ADAPTIVE SEQUENTIAL RECOMMENDER SYSTEM FOR DISRUPTIVE PERSONALIZED DYSLEXIA INTERVENTION

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Abstract

Computer-assisted programs have been proposed as a solution to facilitate the systematic application of scientific knowledge in individualised and progressively more intensive interventions for children with dyslexia. These programs do not always meet the unique needs of each child, highlighting the urgent need for improved adaptive technology-based solutions that can provide tailored support throughout the learning process. This article presents a new adaptive sequential guidance system for personalised dyslexia intervention. The system introduces a number of key innovations: a dynamic word generator that creates phonetically modified words and pseudowords from seed words, a three-dimensional matrix structure (E, W,and F) for effective word difficulty management and user performance, and an algorithm of recommendations based on stochastic gratising semi-monthly matrix factors. The system uses a heuristic initiation process to reduce cold start problems and uses an extension technique to detect difficulties in certain derived words. Furthermore, the text introduces the concept of ”virtual children” based on Bayesian Knowledge Tracking, which allows for comprehensive testing and optimisation of systems before real implementation. The proposed system offers a unique approach to dyslexia intervention by dynamically adapting word difficulties based on individual user performance, ensuring that each child remains in its optimal learning area. The main results conclude that the use of thermal maps and 3D visualization F-matrix allows each user to identify specific difficulty areas, promoting more targeted intervention; additionally, extensive testing shows that the system is sufficiently robust to reduce error rates in several trials; and the parametric study reveals the system's ability to adapt using adjustable parameters such as success and failure modulators and increasing factors; furthermore, the system demonstrates a strong adaptability of individual users, as demonstrated by its performance with different virtual child profiles.

Keywords: Recommendation System, Factorization, Intervention Test, Phonemes, Matrices

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1. Introduction

Developmental dyslexia (DD) is a hereditary neurological disorder characterized by severe and persistent difficulties in reading and spelling despite normal intelligence, education, and intense remedial effort [1]. It is now understood that difficulties in learning to read occur as part of a continuum [2]. For this reason, DD is very prevalent, ranging from 5-12%, depending on specific definitions and cut-off points established as identification criteria. When applying a restrictive criterion, it is estimated that 5% of the school population contributes disproportionately to school failure statistics, with rates as high as 40% [3]. Additionally, DD has serious implications for personal development, family dynamics, and social adjustment.

Despite various goals being established, remedial programs have primarily focused on developing grapheme-phoneme correspondences and achieving fluency in word reading [4]. While interventions show promise, they do not uniformly benefit all children with dyslexia. Conventional strategies aimed at word decoding have demonstrated substantial effect sizes (up to 0.70), irrespective of the specific approach employed [5], particularly when they also incorporate phonological skills training [6]. Computer-assisted programmes (CAPs) have been proposed as a solution to overcome these results, as they provide individualised and progressively more intensive interventions for children with dyslexia. However, CAPs targeting grapheme-phoneme correspondence and word reading in children with DD have yielded similar results. Adaptive technology solutions applied in CAPs allow children with mild to moderate dyslexia to moderately improve their skills, bringing them closer to their peers. They improve in accuracy although they remain slow readers. However, neither conventional treatments nor CAPs have succeeded in bridging the gap in reading fluency for children at the more severe end of the dyslexia spectrum. As a result, about 5% of children and adults with dyslexia remain very slow and ineffective readers [2].

The recommended systems have become popular in different areas, such as ecommerce, advertising and entertainment. The application of recommendation systems to dyslexic intervention may be essential in personalised learning [7]. This can be done through intervention based on recommendation systems, which takes into account cognitive profiles, skills, special difficulties and previous performance, to suggest certain activities for children with various abilities [8]. However, the application of Recommendation systems in the context of dyslexia is difficult. One of the major obstacles is the starting syndrome. A second difficulty is the adaptability of the system to the user's responses, making the difficulty of pregnancy adjustable in real time, based on how students perform them.

Collaborative and content-based filtration approaches are widely used in several areas. However, there are some limitations to these dyslexia treatment techniques [9][10]. For example, collaborative filtering involves a large amount of interaction data to make a correct recommendation that may not work where data is limited or if users have unique learning profiles. On the other hand, contentbased filtration depends mainly on the quality and completeness of metadata, limiting the ability to capture the complexity of individualised learning processes.

The recommended system design in this work addresses these challenges by using a hybrid time sequence based method in view of successful or unsuccessful recommendations sequences. This approach takes into account the levels of difficulty of words and means the sequence of words and the response of students to them, allowing dynamic and continuous adjustment of recommendations. For dyslexia intervention, sequential order is required because learning is not done in a straight line and there may be significant variations between individuals along this line.

In addition to the system of recommendations, this paper introduces many news that contributes to individualised educational intervention. These include the development of a word generator that can change them phonetically or wrongly, so that complexity can vary according to the needs of each child, so that the situation becomes more difficult according to their circumstances. The rules presented are used to amend these words while assessing the type of challenge, each change brings in content a more granular and precise adaptation of content. Moreover, in the data generated by silico, called "virtual copies," it is allowed to simulate various learning profiles, thus allowing for comprehensive testing of the system prior to its application in natural environments and reducing cold start problems using the Bayesian knowledge tracking model.

In addition, the proposed solution introduces original ideas such as the threedimensional matrix structure of the system for efficient management of information about the complexity of words, along with the user's performance during interactive sessions. Finally, we have implemented a new cross-validation technique to estimate the error in matrix factorization to ensure the specificity and reliability of recommendations related to future difficulties. These innovations increase the functionality and efficiency of the system and offer new directions for designing customised educational technologies in other configurations.

Following section 1, the remaining sections of the work are organized as follows: Section 2 discusses previous research into dyslexic intervention systems and other systems of recommendations for education. The third section presents the basic data used at the intervention stage, the word-generating module and the system of recommendations. In section 4, we present the results of the reader's evaluation using the factorized matrix method and evaluating the system stability through virtual copies. This document shall be completed in the fifth section after the system parametric studies have been carried out.

2. Related Work

Reading consists of connecting two neuronal systems that are in principle independent. An oral language comprehension system that pre-exists literacy, and a viso-attentional system that is 'recycled' at the same time as the connection between the two systems is built [11]. According to Scarborough (2001) [12], word recognition - decoding - is the key to connecting these two systems. It has been pointed out that the proximate cause of dyslexia is the difficulty in learning, integrating and automating grapheme-phoneme correspondences [13][14]. The neural signature of the ortho-phonological connection deficit has even been found in the occipitotemporal reading network [15].

Computer-assisted programmes (CAPs) have been proposed as a solution to facilitate the systematic application of scientific knowledge in individualised and progressively more intensive programmes [4]. Pioneering studies with CAPs have found positive effects on the development of word decoding skills in children at risk or with learning difficulties [16][17][18][19]). The effectiveness of CAPs based on phonological awareness and decoding in improving reading skills has been corroborated in a number of studies focusing on word attack [20]; on phonetic features [21]; or, on phonemic awareness and letter- sound relations [22].

The most recent experiences share certain design features, such as a structured sequence of sessions through which progress is made using an adaptive algorithm to individualise the difficulty, pace and intensity of treatment. The aim of the GraphoGame programme is to intervene directly on the relationship between orthographic representations - graphemes - and phonological representations - phonemes [23]. The sequence includes first the simultaneous and repeated presentation of grapheme-phoneme correspondences (first in isolation, then included in syllables and then in words) up to the phase of fluency training with words and phrases. GraphoGame is supported by several studies in different languages representing a wide range of levels of orthographic transparency [24][25][26][27]. The effects of LEXY have also been shown to be significant [14], with evidence of functional changes in the amplitude of the N170 evoked potential related to word reading fluency [14][28]. Finally, the study by Giménez et al. (2020) [29] shows the characteristic efficacy of CAPs , with 75% of children leaving the risk zone, i.e. exceeding the 30th percentile on reading measures.

In conclusion, CAPs have proven to be valuable tools that bring readers with dyslexia closer to adaptive reading levels. However, since the seminal study by Vellutino et al. (1996) [30], it has been shown that a group of approximately 5% of the population is resistant to conventional or CAPs treatments. Recommender systems seem a suitable tool to challenge this problem. Recommender systems do not require a closed session design. Moreover, they allow for fully individualised progressive adaptation, thus keeping the intervention in the optimal learning zone of the readers. These properties can be expected to have a positive impact even on treatment-resistant dyslexics.

Recommender systems have become very popular across sectors such as e-commerce, advertising, or entertainment and are important in order to make dyslexia interventions efficient. The theory underlying these systems is based on the fact that user preferences or needs help in coming up with personalized and relevant recommendation [7]. One way through which recommender systems have been used in addressing dyslexia intervention is by looking at the student's cognitive profile, skills, specific difficulties and their performance in the previous activities to propose tasks and materials that are tailored to their unique requirements [8].

Benmarrakchi, El Kafi, and Elhore (2016) [31], explore the contribution of ICT in adaptive virtual learning environments in benefiting dyslexic students regarding their learning style preferences in the education set up. In addition, based on previous performance of particular students and trends among other students with comparable profiles, a recommender system could propose exercises having the right level of challenge for that specific learner. In the most effective intervention strategies that leverage emerging technologies and improve detection and intervention in dyslexia from childhood through adulthood, Farah, Ionta, and Horowitz-Kraus (2021) [32] have suggested.

Different methods and techniques are employed in recommending systems these comprise collaborative filtering, content based filtering and hybrid approaches [33]. These systems have been found to work well in different settings and could be very effective for dyslexia intervention by personalizing educational activities and materials according to each student's unique requirements [8]

Collaborative filtering assumes that future choices will choose similar choices from the past from other similar people [9]. This way it can recommend exercises to a child during an activity based on the performance of other students with similar profiles. Walker et al., (2004) [34], investigated a collaborative information filter system based on educational environment, known as Altered Vista, which proved its efficiency and effectiveness through a three-month trial. This is an example of how collaborative filtering applied to education can be used to make recommendations on how to improve treatments for dyslexia through personalised recommendations based on student ability and performance. Conversely, there is also the content-based approach that takes into account the characteristics or characteristics that distinguish different educational activities [10]. In essence, this method includes the viewing of metadata such as the type of skill domain, skill level or other useful information. This may require a modification of the curriculum [35].

Both collaborative filtering and content-based filtering have strengths and disadvantages respectively. Great strength to propose subjective and/or contextual aspects is obtained from these approaches, although the latter require more interaction data than the first to deliver better results. In particular, while content-based filtering provides clear understandable recommendation according to current available information [8]. Conversely, collaborative filtering leverages data from users with similar interests, potentially broadening the scope of recommendations; Au Otaiba et al. (2018) [36] give an example of interventions for dyslexic learners' Elementary level programs in which content-based approach can be crucial during instruction design. design. Often witness by merging several shortcomings in addition to benefits related to the two techniques; Hybrid models have been widely used in many recommendations integrating collaborative filtering and content based filtering [37]. For example, collaboration filter is used to find a number of similar students in a hybrid system for intervention of dyslexia, then content base is used to recommend activities and materials that meet the needs of a specific student. Cardona et al. (2021) [38] evaluated remodeling strategies aimed at reducing dyslexia in children who showed a fusion using computer technology as more useful for demonstrations and record keeping. The development has made hybrid and multidimensional content personalization recommendation systems an important step in improving interventions aimed at curbing this reading disorder [37].

The use of multiple data sources and recommendation strategies in hybrid recommendation systems makes it possible to address individual constraints from a single perspective. Meanwhile, multidimensional approaches allow for different dimensions related to reading disability; For example, those may include factors such as the cognitive profile of an individual student, his or her level of performance in different areas (such as phonological awareness or reading rate), preferred learning methods and social background. By taking into account many factors, these systems can provide comprehensive but personal advice to all pupils with dyslexia who need help appropriate Machine learning and data mining are some of the advanced techniques that can be used to analyze this multidimensional data to discover complex patterns [7].

Validation and evaluation of recommended systems are crucial to their effectiveness, reliability and usefulness in dyslexia. These processes include a mix of methodological approaches and metrics intended to measure system performance and its impact on endusers [39]. In order to assess the effectiveness of the recommended system in dyslexia intervention tests, it is possible to use experimental and quasi experimental designs comparing student results with those received as a control group [8]. In addition to experimental approaches, the evaluation of recommended dyslexia systems should also include qualitative and participatory methods involving users directly in this process, as proposed by Mejía Corredor, Diaz, Jiménez and Fabregat Gesa (2012) [40]. We must stress that the evaluation and validation of these systems is a continuous process requiring close cooperation between researchers, educators and technology developers to develop dyslexic student-specific systems based on effective instruction methods [41].

Therefore, recommended systems offer a promising way to provide individual support tailored to each student's cognitive profile, skills, challenges, previous activities' performance, and finally propose tasks and materials that match their unique characteristics.

3. Methodology

3.1. General Outline

The general framework is as follows: The aim is to design an intervention method for dyslexic children that presents a series of word-reading tests, with the words dynamically selected based on the user's previously mastered difficulty level. Firstly, a screening test is conducted to classify the child into one of three reading groups (initial, intermediate, and advanced), using words that will serve as seeds for the intervention trials. The intervention phase generally involves presenting 100 words per trial, where these words are derived from the seed words. The derived words are provided by a ”word generator” module and selected by a recommendation system. The system recommends levels of difficulty as the tests evolve. These difficulties are on the one hand calculated a priori, by the combined experience of the words of the screening test (which will be the seed words), and the difficulties added according to the changes made by the word generator. These difficulties, which for the moment have been expressed as general, are modified by the user's experience (whether the user gets it right or wrong) in order to reflect the difficulty actually experienced, and a factor of increasing difficulty in order to progress the test to more challenging levels..

After the interventions, a final evaluation test is conducted to assess the new difficulty level the child has reached.

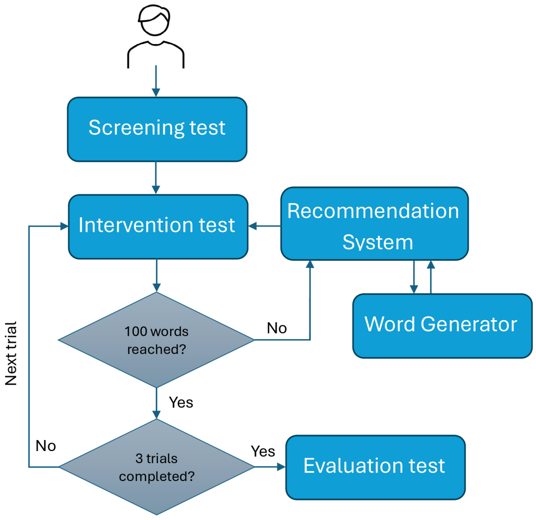


Figure 1: General outline of the Recommendation System.

3.2. Data and Screening Test

The initial data comes from comprehensive screening tests conducted on 5,478 children aged 4 to 10, in the framework of the Leeduca project. These tests evaluate reading skills, focusing on speed and accuracy.

The tests consist of 4 primary batteries: Visual Route (VR), which assesses the reading of words from one to three syllables; Phonological Route (PR), which focuses on phonological decoding using pseudo-words [42]; Reading Speed (RS), which measures fluency by estimating the number of words read per minute; and Reading Comprehension (RC), which evaluates comprehension through a questionnaire. Additionally, phonological deficits are evaluated, including Phonological Awareness (PA) and Verbal Short-Term Memory (VSTM) through Rapid Naming (RN) tasks [43][44].

The results are used to calculate a comprehensive performance measure in each test, weighting the correct answers over the total responses and multiplying by the time spent. This makes it possible to identify strengths and weaknesses in each child's reading skills.

3.3. Intervention Test

After the screening tests, each child undergoes iterative intervention tests that adapt the difficulty of words according to their performance. The words used, called ”seed words” have an intrinsic difficulty based on the aggregate performance of all children in the screening tests, modified by the Success Modulator or Failure Modulator (↑↓, SM, FM, that express whether a child has got the word right or wrong, thus changing the individual perception of difficulty). These seed words generate derived words and pseudowords using a specialized generator that applies phonetic changes, introducing additional difficulty [45].

Each intervention trial consists of a sequence of 100 words, whose difficulty is dynamically adjusted according to the child's previous and current performance. The words presented have an intrinsic average difficulty, proposed by the word generator, but this difficulty is modified according to the user's experience with the SM or FM, if applicable.

Correct responses lead to more difficult and complex words, while incorrect ones lead to easier words. This increase or decrease in difficulty is determined by the Increase Factor (+/-, IF), keeping the child in their zone of proximal development [46].

These tests offer a personalized and adaptive learning experience, allowing children to progress at their own pace and maximizing the effectiveness of interventions by adapting instruction to each child's specific needs [47][48].

3.4. System Parameters

Thus, the performance of the proposed system depends on three modifying parameters, SM, FM and IF. Although the values of these parameters can be fixed empirically, a comprehensive study can be done by means of a parametric study to choose the optimal values, as can be seen in the Results Section.

3.5. Word Generator

The word generator is crucial in the intervention system, as it creates derived words from the seed words to adjust the difficulty of the tests according to each child's individual needs. The generator performs variations on the given seed word through changes in vowels, consonants, or alterations in the order of letters, introducing an added difficulty to the intrinsic difficulty of the seed word, thus modulating the complexity of the words presented [49].

The generator considers seven possible fundamental changes for each seed word and combinations, each with an assigned difficulty according to the phonological distance from the original word. The exact change can generate a variable number of derived words (0, 1, 2, 3, or more) from a given seed word. The added difficulties of each change are denoted as Iij, where i represents the seed word, and j is the type of change applied, generating a matrix of initial difficulties.

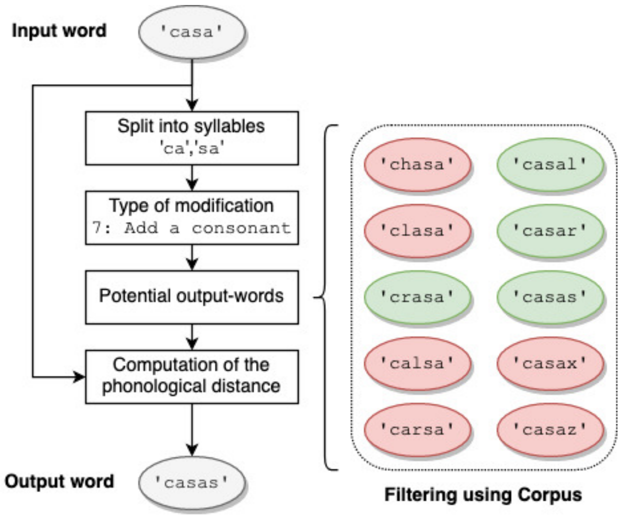


Figure 2: Example of modification (adding a consonant) for the input word 'casa'. Valid words are shown in green. Pseudo-words are shown in red.

Initially, each change implies a similar difficulty jump for all derived words, but later, as the child interacts with the recommender system, the assignment of difficulties for each derived word is refined individually. The phonological distances between the seed words and their derivatives are determined using metrics based on the similarity of the phonemes that compose them [50].

The generator can produce both existing words in the Spanish vocabulary and pseudowords (letter sequences that respect the language's phonotactic rules but without associated meaning) [51]. Pseudowords represent a greater challenge to the child's phonological decoding ability than words, eliminating the possibility of stimulus recognition through familiarity or prior memorisation. The system allows to generate just word type stimuli, omitting pseudowords if necessary.

4. Recommendation System

4.1. General Organizarion of the Matrices

The user recommendation system adapts reading tests to each participant's specific needs by organizing three main matrices: E, W, and F (in addition to I, used at the beginning).

E-matrix stores the difficulties faced by the user for each word presented, modulated according to their performance level. F-matrix contains the derivative difficulties for each word obtained by measuring the matrix [52], estimating the difficulty of words not yet found on the basis of previous performance models and similar words. W-matrix retains the words associated with each level of difficulty, including both the original words of seeds and derivatives generated. The system starts with an initial difficulty, a combination of a priori estimation of the scores of the seed words and the difficulty added by the specific change, which is stored in the I matrix.

Each cell of the matrix system shall contain a numerical value reflecting the difficulty (initially, experienced, derived) of the corresponding word or words so that the complexity and fine-tuning of the reading tests can be accurately graduated. The rows always correspond to the words of seed $(S_1, S_2, \ldots, S_i, \ldots, S_n)$, while the columns represent the derivation obtained by phonological and spelling variations. Each column initially groups the words generated by the same variation or modification $(C_1, C_2, \ldots, C_j, \ldots, C_m)$. However, since the system collects information on user performance, the columns are broken down (expanded) to take into account separately the words resulting from the same variation, allowing for a more precise adjustment of the difficulties [53].

The organisation of the matrix allows efficient storage and processing of information on the difficulties encountered and deducted and the words related to each level of complexity, with dynamic adjustment of reading tests to promote child progress. The E, W and F matrix combination, together with factorization and disaggregation processes, is an innovative approach to personalizing read interventions and maximizing learning efficiency.

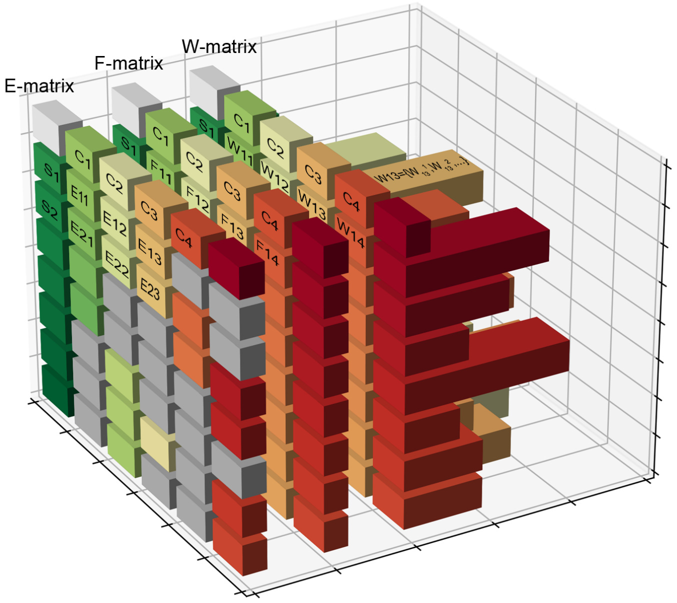


Figure 3: Organisation and equivalence of matrices E, F and W.

4.2. I-matrix

The I-matrix has rows representing the seed words $S_1, S_2, \ldots, S_i, \ldots, S_n$ and columns representing the possible changes and their combinations derived from the word generator $C_1, C_2, \ldots, C_j, \ldots, C_m$. Each cell I_{ij} in the matrix corresponds to the initial difficulty of the word derived from the seed word S_i after applying the change C_j.

The difficulty I_{ij} for each cell can be expressed as:

$$I_{ij} = D_{i\text{–apriori}} \times M \times \Delta D_j \tag{1}$$

where:

- $D_{i\text{–apriori}}$ is the a priori difficulty of the seed word S_i before considering user experience during the screening test.
- M_i is a fixed modifier that adjusts the difficulty based on the user's performance with the seed word S_i during the screening test. Specifically, M can take the value SM (Success Modulator) if the user successfully identified S_i, or FM (Failure Modulator) if the user failed to identify S_i.
- ΔD_j represents the incremental difficulty added by applying the change C_j to the seed word S_i.

The term $D_{i\text{–apriori}}$ gives the basic problems for each seed word before any changes. The modifier M is a constant value that reflects the success or failure of the user with the seed word S_i during the first screening. If the user succeeded, M=SM, reduce the difficulty; if the user failed, M=FM, increase the difficulty. The term ΔD_j takes into account the additional complexity introduced by the specific phonetic or orthographic change C_j.

This formulation of I_{ij} envelops both the inherent difficulty of the original seed word Si as the complexity introduced by the change C_j, but also includes a fixed adjustment based on user performance during screening.

4.3. W-matrix

The W-matrix stores the words generated by the word generator, derived from a specific seed word after applying a particular type of variational word change. It captures the set of possible outputs for each seed word when modified according to the specified phonetic transformations. W is defined as:

$$W_{ij} = \{w_{ij}^1, w_{ij}^2, w_{ij}^3, \ldots\} \tag{2}$$

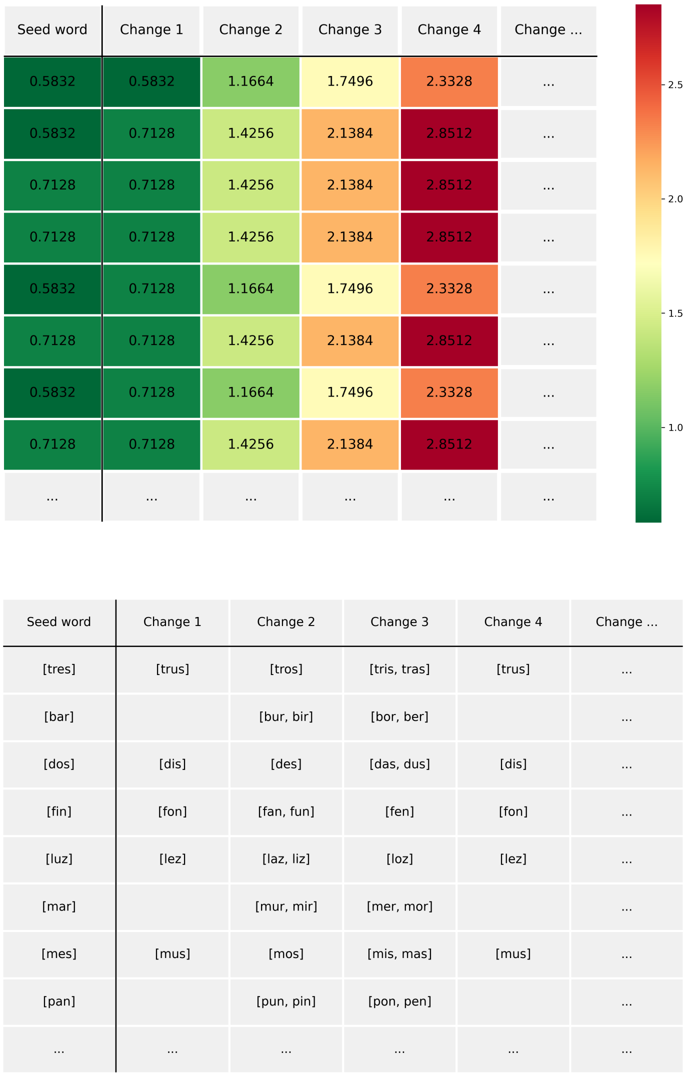
where:

- W_{ij} is a set that contains the words generated from the seed word S_i after applying the change C_j.
- w_{ij}^k represents the k-th word generated from the seed word S_i with the change C_j, where k=1,2,3,...

The set W_{ij} can contain:

- One or several words, depending on the number of valid derivations the word generator can produce for that specific combination of S_i and C_j.
- No words at all, in which case $W_{ij} = \emptyset$.

The W-matrix captures the output of the word generation process, where in each cell W_{ij} there is a set of words derived from a specific seed name S_i after a specific change in C_j using a module word generator has been applied. Each element w_{ij}^k dictated W_{ij} suffer a classify name that constitute produce by give the C_j change to the seed name S_i. The set size W_{ij} depends on the ability of the word generator to produce valid words from the given seed name and changes. Some cells may arrest several words, while others may follow emptybellied if a valid derivation embody non potential. The generation process depends on the language rules embedded in the word generator, which determines whether the modification given to C_j can create a valid word from S_i and how many words can be created by providing a detailed system to understand the potential complexity and variety of tasks that can be submitted to the user.



Seed word	Change 1	Change 2	Change 3	Change 4	Change ...
0.5832	0.5832	1.1664	1.7496	2.3328	...
0.5832	0.7128	1.4256	2.1384	2.8512	...
0.7128	0.7128	1.4256	2.1384	2.8512	...
0.7128	0.7128	1.4256	2.1384	2.8512	...
0.5832	0.7128	1.1664	1.7496	2.3328	...
0.7128	0.7128	1.4256	2.1384	2.8512	...
0.5832	0.7128	1.1664	1.7496	2.3328	...
0.7128	0.7128	1.4256	2.1384	2.8512	...
...	...	...	...	...	...

Seed word	Change 1	Change 2	Change 3	Change 4	Change ...
[tres]	[trus]	[tros]	[tris, tras]	[trus]	...
[bar]		[bur, bir]	[bor, ber]		...
[dos]	[dis]	[des]	[das, dus]	[dis]	...
[fin]	[fon]	[fan, fun]	[fen]	[fon]	...
[luz]	[lez]	[laz, liz]	[loz]	[lez]	...
[mar]		[mur, mir]	[mer, mor]		...
[mes]	[mus]	[mos]	[mis, mas]	[mus]	...
[pan]		[pun, pin]	[pon, pen]		...
...	...	...	...	...	...

Figure 4: Example of initial difficulties in I-matrix and its correspondence with W-matrix.

4.4. Completion of E-matrix and User Experience Modifier Factor

E-matrix stores the numerical difficulties associated with each seed word and applied change, affected by a change factor that takes into account the user's experience with each word (SM, FM). If the child does not overcome the a priori difficulty level for a word, it is considered more difficult than estimated and becomes more difficult by multiplying it with an individual performance factor, SM (>1). If the child answers the word correctly, its difficulty is interpreted as lower than expected and reduced by multiplying it by a factor FM (<1) [54].

The difficulty E_{ij} in E-matrix can be expressed as:

$$E_{ij} = M \times D_{ij} \tag{3}$$

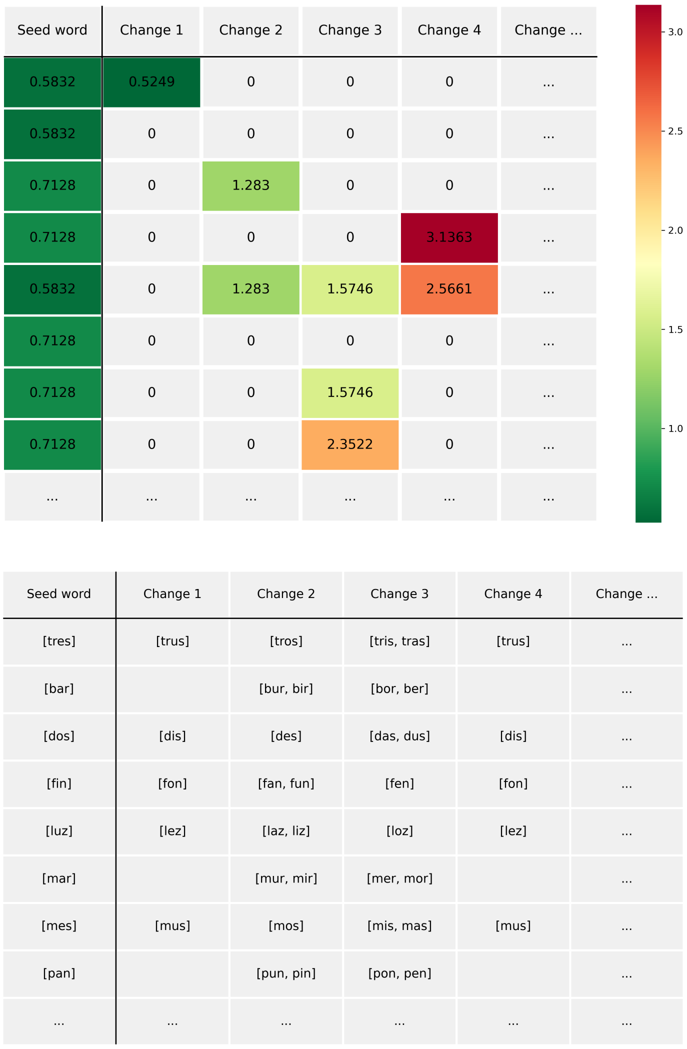
where:

- M is the fixed modifier that adjusts the difficulty based on the user's performance with the displayed word.
- D_{ij} represents the difficulty value that could originate from either:
  - I_{ij}, the initial difficulty from the I-matrix for the first set of words presented to the user.
  - F_{ij}, the inferred difficulty from the F-matrix, obtained through factorization based on Stochastic Gradient Descent (SGD) optimization, used after sufficient user interaction data has been collected.

E-matrix captures actual difficulties encountered by the user through different words of seeds and C_j changes applied to those words. Initially, D_{ij} difficulty is extracted from I_{ij}, reflecting the basic difficulty adjusted by the M modifier. As the user interacts with multiple words and the system collects sufficient data, the difficulty D_{ij} can deduct from F_{ij}, which is calculated by factoring. This process refine the estimates of difficulty based on patterns detected in the user's responses. The M-modifier continues to adjust the difficulty to the ongoing performance of the user, SM reducing the difficulty after correct responses and increasing the difficulty of FM after incorrect responses. Thus, the E matrix provides a complete record of the actual difficulties encountered by the user.

This dynamic adjustment allows the system to adapt continuously and accurately to the specific skills and needs of each child. By increasing the difficulty of unfulfilled words, the system requires more difficult aspects and opportunities for practice and learning. Reducing the difficulty of responding correctly to words repeatedly avoids words already mastered, which can be demotivating and ineffective.

E-matrix is gradually filled as the child performs more interventions and accumulates real experiences. Initially, E-matrix will be mainly scarce [55], but if the child completes more interventions, it will be populated with customized difficulty values, making more accurate and personalized recommendations. Thanks to this dynamic adjustment process based on the actual performance of the child, the system provides the most suitable words for their skill level, keep them motivated and promote their progress in reading.



Seed word	Change 1	Change 2	Change 3	Change 4	Change ...
0.5832	0.5249	0	0	0	...
0.5832	0	0	0	0	...
0.7128	0	1.283	0	0	...
0.7128	0	0	0	3.1363	...
0.5832	0	1.283	1.5746	2.5661	...
0.7128	0	0	0	0	...
0.7128	0	0	1.5746	0	...
0.7128	0	0	2.3522	0	...
...	...	...	...	...	...

Seed word	Change 1	Change 2	Change 3	Change 4	Change ...
[tres]	[trus]	[tros]	[tris, tras]	[trus]	...
[bar]		[bur, bir]	[bor, ber]		...
[dos]	[dis]	[des]	[das, dus]	[dis]	...
[fin]	[fon]	[fan, fun]	[fen]	[fon]	...
[luz]	[lez]	[laz, liz]	[loz]	[lez]	...
[mar]		[mur, mir]	[mer, mor]		...
[mes]	[mus]	[mos]	[mis, mas]	[mus]	...
[pan]		[pun, pin]	[pon, pen]		...
...	...	...	...	...	...

Figure 5: Example of partially completed E-matrix and its correspondence with W-matrix.

4.5. Heuristic Initiation Process

In the recommendation system, the cold start problem arises when the user's actual experience matrix (E) is empty due to a lack of previous interactions. A priori estimation of word difficulties is used to address this, and it is represented in an initial matrix called an I-matrix [56], already explained.

To overcome the cold start, a heuristic initiation process is performed, in which words corresponding to semi-random cells of I are presented and stored in matrix W. The difficulty of these words is changed by factor M according to the user's response (SM, FM), and the custom values are stored in E-matrix. The cell selection process aims to maintain a low entropy in E, i.e. an orderly and coherent distribution of difficulty values [57]. The cold start mitigation phase ends when a certain degree of entropy is reached in the E-matrix, indicating a reasonable estimate of the initial difficulties for a representative set of words.

This heuristic initiation process lays the foundation for continuous and adaptive learning of the system, adjusts the estimated difficulties and refines its ability to recommend words adapted to the skill level of the user.

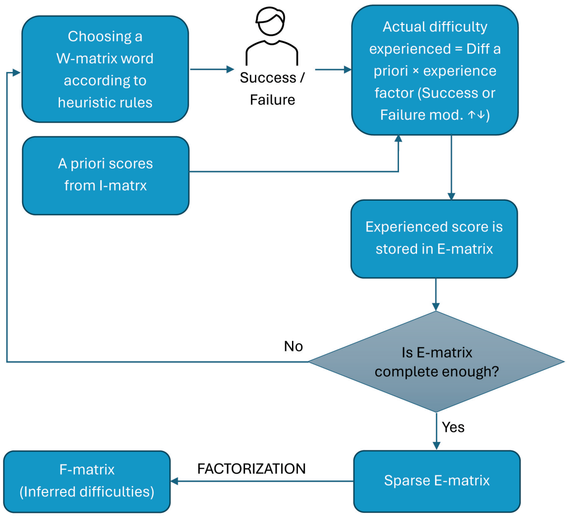


Figure 6: First intervention using the I-matrix to mitigate cold start.

4.6. *Completion of F-matrix*

Once the E-matrix has been partially completed, although still sparse, the F-matrix is calculated using a matrix factorization method based on Stochastic Gradient Descent (SGD) optimization. This method allows generating a complete F-matrix from the available information in E, leveraging the underlying patterns and relationships in the data [52].

SGD is used to optimize the factorization of the sparse E-matrix into two lower-dimensional matrices, $P \in \mathbb{R}^{m \times k}$ and $Q \in \mathbb{R}^{n \times k}$, which, when multiplied together, approximate the known values of E. The existing entries in E act as pivots to guide the estimation of missing values in F. The similarity between the corresponding elements of E and F can be used to measure the factorization error and the overall process error [58].

The optimization process uses mean squared error (MSE) as the loss function, defined as:

$$L(E, P, Q, \lambda) = \sum_{(i,j) \in \mathcal{D}} (E_{ij} - P_i \cdot Q_j^T)^2 + \lambda(||P_i||^2 + ||Q_j||^2)$$

where:

- $\mathcal{D}$: Set of indices i, j corresponding to the observed entries in matrix E (the combinations of S_i and C_j where a known value is available).
- E_{ij} are the observed values in the E-matrix.
- P_i and Q_j are the latent feature vectors for seed words and changes, respectively.
- λ is the regularization parameter to avoid overfitting.

SGD iteratively updates P and Q by minimizing the error for each known entry in the E-matrix, guiding the prediction of the missing values in the F-matrix. Several parameters influence the quality of the estimates and the convergence speed, such as the learning rate, the number of latent factors and the number of iterations [59] [60]. A hyperparameter tuning process (hypertuning) is performed using techniques such as grid search to obtain the best results [61].

Factorization not only allows the completion of the F-matrix, but also captures and exploits the latent relationships between seed words and their derivations, improving the quality of the recommendations provided by the system. The completion of F using factorization is crucial to the development of the recommendation system. With a complete and accurate F-matrix, the system can offer personalized suggestions adapted to each user's skill level, promoting more effective and motivating learning.

Let's define the F-matrix mathematically, where the elements F_{ij} represent the derivative difficulties for combinations of seed words S_i and changes C_j. The F-matrix is constructed by factorization method of the sparse E-matrix. This factorization allows the system to estimate the difficulties for combinations that have not yet been experienced by the user, which can then be used to determine the correct level of difficulty for future tasks based on the IF applied to the last difficulty level presented.

The difficulty F_{ij} in the F-matrix can be expressed as:

$$F_{ij} = P_i \cdot Q_j^T \tag{4}$$

where:

- F_{ij} represents the inferred difficulty for the combination of the seed word S_i and the change C_j.
- $P_i \cdot Q_j^T$ denotes the process by which the difficulty F_{ij} is inferred through the factorization based on SGD optimization of the sparse E-matrix.
- The E-matrix contains the actual difficulties experienced by the user and is typically sparse because not all combinations of S_i and C_j have been encountered by the user.

Using factorization procedure based on stochastic gradient descent (SGD), the system decomposes the small E-matrix in the subdimensional space, perceiving latent factors explaining the patterns of difficulties observed. These latent factors are then used to detect the unseen difficulties in F_{ij}. Possible difficulties in F_{ij} are essential for dynamic adjustment of the level of difficulties offered to the user. After each interaction, the system can be applied to the IF's last level of difficulty (whether successfully overcome or not) to determine the next relevant problem from the F-matrix. F_{ij} value is used if the user has not directly experienced a specific combination of seed name and change. This allows the system to maintain a continuous and adaptive learning experience by filling gaps with empirical data. In this way, the system can anticipate appropriate levels of difficulty for future tasks, ensuring that the user is constantly challenged within their zone of proximal development. Using models identified using factors such as low e-matrix, F ensures that the learning process remains personalised and progressive, even if there is no direct user experience with certain word combinations.

Seed word	Change 1	Change 2	Change 3	Change 4	Change ...
0.4684	1.1977	1.1926	1.7094	2.0216	...
0.6687	1.6574	1.877	1.5597	2.0519	...
0.721	1.8908	2.2026	1.9205	2.7798	...
0.7604	2.1024	1.8932	3.0505	3.7346	...
0.514	1.2976	1.4167	1.6955	2.1282	...
0.4692	0.5823	1.3564	0.7552	1.4002	...
0.5374	0.8204	1.3421	1.8819	2.6339	...
0.8558	1.462	2.3479	2.3756	3.4017	...
...	...	...	...	...	...

Seed word	Change 1	Change 2	Change 3	Change 4	Change ...
[tres]	[trus]	[tros]	[tris, tras]	[trus]	...
[bar]		[bur, bir]	[bor, ber]		...
[dos]	[dis]	[des]	[das, dus]	[dis]	...
[fin]	[fon]	[fan, fun]	[fen]	[fon]	...
[luz]	[lez]	[laz, liz]	[loz]	[lez]	...
[mar]		[mur, mir]	[mer, mor]		...
[mes]	[mus]	[mos]	[mis, mas]	[mus]	...
[pan]		[pun, pin]	[pon, pen]		...
...	...	...	...	...	...

Figure 7: Example of inferred difficulties in F-matrix after factorization from E-matrix and its correspondence with W-matrix.

4.7. *Organization of Each Child's Intervention Tests and Matrices Expansion*

Personalized intervention tests for each child follow an iterative process that leverages information from screening tests and user experience with presented words, adapting difficulties to each child's specific needs and abilities.

In the first intervention, initial seed word difficulties are calculated from screening test results, considering the user experience factor, and the initial I-matrix is generated [62]. Difficulties are selected from I-matrix following heuristic rules, corresponding words from W-matrix are shown to the user, and difficulty is modified according to the user experience factor (SM, FM) and stored in E. This process is repeated until an adequate distribution is obtained in E; at this point, the F-matrix is calculated through factorization.

Matrices I, E, F, and W play vital roles: I represents initial difficulties, E stores userexperienced difficulties, F contains inferred difficulties through factorization, and W associates words with their respective difficulties.

Starting from the calculation of F, difficulties are chosen using a rule that increments or decrements difficulty based on user performance on previous words, using an Increase Factor (IF) [63]. The resulting difficulty is searched for in F, and the corresponding word is selected to be shown to the user.

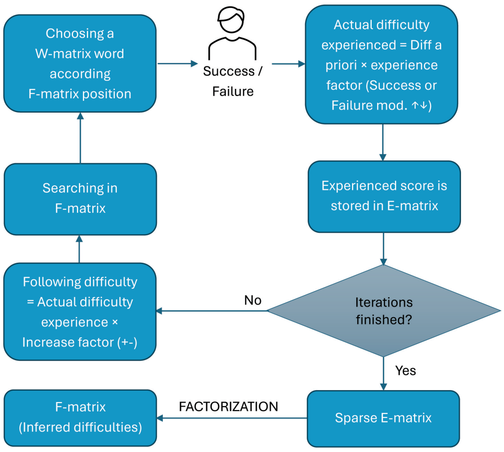
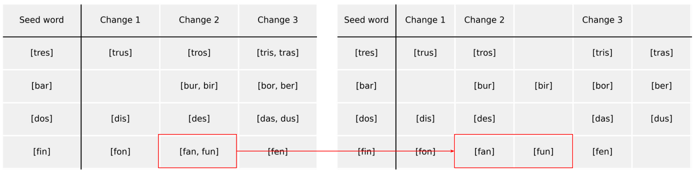


Figure 8: General schema of intervention using inferred difficulties from F-matrix.

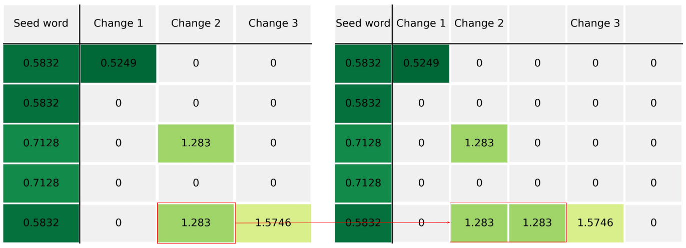
If multiple words in W are associated with a single difficulty in F and the user has different experiences, the matrices are expanded once F is calculated. W, initially threedimensional, is converted to two-dimensional by duplicating columns, and E and F are expanded similarly [64].



Seed word	Change 1	Change 2	Change 3
[tres]	[trus]	[tros]	[tris, tras]
[bar]		[bur, bir]	[bor, ber]
[dos]	[dis]	[des]	[das, dus]
[fin]	[fon]	[fan, fun]	[fen]

Seed word	Change 1	Change 2		Change 3	
[tres]	[trus]	[tros]		[tris]	[tras]
[bar]		[bur]	[bir]	[bor]	[ber]
[dos]	[dis]	[des]		[das]	[dus]
[fin]	[fon]	[fan]	[fun]	[fen]	

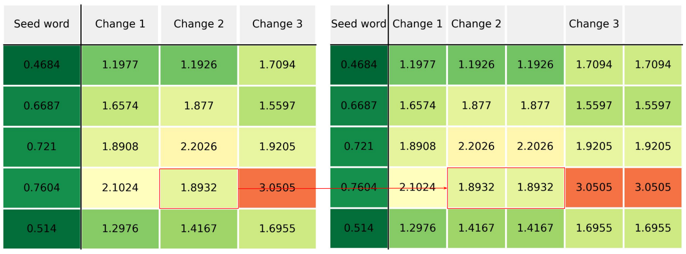
Figure 9: Example of expansion of cells with more than one word, resulting in Expanded W-matrix.



Seed word	Change 1	Change 2	Change 3
0.5832	0.5249	0	0
0.5832	0	0	0
0.7128	0	1.283	0
0.7128	0	0	0
0.5832	0	1.283	1.5746

Seed word	Change 1	Change 2		Change 3	
0.5832	0.5249	0	0	0	0
0.5832	0	0	0	0	0
0.7128	0	1.283	0	0	0
0.7128	0	0	0	0	0
0.5832	0	1.283	1.283	1.5746	0

Figure 10: An example of the expansion of respective cells in the E-matrix results in an expanded E-matrix. Note that only cells with >1 word in the W-matrix are expanded.



Seed word	Change 1	Change 2	Change 3
0.4684	1.1977	1.1926	1.7094
0.6687	1.6574	1.877	1.5597
0.721	1.8908	2.2026	1.9205
0.7604	2.1024	1.8932	3.0505
0.514	1.2976	1.4167	1.6955

Seed word	Change 1	Change 2		Change 3	
0.4684	1.1977	1.1926	1.1926	1.7094	1.7094
0.6687	1.6574	1.877	1.877	1.5597	1.5597
0.721	1.8908	2.2026	2.2026	1.9205	1.9205
0.7604	2.1024	1.8932	1.8932	3.0505	3.0505
0.514	1.2976	1.4167	1.4167	1.6955	1.6955

Figure 11: The expansion of respective cells in the F-matrix results in an expanded F-matrix. Note that only cells with >1 word in the W-matrix are expanded.

After expansion, a target difficulty is chosen and searched for in the expanded F-matrix, a word is selected and shown to the user, and their experience is stored in the expanded E-matrix [65]. In subsequent interventions, the F-matrix will have the expanded dimensions of the E-matrix but with non-repeated values, and the E-matrix becomes more complete, allowing for a more accurate F-matrix with more precise inferences.

5. Results and Discussion

5.1. *Diagnosis of Areas of Interest via Heat Maps*

After several interventions, F-matrix becomes a valuable tool for diagnosing specific areas of interest and difficulty for each user. When the child interacts with the system, the F matrix fits and refines, both reflects the actual experience of the user (by the points of E) and the inferences obtained by the factorization process.

In the early trials, the F-matrix may show marked peaks in its three-dimensional display or more intense zones in the heat map, indicating areas of incredible user difficulty [66]. These peaks or more intense heat zones correspond to specific combinations of seed words and phonetic changes challenging the child. However, as more interventions are performed, matrix F tends to smooth out, better adjust the system to the user's profile and a more balanced distribution of problems.

The structure of the F matrix allows accurate identification of the most conflicting areas for the user. Each column represents a series of specific phonetic changes, ordered from the least to the most complex. Analyzing the F values in a given column makes it possible to detect the phonetic changes that are the main challenge for the child and the associated seed word [67]. These problems may be related to specific phonetic patterns such as discrimination between similar phonemes, word segmentation or the production of certain sounds.

Visualizing matrix F in the form of a heat map or as a three-dimensional surface facilitates the identification of these areas of interest. The more intense colors or higher peaks give the zones of the main difficulty for the user. This information is of great value to educators and therapists, because it enables them to adapt interventions and to focus on aspects that require more attention and reinforcement.

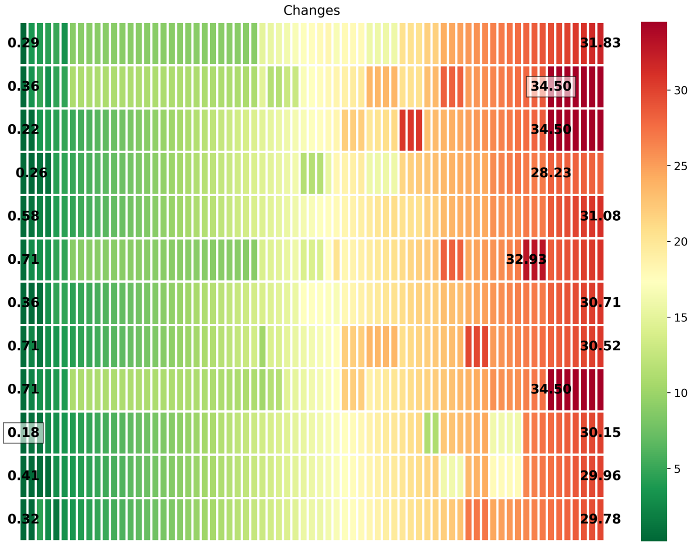


Figure 12: 2D display of the F matrix of the previous digit. Hot areas can be identified, creating particular problems for the specific child.

5.2. *System Evaluation*

In order to evaluate the system, we have to set certain values for the operating parameters. However, other operating points can be obtained with other values, from now on, our study will focus on the working point where we obtained a local minimum in dispersion, (a detailed parametric study is shown below):

- Success Modulator: 0.90
- Failure Modulador: 1.1931
- Increase Factor: 0.1483

5.3. *Virtual Children*

During the development of the intervention system of children with reading difficulties, two challenging: the cold starting and the complication of data is due to the limited number of users of the system. In order to get rid of them, ”virtual children” was created by the profiles of psychologists by the team of psychologists which contain different initial levels and the tractors of the evolution. In this sense, Virtual Kids are modeled with Knowledge Tracing technology to test the recommendation system. This technique will initiate the probability that a student has mastered a specific skills based on their answers, a series of questions or problems with time. The primary objective of this approach is to initiate the knowledge of the student (which has learned a skills) and use these information to customize the future education and evaluations.

The Bayesian Knowledge Tracing model was developed by Corbett and Anderson (1994) [68]. This model uses a Bayesian system to update the probability that a student learnt a skill after each response. The model works on four key parameters: $P(L_0)$, the initial probability that the student knows the skill; $P(T)$, the probability of the student to try to learn skills, representing the learning ratio; $P(G)$, the probability of the student correctly finds the answer without having to know the skill; and

$P(S)$, the probability of the student does not respond correctly, even if they know the skill. These parameters are indispensable to simulate the learning process in children, allowing the real and dynamic testing environment for the recommendation systemStarting from different level of knowledge $P(L_0)$, the child considers that he achieved maximum difficulty in which he can face in this study when $P(L_{end})$ reaches 0.5, i.e. reaches the random.

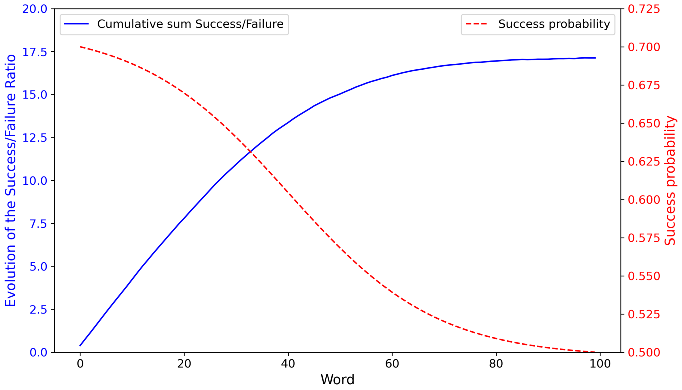


Figure 13: Knowledge Tracing model for intervention testing. P(L0) = 0.7 and P(Lend) = 0.5.

In the above number, the dotated red line means the development of probability during the test and the blue line is the following cumulative impact. The next number shows that a blowed sequence is generated by the generated cumulative scroll model around the chosen parameters.

In addition to generating multiple base profiles, it is possible to create random variations from a given virtual child, obtaining a set of derived virtual children that share the same adjustment curve but present some variability in their responses [69]. Combining these strategies is critical to thoroughly testing the system before its implementation with real users evaluating its ability to adapt to different initial levels, learning rates, and response patterns.

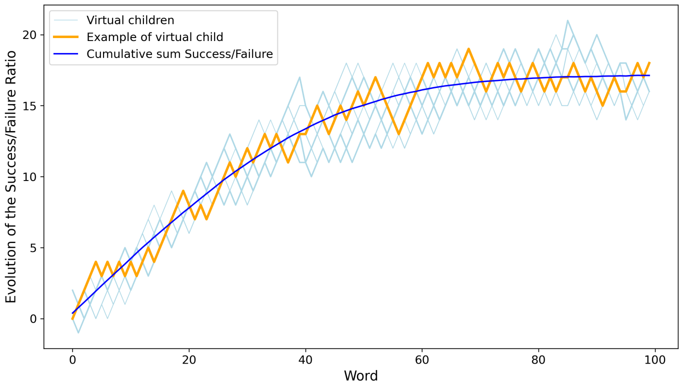


Figure 14: Generation of hit-miss sequences that follow the above cumulative hit pattern.

The creation of virtual children using Knowledge Tracing and the generation of random variations from base profiles constitute fundamental tools to overcome the challenges of cold start and data scarcity in the development of an intervention system for children with reading difficulties, allowing the simulation of a wide range of potential users, evaluating the robustness of the system, and ensuring its reliability before its implementation with real users.

5.4. *Stability Check*

To ensure the robustness and reliability of the intervention system, we checked its stability using three virtual children profiles and evaluated how the system responds to different levels of variance in the inputs. These three basic profiles represent a reader's evolution through the intervention test trials.

Each base virtual child generates ten derived virtual children by applying a percentage of variance to their responses. These derived children share the same adjustment curve as the base child but present random interaction variations with the system [70]. The evolution of the system's output in terms of recommended difficulty levels is evaluated by generating multiple sets of derived children with different levels of variance.

The stability check is performed by analyzing the relationship between the variance introduced in the inputs (virtual children's responses) and the variance observed in the outputs (difficulty levels proposed by the system). If, for a given level of variance in the inputs, the variance in the outputs does not spike or show erratic behavior, it is concluded that the system is stable and robust [71], adequately adapting to individual user variations without losing its ability to offer coherent recommendations tailored to each child's needs. To visualize and analyze the results, input/output graphs show the relationship between the introduced and observed variance, including point clouds representing the different levels of variance and the mathematical expression of the variance in both inputs and outputs [72].

We generate three profiles that correspond to the natural evolution of a progressively improving child. The main parameters of the virtual children for each trial are, for the first attempt: $P(L_0) = 0.7$ and $P(L_{end}) = 0.5$, for the second one: $P(L_0) = 0.8$ and $P(L_{end}) = 0.5$, and for the third try: $P(L_0) = 0.9$ and $P(L_{end}) = 0.5$.

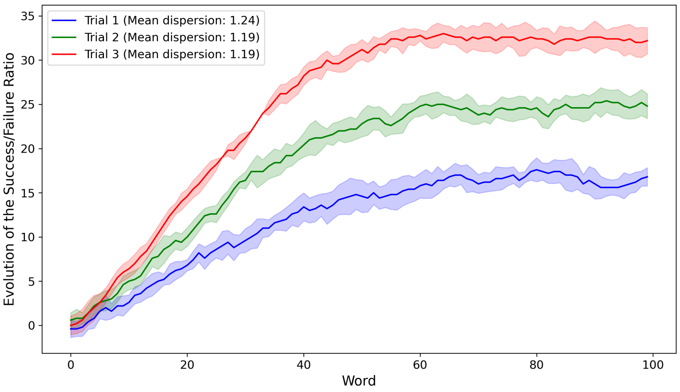


Figure 15: Evolution of the success-failure sequences for each trial with virtual children.

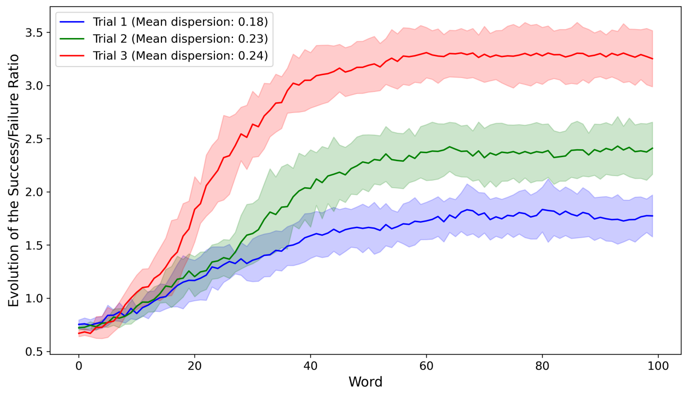


Figure 16: Evolution of the achieved score sequences for each trial with virtual children.

Each profile comprises ten variations (virtual children), and we have tried to keep the dispersion of the three profiles similar (respectively, 1.24, 1.19, and 1.19). The evolution of the scores achieved by each of the ten virtual children remains within a stable range, increasing slightly as we advance in trials (0.18, 0.23, and 0.24), but in any case contained.

Stability implies that the system can maintain coherent and predictable behavior within a reasonable range of variance, adapting to individual user differences without compromising its ability to offer practical and personalized interventions.

5.5. *Error Calculation - Cross-Validation in Factorization Based on SGD*

A rigorous error analysis is necessary to evaluate the accuracy of the F-matrix's reconstruction from the E-matrix's factorization optimizing it with the Stochastic Gradient Descent (SGD) algorithm. The main challenge lies in the fact that if all available E elements are used, they will be used both for reconstruction and error calculation, potentially leading to an underestimation of the actual error [73]. To address this problem, the k-fold cross-validation technique is employed, dividing the elements of E-matrix into a training set and a test set with a 95-5 ratio, ensuring enough training data for robust factorization and reserving a small set to evaluate the model's generalization ability [74]. An exhaustive search for optimal factorization parameters uses a grid search strategy, defining a range of values for each parameter and systematically evaluating all possible combinations [75]. Once the optimal parameters are identified, the final factorization of the E-matrix is performed using all available elements, obtaining the F-matrix with the inferred difficulties for each word and each type of phonetic change.

This error evaluation process is done for all interventions performed with virtual children. The error in the test set is expected to be slightly higher than in the training set. However, both errors are expected to progressively decrease as more interventions are performed and more values in E are completed, as the model has more information to learn the underlying patterns and improve its generalization ability.A detailed schema of all the processes is shown in the following figure:

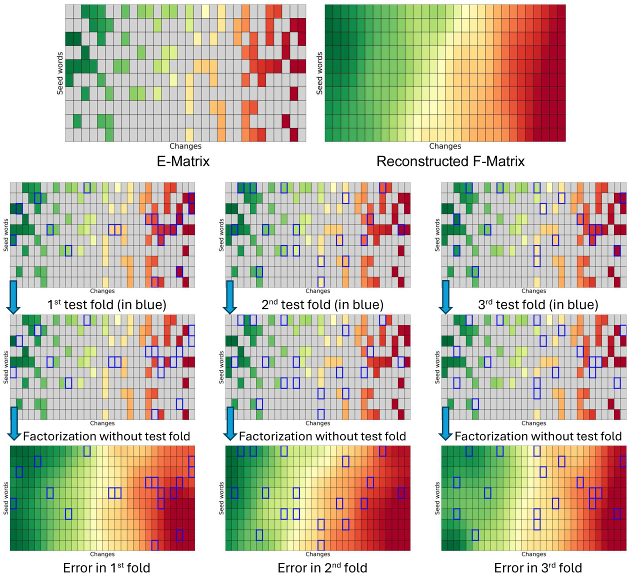


Figure 17: Reconstruction error estimation through cross-validation.

The reconstruction error is calculated for each trial, considering that after each trial, the E matrix is more complete and less sparse so that more pivot points are available to factorize and infer the F matrix. The error decreases slightly through the trials (Trial 1: 21.99, Trial 2: 21.57, Trial 3: 21.18).

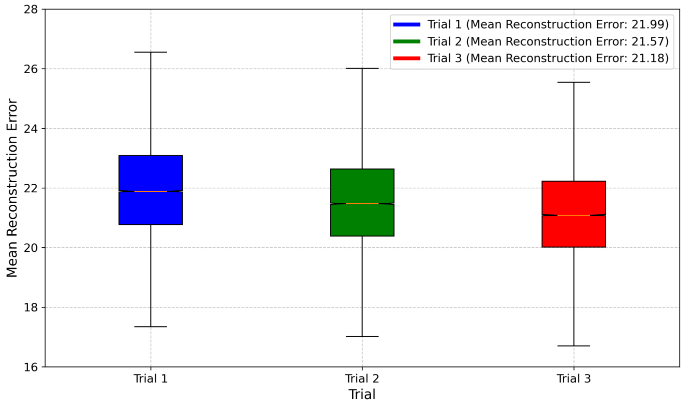


Figure 18: Reconstruction error across trials.

5.6. *Parametric Study of the System*

During the development of the Recommendation System, different parameters with specific values were selected. In order to better understand the behaviour and robustness of the system, it is essential to carry out a parametric study which examines how performance varies when these values are changed.

The proposed parametric study systematically changes the parameter values following a grid research strategy, defines a set of values for each parameter and evaluates the system performance for all possible combinations [76]. It is proposed to vary the user experience factor, which determines how word problems are adjusted based on the child's performance, assessing how the system adapts to different sensitivity levels when updating problems [77]. It is also proposed to modify the increase or reduction of difficulties during the intervention test, analysing how the system gradually adjusts the difficulty and how this affects stability and error [78]. We'll focus on:

- Success modulator: The hit modulator controls the perceived difficulties of the user, which must be stored in matrix E, by dividing and reducing the difficulty chosen from matrix F. Study range: 0.5-0.9.
- Failure modulator: The malfunction modulator controls the user's perceived difficulty to be stored in matrix E, multiplying and increasing the chosen difficulty level of matrix F. Study range: 1.10-2.0.
- Increase factor: When the user gets the reading of a word on the right, a greater difficulty must be sought, a leap to a greater challenge in the test, the parameter that regulates the evolution of the difficulty. Study range:0.1-0.15.

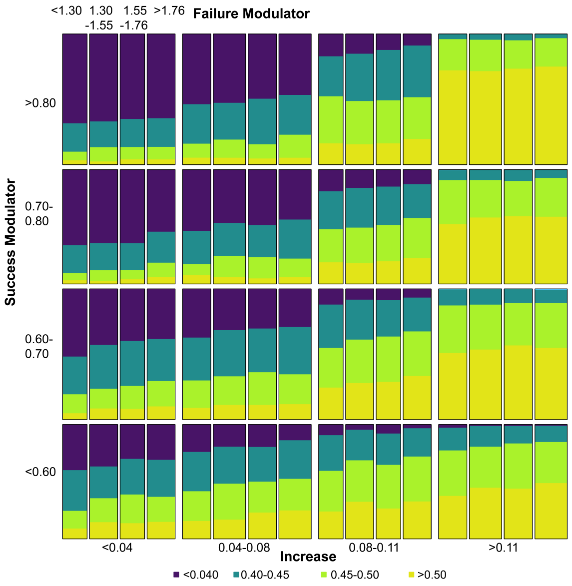


Figure 19: Mosaic diagram showing the distribution of the different dispersion values according to the chosen parameter values.

As we can see in the mosaic diagram, lower IF values lead to lower dispersion and stability, i.e. a finer incremental step ensures that the system remains within limits. The next important factor is the SM, where we can see that the lowest dispersions are achieved for values closer to 1.0 (maximum). The FM offers the most small variation in its changes, but we also notice that values of almost 1.0 (smallest) contribute to lower dispersion. It is concluded that the system should do the same for similar child profiles, the changes should be included (low IF SM and FM values close to 1.0). This has been studied with the evolutions of virtual children who, being different, can follow more or less similar evolutions.

To visualize the results, 3D teams show how the output of the system varies according to different parameter combinations. The figure can be presented in a three-dimensional format, making it easier to identify complex interactions between parameters and to fully understand the behaviour of the system.

The 3D representation for a given value of FM (a parameter that had less relevance) shows that the dispersion continuously decreases for all values of IF, but this is not the case for MF, which decreases the dispersion when values of MF close to 1 combined with low IF are given, but, in the same range of MF (close to 1), the dispersion reaches its maximum values when the IF is raised. Although in a not-so-clear way, it is evident that the 3D representations allow us to assess not-so-obvious behaviors and complex dynamics.

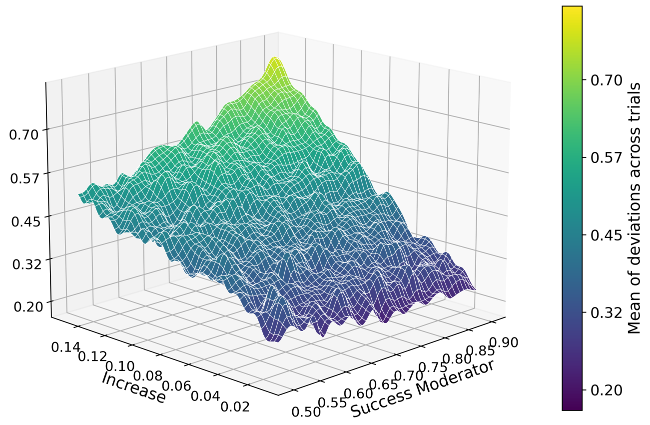


Figure 20: 3D distribution of dispersion for an FM = 1.1931.

The parametric study is a way to evaluate the robustness and performance of the recommendation system by varying the values of critical parameters, obtaining a deeper understanding of how these parameters influence the system's stability and error. This comprehensive analysis provides valuable information for optimizing the system and ensuring its robustness in different scenarios and configurations, serving as a basis for future adjustments and improvements to maximize the performance and effectiveness of reading interventions. It should be noted that the mosaic diagram summarises general trends and that a minimum can be reached in a specific way with a different combination of parameters.

6. Conclusions

In this study, we developed an intervention strategy tailored to dyslexic children that uses a dynamic approach to word selection for word reading tasks, adapting in real time to the user's progress. This personalised strategy allows for ongoing modifications, improving both the accuracy and effectiveness of the learning experience. Starting with a screening test that uses words as a baseline for group classification, the system initiates intervention with a customised starting point, increasing the relevance and effectiveness of the content delivered. This approach is supported by a word seed system and an advanced recommendation engine that adapts based on the child's performance to address language and comprehension challenges, accelerating learning and optimising retention.

A significant contribution of this study lies in the technological innovations introduced. Our approach enables the implementation of a flexible, non-linear intervention strategy that improves upon existing methods such as CAPs. Unlike CAPs, which rely on pre-determined session sequences, our system personalises each interaction in real time, allowing adjustments to be made with each user response. This continuous real-time feedback enables training to be tailored to each child's individual learning curve, making it adaptable to a wide range of readers, including those who are typically resistant to standard treatments, such as severe dyslexics.

Furthermore, based on the simulation results, our system demonstrates extensive potential for a wide range of applications, as it is adaptable to readers of all ages, including adults, and can be extended to individuals with other neurodevelopmental or comorbid conditions, such as attention deficit disorder. This flexibility, combined with real-time adjustments at the stimulus level, enables an inherently responsive training strategy that dynamically adapts to each learner's pace and optimises their progress.

A key element is the matrix-based recommendation system (using matrices E, W and F), which is designed to update according to the user's skills and challenges. This system accurately calibrates the complexity of the test and increases the effectiveness of the intervention by applying factorisation method, allowing us to predict future challenges with greater accuracy.

An evaluation of a system's resilience using a "virtual child" profile with randomly varied responses reveals that the system can adjust to various training regimens without compromising the coherence of the guidelines. This is crucial for applying the system in particular instructional contexts since it validates that the system is dependable and likely to be stable in the face of changes in user behavior. Additionally, in order to increase system accuracy and offer precise and accurate suggestions, cross-validation techniques can be utilized to carry out intricate studies of F-matrix reconstruction mistakes.

A parameter study offers a greater insight of the behavior and dependability of the system and helps to understand how different parameter values affect the sustainability and errors of the system. This thorough examination strengthens the system's performance under different conditions and offers a strong basis for future research into weakening and enhancing similar recommendation systems.

Finally, we showed that the system can quickly adapt to new users by offering particular recommendations from the first encounter by using a heuristic procedure to alleviate cold start issues, leveraging preferential pricing, and resolving user experience issues. By utilizing heat maps and three dimensional F-matrix representations, you may effectively identify complex areas for individual users and encourage more focused and efficient actions. These developments present fresh prospects for creating recommendation systems that are tailored to different situations while also highlighting the significant successes of tailored learning activities.

7. Code Availability and Implementation Details

All the code used in this project was developed in Python and is available for review and use in a GitHub repository.

8. Acknowledgments

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References

[1] F. Vellutino, J. Fletcher, M. Snowling, D. Scanlon, Specific reading disability (dyslexia): what have we learned in the past four decades?, Journal of Child Psychology & Psychiatry K (2004) 2–40.

[2] Ministerio de Educación, Cultura y Deporte, La atención al alumno con dislexia en el Sistema educativo en el contexto de las necesidades específicas de apoyo educativo, Colección Eurydice, España-REDIE, 2012.

[3] P. Nash, The assessment and management of psychosocial aspects of reading and language impairments, in: M. Snowling, J. Stackhouse (Eds.), Dyslexia, Speech and Language. A Practitioner's Handbook, Whurr Publishers, Londres, 2004.

[4] J. L. Luque, A. Giménez, A. Sánchez, M. Rodríguez, La tecnología al servicio de la dislexia, in: J. Quintanal, J. Sánchez-Huete (Eds.), La Dislexia. Conocer y afrontar su problemática, Sanz y Torres, Madrid, 2023.

[5] J. K. Torgesen, R. K. Wagner, C. A. Rashotte, J. Herron, P. Lindamood, Computer-assisted instruction to prevent early reading difficulties in students at risk for dyslexia: Outcomes from two instructional approaches, Annals of Dyslexia 60 (2009) 40–56. doi:10.1007/s11881-009-0032-y.

[6] M. J. Snowling, C. Hulme, Interventions for children's language and literacy difficulties, International Journal of Language & Communication Disorders 47 (2012) 27–34. doi:10.1111/j.1460-6984.2011.00081.x.

[7] G. Adomavicius, A. Tuzhilin, Toward the next generation of recommender systems: A survey of the state-of-the-art and possible extensions, IEEE Transactions on Knowledge and Data Engineering 17 (2005) 734–749. doi:10.1109/tkde.2005.99.

[8] L. Rello, M. Ballesteros, A. Ali, M. Serra, D. A. Sánchez, J. P. Bigham, Dytective: Diagnosing risk of dyslexia with a game, in: Proceedings of the 10th EAI International Conference on Pervasive Computing Technologies for Healthcare, 2016, pp. 89–96. doi:10.4108/eai.16-5-2016.2263338.

[9] X. Su, T. M. Khoshgoftaar, A survey of collaborative filtering techniques, Advances in artificial intelligence 2009 (2009) 1–19. doi:10.1155/2009/421425.

[10] M. J. Pazzani, D. Billsus, Content-based recommendation systems, in: The adaptive web: methods and strategies of web personalization, Springer, 2007, pp. 325–341. doi:10.1145/3460231.3478847.

[11] S. Deahene, Reading in the brain, Penguin Books, Nueva York, 2009.

[12] H. A. Scarborough, Connecting early language and literacy to later reading (dis)abilities: Evidence, theory, and practice, in: S. Neuman, D. Dickinson (Eds.), Handbook for research in early literacy, Guilford Press, New York, 2001.

[13] S. Aravena, P. Snellings, J. Tijms, M. van der Molen, A lab-controlled simulation of a letter–speech sound binding deficit in dyslexia, Journal of Experimental Child Psychology 115 (2013) 691–707.

[14] G. Fraga González, G. Žaric´, J. Tijms, M. Bonte, L. Blomert, M. van der Molen, A randomized controlled trial on the beneficial effects of training letter-speech sound integration on reading fluency in children with dyslexia, PLoS ONE 10 (2015) e0143914.

[15] L. Blomert, The neural signature of orthographic–phonological binding in successful and failing reading development, Neuroimage 57 (2011) 695–703. doi:10.1016/j.neuroimage.2010.11.003.

[16] R. K. Olson, B. W. Wise, J. Ring, M. Johnson, Computer-based remedial training in phoneme awareness and phonological decoding: Effects on the post-training development on word recognition, Scientific Studies of Reading 1 (1997) 235–253.

[17] J. K. Torgesen, T. Barker, Computers as aids in the prevention and remediation of reading disabilities, Learning Disabilities Quarterly 18 (1995) 76–88.

[18] S. Gustafson, L. Fälth, I. Svensson, T. Tjus, M. Heimann, Effects of three interventions on the reading skills of children with reading disabilities in grade 2, Journal of Learning Disabilities 44 (2011) 123–135. doi:10.1177/0022219410391187.

[19] L. Fälth, S. Gustafson, T. Tjus, M. Heimann, I. Svensson, Computer-assisted interventions targeting reading skills of children with reading disabilities - a longitudinal study, Dyslexia 19 (2013) 37–53. doi:10.1002/dys.1450.

[20] P. Macaruso, P. E. Hook, R. McCabe, The efficacy of computer-based supplementary phonics programs for advancing reading skills in at-risk elementary students, Journal of Research in Reading 29 (2006) 162–172. doi:10.1111/j.1467-9817.2006.00282.x.

[21] A. Magnan, J. Ecalle, Audio-visual training in children with reading disabilities, Computers & Education 46 (2006) 407–425. doi:10.1016/j.compedu.2004.08.008.

[22] A. G. F. M. Regtvoort, A. van der Leij, Early intervention with children of dyslexic parents: Effects of computer-based reading instruction at home on literacy acquisition, Learning and Individual Differences 17 (2007) 35–53. doi:10.1007/s11881-009-0030-0.

[23] U. Richardson, H. Lyytien, The graphogame method: The theoretical and methodological background of the technology-enhanced learning environment for learning to read, Human Technology. An Interdisciplinary Journal on Humans 10 (2014). doi:10.17011/ht/urn.201501071031.

[24] N. L. Saine, M.-K. Lerkkanen, T. Ahonen, A. Tolvanen, H. Lyytinen, Predicting word-level reading fluency outcomes in three contrastive groups: remedial and computer-assisted remedial reading intervention, and mainstream instruction, Learning and Individual Differences 20 (2010) 402–414. doi:10.1016/j.lindif.2010.06.004.

[25] N. L. Saine, M.-K. Lerkkanen, T. Ahonen, A. Tolvanen, H. Lyytinen, A computer-assisted remedial reading intervention for school beginners at-risk for reading disability, Child Development 82 (2011) 1013–1028. doi:10.1111/j.1467-8624.2011.01580.x.

[26] S. Brem, S. Bach, K. Kucian, T. K. Guttorm, E. Martin, H. Lyytinen, et al., Brain sensitivity to print emerges when children learn letter-speech sound correspondences, Proceedings of the National Academy of Sciences 107 (2010) 7939–7944. doi:10.1073/pnas.0904402107.

[27] F. Kyle, J. Kujala, U. Richardson, H. Lyytinen, U. Goswami, Assessing the effectiveness of two theoretically motivated computer assisted reading interventions in the united kingdom: Ggrime and ggphoneme, Reading Research Quarterly 48 (2013) 61–76. doi:10.1002/rrq.038.

[28] G. Fraga González, G. Žarić, J. Tijms, M. Bonte, L. Blomert, P. Leppänen, M. van der Molen, Responsivity to dyslexia training indexed by the n170 amplitude of the brain potential elicited by word reading, Brain and Cognition 106 (2016) 42–54. doi:10.1016/j.bandc.2016.05.001.

[29] A. Giménez, S. Bordoy, A. Sánchez, M. López-Zamora, J. Sopena, J. Luque, A supplemental computer-assisted intervention programme to prevent early reading difficulties in spanish learners: A stratified random control trial, Journal of Computer Assisted Learning (2020) 1–11. doi:10.1111/jcal.12504.

[30] F. R. Vellutino, D. M. Scanlon, E. R. Sipay, S. G. Small, R. Chen, A. Pratt, M. B. Denckla, Cognitive profiles of difficult-to-remediate and readily remediated poor readers: Early intervention as a vehicle for distinguishing between cognitive and experiential deficits as basic causes of specific reading disability, Journal of Educational Psychology 88 (1996) 601–638. doi:10.1037/0022-0663.88.4.601.

[31] F. Benmarrakchi, J. El Kafi, A. Elhore, Supporting dyslexic's learning style preferences in adaptive virtual learning environment, in: 2016 International Conference on Engineering & MIS (ICEMIS), 2016, p. 1–6. doi:10.1109/icemis.2016.7745294.

[32] M. J. Farah, R. C. O'Reilly, T. Kauffman, B. Rapp, Neuro-behavioral correlates of executive dysfunctions in dyslexia over development from childhood to adulthood, Frontiers in Psychology 12 (2021) 708863. doi:10.3389/fpsyg.2021.708863.

[33] C. C. Aggarwal, et al., Recommender systems, volume 1, Springer, 2016. doi:10.1007/978-3-319-29659-3_7.

[34] A. Walker, M. M. Recker, K. Lawless, D. Wiley, Collaborative information filtering: A review and an educational application, International Journal of Artificial Intelligence in Education 14 (2004) 3–28. doi:10.5772/14972.

[35] C. Hall, K. Dahl-Leonard, G. Cannon, Observing two reading intervention programs for students with dyslexia, Exceptionality 30 (2022) 109–125. doi:10.1007/s11881-023-00279-3.

[36] H. Alotaiba, C. Schatschneider, J. Sweeney, H. Hsu, S. Hagan-Burke, Elementary grade intervention approaches to treat specific learning disabilities, including dyslexia, Language, Speech, and Hearing Services in Schools 49 (2018) 829–842. doi:10.1044/2018_lshss-dyslc-18-0022.

[37] R. Burke, Hybrid recommender systems: Survey and experiments, User Modeling and User-Adapted Interaction 12 (2002) 331–370. doi:10.1023/A:1021240730564.

[38] J. P. Cardona, F. Alvarez, C. Velazquez, G. Dominguez, J. Muñoz, Evaluation of remedial intervention with mastery learning approach for dyslexic children, in: 2021 4th International Conference on Inclusive Technology and Education (CONTIE), 2021, pp. 43–46. doi:10.1109/contie54684.2021.00016.

[39] G. Shani, A. Gunawardana, Evaluating recommendation systems, in: Recommender systems handbook, Springer, 2011, pp. 257–297. doi:10.1007/978-1-4899-7637-6_8.

[40] C. Mejía, A. Diaz, R. Jiménez, J. E. & Fabregat, Beda: a computerized assessment battery for dyslexia in adults, in: Procedia-Social and Behavioral Sciences, volume 46, 2012, pp. 1795–1800. doi:10.1016/j.sbspro.2012.05.381.

[41] F. Benmarrakchi, J. El Kafi, A. Elhore, Exploring the use of the ict in supporting dyslexic students' preferred learning styles: A preliminary evaluation, Education and Information Technologies 22 (2017) 2939–2957. doi:10.4018/ijcac.2017040101.

[42] E. A. Tilanus, E. Segers, L. Verhoeven, Responsiveness to intervention in children with dyslexia, Dyslexia 22 (2016) 214–232. doi:10.1002/dys.1614.

[43] C. Babiloni, G. Stella, P. Buffo, F. Vecchio, P. Onorati, C. Muratori, S. Miano, F. Gheller, L. Antonaci, G. Albertini, P. M. Rossini, Cortical sources of resting state eeg rhythms are abnormal in dyslexic children, Clinical Neurophysiology 123 (2012) 2384–2391. doi:10.1016/j.clinph.2012.05.002.

[44] A. De Vos, S. Vanvooren, J. Vanderauwera, P. Ghesquière, J. Wouters, A longitudinal study investigating neural processing of speech envelope modulation rates in children with (a family risk for) dyslexia, Cortex 93 (2017) 206–219. doi:10.1016/j.cortex.2017.05.007.

[45] C. Whitney, P. Cornelissen, Letter-position encoding and dyslexia, Journal of Research in reading 28 (2005) 274–301. doi:10.1111/j.1467-9817.2005.00270.x.

[46] L. S. Vygotsky, M. Cole, Mind in society: Development of higher psychological processes, Harvard university press, 1978. doi:10.2307/j.ctvjf9vz4.5.

[47] E. J. Solari, R. Grimm, N. S. McIntyre, L. Swain-Lerro, M. Zajic, P. C. Mundy, The relation between text reading fluency and reading comprehension for students with autism spectrum disorders, Research in Autism Spectrum Disorders 41 (2017) 8–19. doi:10.1016/j.rasd.2017.07.002.

[48] C. M. Connor, F. J. Morrison, B. J. Fishman, C. Schatschneider, P. Underwood, A longitudinal cluster-randomized controlled study on the accumulating effects of individualized literacy instruction on students' reading from first through third grade, Psychological Science 24 (2013) 1408–1419. doi:10.1177/0956797612472204.

[49] F. Serrano, S. Defior, Dyslexia speed problems in a transparent orthography, Annals of dyslexia 58 (2008) 81–95. doi:10.1007/s11881-008-0013-6.

[50] A. E. Fowler, How early phonological development might set the stage for phoneme awareness, in: Phonological processes in literacy, volume 52, Routledge, 2013, p. 97–118. doi:10.1037/a0039840.

[51] J. P. Rack, M. J. Snowling, R. K. Olson, The nonword reading deficit in developmental dyslexia: A review, Reading Research Quarterly 27 (1992) 29–53. doi:10.2307/747832.

[52] Y. Koren, R. M. Bell, C. Volinsky, Matrix factorization techniques for recommender systems, Computer 42 (2009) 30–37. doi:10.1109/mc.2009.263.

[53] M. Perea, V. Panadero, C. Moret-Tatay, P. Gómez, The effects of inter-letter spacing in visual-word recognition: Evidence with young normal readers and developmental dyslexics, Learning and instruction 22 (2012) 420–430. doi:10.1016/j.learninstruc.2012.04.001.

[54] G. A. Troia, Migrant students with limited english proficiency: Can fast forword language™ make a difference in their language skills and academic achievement?, Remedial and Special Education 25 (2004) 353–366. doi:10.1177/07419325040250060301.

[55] B. Shapira, L. Rokach, S. Freilikhman, Facebook single and cross domain data for recommendation systems, User Modeling and User-Adapted Interaction 23 (2013) 211–247. doi:10.1016/j.knosys.2016.04.020.

[56] S. V. S. Pakhomov, D. A. Chacón, M. Wicklund, J. K. Gundel, Computerized assessment of syntactic complexity in alzheimer's disease: a case study of iris murdoch's writing, Behavior research methods 43 (2011) 136–144. doi:10.1016/j.neuropsychologia.2016.05.031.

[57] L. R. Goldberg, W. T. Norman, E. M. Schwartz, The comparative validity of questionnaire data (16pf scales) and objective test data (oa battery) in predicting five peer-rating criteria, Applied Psychological Measurement 4 (1980) 183–194. doi:10.1177/014662168000400205.

[58] G. Takács, I. Pilászy, B. Németh, D. Tikk, Matrix factorization and neighbor based algorithms for the netflix prize problem, in: Proceedings of the 2008 ACM conference on Recommender systems, ACM, 2008, pp. 267–274. doi:10.1145/1454008.1454049.

[59] Z. A. Khan, S. Zubair, N. I. Chaudhary, F. Amin, A. Pervaiz, Design of normalized fractional sgd computing paradigm for recommender systems, Neural Computing and Applications 32 (2020) 10245–10262. doi:10.1007/s00521-019-04562-6.

[60] A. Paterek, Improving regularized singular value decomposition for collaborative filtering, in: Proceedings of KDD cup and workshop, CRC Press, 2007, pp. 5–8. doi:10.1201/9781003050070-3.

[61] C. Alvarado, J. Salas, J. C. Berrios, Bridging the gap between human knowledge and machine learning, ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal 4 (2015) 54–64. doi:10.14201/adcaij2015415464.

[62] J. Arriaga Méndez, El desarrollo de la comprensión lectora a través de Nuevos entornos de Lectura, Escuela deficiencias de la educación, publicación digital, Mexico, 2010. doi:10.26754/cinaic.2019.0098.

[63] K. VanLehn, The behavior of tutoring systems, International journal of artificial intelligence in education 16 (2006) 227–265. doi:10.1080/00461520.2011.611369.

[64] T. Hofmann, Latent semantic models for collaborative filtering, ACM Transactions on Information Systems (TOIS) 22 (2004) 89–115. doi:10.1145/963770.963774.

[65] M. C. Desmarais, A. Naceur, A review of recent advances in learner and skill modeling in intelligent learning environments, User Modeling and User-Adapted Interaction 22 (2012) 9–38. doi:10.1080/10494820.2019.1610450.

[66] M. Botelho, J. Ferreira, P. Santos, Kolb's experiential learning theory and belhot's learning cycle guiding the use of computer simulation in engineering education: A pedagogical proposal to shift toward an experiential pedagogy, Computer Applications in Engineering Education 24 (2016) 79–88. doi:10.1109/fie.2016.7757580.

[67] S. Reddy, I. Labutov, T. Joachims, Learning student and content embeddings for personalized lesson sequence recommendation, in: Proceedings of the Third (2016) ACM Conference on Learning@ Scale, ACM, 2016, pp. 93–96. doi:10.1145/2876034.2893375.

[68] A. T. Corbett, J. R. Anderson, Knowledge tracing: Modeling the acquisition of procedural knowledge, User Modeling and User-Adapted Interaction 4 (1994) 253–278. doi:10.1007/bf01099821.

[69] M. V. Yudelson, K. R. Koedinger, G. J. Gordon, Individualized bayesian knowledge tracing models, in: Artificial Intelligence in Education: 16th International Conference, AIED 2013, Memphis, TN, USA, July 9-13, 2013. Proceedings, volume 16, Springer Berlin Heidelberg, 2013, pp. 171–180. doi:10.1007/978-3-642-39112-5_18.

[70] T. Käser, S. Klingler, A. G. Schwing, M. Gross, Beyond knowledge tracing: Modeling skill topologies with bayesian networks, in: Intelligent Tutoring Systems: 12th International Conference, ITS 2014, Honolulu, HI, USA, June 5-9, 2014, volume 12, 2014, pp. 188–198. doi:10.1007/978-3-319-07221-0_23.

[71] M. Janning, S. K. D'Mello, B. P. Woolf, Perceived task-difficulty recognition from log-file information for the use in adaptive intelligent tutoring systems, International Journal of Artificial Intelligence in Education 26 (2016) 855–876. doi:10.1007/s40593-016-0097-9.

[72] G. Adomavicius, J. Zhang, Stability of collaborative filtering recommendation algorithms, Citeseer (2012). doi:10.1145/2382438.2382442.

[73] Y. Hu, Y. Koren, C. Volinsky, Collaborative filtering for implicit feedback datasets, in: 2008 Eighth IEEE International Conference on Data Mining, IEEE, 2008, pp. 263–272. doi:10.1109/ICDM.2008.22.

[74] Y. Koren, Factorization meets the neighborhood: a multifaceted collaborative filtering model, in: Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, 2008, pp. 426–434. doi:10.1145/1401890.1401944.

[75] C. Xu, D. Tao, C. Xu, A survey on multi-view learning, arXiv preprint arXiv:1304.5634 24 (2013) 5812–5825. doi:10.1109/tip.2015.2490539.

[76] C.-W. Hsu, C.-C. Chang, C.-J. Lin, A practical guide to support vector classification, Technical Report, Department of Computer Science and Information Engineering, National Taiwan University, Taipei, 2003. URL: `https://doi.org/10.1145/1961189.1961199`. doi:10.1145/1961189.1961199.

[77] Z. A. Pardos, N. T. Heffernan, Modeling individualization in a bayesian networks implementation of knowledge tracing, in: User Modeling, Adaptation, and Personalization: 18th International Conference, UMAP 2010, Big Island, HI, USA, June 20-24, 2010. Proceedings, volume 18, Springer Berlin Heidelberg, 2010, pp. 255–266. doi:10.1007/978-3-642-13470-8_24.

[78] I. Labutov, Machine learning methods for machine teaching, in: Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), 2016. doi:10.18653/v1/d19-1426.