016**, *112*, 3842–3851. [CrossRef]
67. Lantto, E.; Simpura, F.; Uusitalo, J.; Lukander, K.; Räsänen, T.; Teperi, A.-M. Evaluation of the Efficacy of a Virtual Reality-Based Safety Training and Human Factors Training Method: Study Protocol for a Randomised-Controlled Trial. *Inj. Prev.* **2020**, *26*, 360–369. [CrossRef]
68. Herrero, J.F.; Lorenzo, G. An Immersive Virtual Reality Educational Intervention on People with Autism Spectrum Disorders (ASD) for the Development of Communication Skills and Problem Solving. *Educ. Inf. Technol.* **2020**, *25*, 1689–1722. [CrossRef]
69. El Naqa, I.; Pedroli, E.; Padula, P.; Guala, A.; Meardi, M.T.; Riva, G.; Albani, G. A Psychometric Tool for a Virtual Reality Rehabilitation Approach for Dyslexia. *Comput. Math. Methods Med.* **2017**, *2017*, 7048676. [CrossRef]
70. Kalyvioti, K.; Mikropoulos, T.A. Memory Performance of Dyslexic Adults in Virtual Environments. *Procedia Comput. Sci.* **2012**, *14*, 410–418. [CrossRef]
71. Siti Suhaila, A.H.; Admodisastro, A.N.; Manshor, N.; Kamaruddin, A.; Abd Ghani, A.A. Dyslexia Adaptive Learning Model: Student Engagement Prediction Using Machine Learning Approach. In Proceedings of the International Conference on Soft Computing and Data Mining (SCDM 2018), Johor, Malaysia, 12 January 2018; pp. 372–384. [CrossRef]
72. Costantini, A.; Ceschi, A.; Sartori, R. Psychosocial Interventions for the Enhancement of Psychological Resources among Dyslexic Adults: A Systematic Review. *Sustainability* **2020**, *12*, 7994. [CrossRef]
73. Sprenger-Charolles, L.; Siegel, S.L.; Jiménez, J.E.; Ziegler, J.C. Prevalence and Reliability of Phonological, Surface, and Mixed Profiles in Dyslexia: A Review of Studies Conducted in Languages Varying in Orthographic Depth. *Sci. Stud. Read.* **2011**, *15*, 498–521. [CrossRef]
74. Moll, K.; Kunze, S.; Neuhoff, N.; Bruder, J.; Schulte-Körne, G. Specific Learning Disorder: Prevalence and Gender Differences. *PLoS ONE* **2014**, *9*, e103537. [CrossRef] [PubMed]
75. Scuola, Pubblicati I Dati Sugli Alunni Con Disturbi Specifici Dell'apprendimento. Available online: https://www.miur.gov.it/web/guest/-/scuola-pubblicati-i-dati-sugli-alunni-con-disturbi-specifici-dell-apprendimento#:~{}:text=Complessivamente%2C%20nel%202017%2F2018%2C,(disturbo%20nel%20calcolo%20matematico) (accessed on 14 February 2021).
76. Katz, J. The Three Block Model of Universal Design for Learning (UDL): Engaging students in inclusive education. *Can. J. Educ.* **2013**, *36*, 153–194.
77. Smeby, J. Disciplinary differences in university teaching. *Stud. High. Educ.* **1996**, *21*, 69–79. [CrossRef]

78. Ray, S. A Quick Review of Machine Learning Algorithms. In Proceedings of the 2019 International Conference on Machine Learning, Big Data, Cloud and Parallel Computing (COMITCon), Faridabad, India, 14–16 February 2019; pp. 35–39. [CrossRef]
79. Taborri, J.; Palermo, E.; Rossi, S. Automatic detection of faults in race walking: A comparative analysis of machine-learning algorithms fed with inertial sensor data. *Sensors* **2019**, *19*, 1461. [CrossRef]
80. Freire, A.P.; Petrie, H.; Power, C. Empirical results from an evaluation of the accessibility of websites by dyslexic users. In Proceedings of the Workshop on Accessible Design in the Digital World, Lisboa, Portugal, 5–9 September 2011; pp. 41–53.
81. Bergua, V.; Meillon, C.; Potvin, O.; Bouisson, J.; Le Goff, M.; Rouaud, O.; Ritchie, K.; Dartigues, J.-F.; Amieva, H. The STAI-Y trait scale: Psychometric properties and normative data from a large population-based study of elderly people. *Int. Psychogeriatr.* **2012**, 1–9. [CrossRef]
82. Luszczynska, A.; Scholz, U.; Schwarzer, R. The General Self-Efficacy Scale: Multicultural Validation Studies. *J. Psychol.* **2005**, *139*, 439–457. [CrossRef]
83. Sica, C.; Chiri, L.R.; Favilli, R.; Marchetti, I. *Test Q-PAD-Questionario per la Valutazione Della Psicopatologia in Adolescenza*; Erickson: Trento, Italy, 2011; ISBN 9788861378797.
84. Goldsmith, R.E. Dimensionality of the Rosenberg Self-Esteem Scale. *J. Soc. Behav. Personal.* **1986**, *1*, 253–264.
85. Mikropoulos, T.A.; Natsis, A. Educational Virtual Environments: A Ten-Year Review of Empirical Research (1999–2009). *Comput. Educ.* **2011**, *56*, 769–780. [CrossRef]
86. Mikropoulos, T. A Virtual Reality Test for the Identification of Memory Strengths of Dyslexic Students in Higher Education. *J. Univers. Comput. Sci.* **2013**, *19*, 2698–2721. [CrossRef]
87. Seymour, P.H.K.; Aro, M.; Erskine, J.M. Foundation literacy acquisition in European orthographies. *Br. J. Psychol.* **2003**, *94*, 143–174. [CrossRef] [PubMed]