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An Adaptive, Comprehensive Application to Support Home-Based Visual Training for Children With Low Vision

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ABSTRACT Low vision is a visual impairment that cannot be improved by standard vision aids such as glasses. Therefore, to improve their visual skills, people affected by low vision usually follow a visual training program *planned* and *supervised* by an expert in this field. Visual training is especially suitable for children because of their plasticity for learning. However, due to a lack of specialists, training sessions are usually less frequent than optimal. Thus, home-based visual training has emerged as a solution to this problem because it can be undertaken by experts and families together. We implemented the Visual Stimulation on the Internet (EVIN) application, which provides comprehensive visual training tasks through games. It also provides reports on children's performance in these visual training tasks. Although EVIN has shown its usefulness in previous works, two main solutions are needed: (i) a support setup to help experts and families work together to address, among other things, the large variety of exercises and different configurations that can be prescribed and (ii) a rigorous experimental design to compare children trained with EVIN and those trained with traditional materials. To face these challenges, we present an adaptive version of EVIN that provides a new design tool that allows experts to plan visual training tasks through templates in advance. In addition, we developed new metrics and reports to achieve a more accurate assessment of a child's improvement. Among other results, it allowed us to develop an reliable experiment to evaluate significant improvements in children trained with EVIN.

INDEX TERMS Educational technology, computer applications, adaptive systems, low vision.

I. INTRODUCTION

Visual development is a process that begins even before birth. In fact, it is a continuum in which visual skills do not evolve by themselves, but they are built through experience and practice [1]. Usually, this experience and practice naturally occur. However, vision does not mature naturally in a significant number of children, which is the case for children with low vision[1].

Low vision is a condition caused by an eye or brain disease in which the visual acuity is below a certain threshold in the best eye and cannot be corrected or improved with normal lenses [2]. To characterize binocular visual impairment, visual acuity should be measured with both eyes open and while wearing any corrective lenses. More concretely, the International Classification of Diseases 11 (2018)[2] classifies low vision as binocular visual acuity equal to or worse than 6/18 (0.3) but greater than 3/60 (0.05). In addition to aging or congenital causes, low vision can be provoked by injuries (both to the eyes and to the brain) or eye diseases (glaucoma, retinopathy or macular degeneration). As a way to mitigate and improve this condition, visual training emerged.

To a certain extent, vision is a function that can be learned, and its quality can be improved with training [3]. Therefore, children with low vision can develop visual functions through a systematic program. If these children do not participate in a visual training program, they will reinforce worse conditions than they normally would due to their visual or perceptual impairment. The evidence that extending visual experiences

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[1]Although, of course, the cause cannot be only low vision; many (normal vision) children have perceptive difficulties for different reasons.

[2]World Health Organization: https://www.who.int/news-room/fact-sheets/detail/blindness-and-visual-impairment

increases neuronal growth in the visual cortex [4] strongly suggests that the best approach is to provide opportunities for visual development when possible, supplying experiences that require visual behaviors that gradually become more complex [1]. The objective of visual training is to optimize vision through eye exercises to retrain them to function as a unit and to coordinate the processing of visual information in the brain. These exercises favor visual learning or visual perceptual development [3].

Some studies have questioned the effectiveness of visual stimulation programs. López-Justicia and Martos [5] tested the efficacy of two of the most common programs [3], [6], concluding that they are not effective in children with moderate visual impairment. However, the low visual capacity in children with severe congenital visual impairment means that they do not autonomously reach maximal visual development, as they cannot access many of the visual stimuli of their surrounding environment. Thus, they require visual stimulation programs focused on implementing visual tasks to develop their vision.

Among the main visual tasks in a visual training program, the most common are visual attention, fixation, gaze changes, exploration of objects in order, spacial perception and visual memory.

This training is supervised by an expert in low vision. The expert works with each child individually, assesses his or her progress and plans the visual exercises for each session.

Specifically, a visual training program is composed of the following phases:

- Initial evaluation: in this phase, an expert in low vision evaluates the visual skills of each child and defines a work plan for the visual training sessions.
- Intervention: in this phase, the child performs the visual exercises included in the work plan. This phase involves one or several training sessions. These sessions are expected to be supervised by the expert.
- Progress assessment: once the intervention phase is complete, the expert again evaluates the visual skills of the child.

During the intervention phase, the expert should go to the child's school or home to perform the planned visual training sessions. Nevertheless, because of the very low number of experts per child, these sessions usually become much less frequent than optimal. To overcome this limitation, training must be accomplished at home and/or at school with the help of family members and/or teachers[3] Hence, we call this whole process *home-based visual training* [7], [8]. To this end, the expert must assess each child's needs and plan the required visual training sessions.

The organization of home-based visual training exercises should be supported by applications that allow the expert to be unencumbered by details and focus mainly on assessing the child's visual skills and planning the intervention phase. In addition, both visual exercises and plans should be intuitive for families and teachers so that they can help their child correctly. Finally, these applications should provide feedback mechanisms to keep the expert informed about the child's performance during the visual training sessions.

It is difficult to find a currently available application for visual training that provides typical visual exercises for young children and, at the same time, helps in the whole visual training process. This is why we implemented the Visual Stimulation on the Internet (EVIN) application, which provides games for exercising primary visual tasks [9]. In EVIN, each game can be configured by the expert for different visual tasks with different levels of difficulty. However, this high variety of configurations makes EVIN difficult to use by inexperienced people. To ease the collaboration with families and/or teachers, we describe an adaptive version of EVIN with a new design tool that allows the expert to plan visual tasks in advance through a template; it allows the expert to organize an adaptive sequence of visual exercises. In addition, we developed new metrics and reports for a more accurate assessment of improvement. Among other results, it allowed us to present an accurate experiment on the significant improvement of children trained with EVIN.

The rest of the paper is organized as follows. First, we describe in depth the role of each participant in the home-based visual training program. Next, we describe visual training applications that are currently available. We also describe EVIN [9], an application for visual training over the Internet. In section III, we describe how we have improved EVIN to be adaptive to better support home-based visual training. In section IV, we describe the metrics defined and the experiments performed. Finally, in section V, we describe our conclusions and proposal for future work.

II. FAMILIES' INVOLVEMENT IN HOME-BASED VISUAL TRAINING

A. RELATED WORK

Families and experts play different roles in traditional home-based visual training. Figure 1 shows the traditional framework of the common visual training process, and the different roles assumed by each of the participants involved are marked. Therefore, the expert's main role is to evaluate a child's visual skills and plan visual training sessions. The family's role is to supervise the child to help him or her perform these exercises. Once the sessions have ended, families report back to the expert.

Traditionally, materials used for visual training fit this framework. They have mainly been physical worksheets and computer programs. For example, computer-generated visual stimuli for visual training [10], such as stimuli created with the MATLAB toolbox called Psychtoolbox [11], are available. Other examples of well-known video games used in visual training are Ratchet & Clank and Lumies [12].

Specialists in low vision also create their own materials using popular software tools such as word processors

[3]Because family members at home and teachers at school play a similar role of *people who are very close to the child*, for simplicity, we use the term *family* to include both family members and teachers.

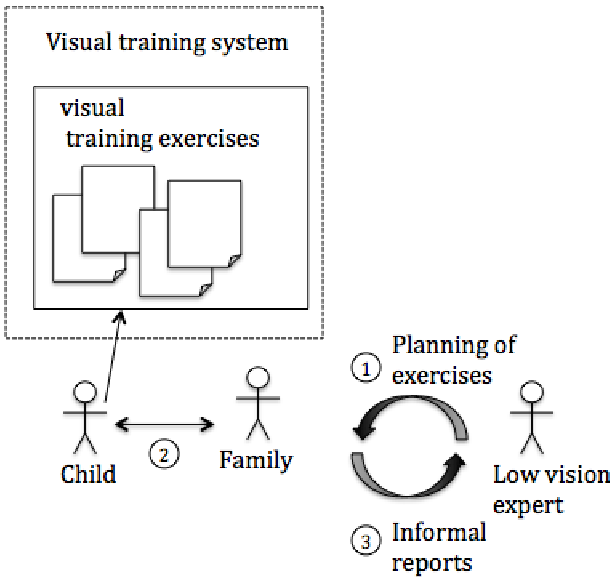


FIGURE 1. Traditional framework of a home-based visual training process. ① The expert plans each session by organizing the exercises that should be carried out at home. ② The family helps the child during the visual training sessions. ③ The family reports back to the supervising expert.

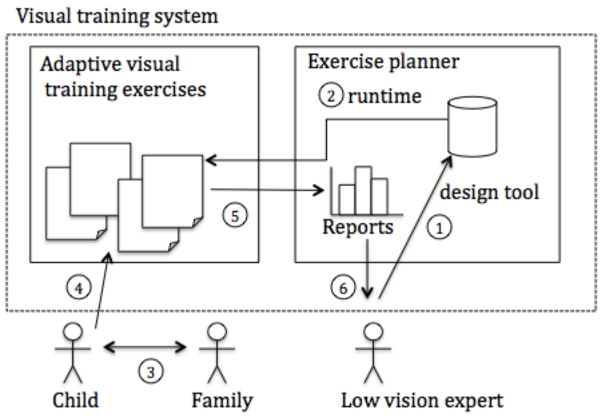


FIGURE 2. New framework of an adaptive, home-based visual training system with familial support. ① First, the expert in low vision plans the exercises for the visual training sessions. ② Next, the exercise planner runtime system (in the visual training system) presents the exercises to the child and adapts them to his or her needs. ③ Next, the child performs the exercises by interacting with the system with the help of his or her family ④, and ⑤ the visual training system registers the child's interactions. Once the visual training session has finished, ⑥ the system generates reports about the child's performance and allows the expert to access them.

or presentation programs [9]. Additionally, more advanced tools to support visual training are being developed. For example, companies such as Vision Coach[4] have developed blackboards on which people can perform visual exercises (such as games in which they hit bulbs as they flash on and off). These blackboards are intended not only for visually impaired people but also to promote, for example, visual training as a way to sports vision. Although these resources are extremely useful for visual training, (i) these blackboards are not particularly suitable for visually impaired children, and (ii) they must be used at an optometrist's office.

This traditional framework poses three main challenges to families. First, families should be aware of the exercises and the instructions in order to help them. In addition, they must adequately sequence the exercises in each session, taking into account how the child is performing. Moreover, the assessment compliance and the guarantee of focused attention are also the responsibility of the supervising adult. Finally, families and experts should share information about the results of the visual training sessions so that they can work together.

To face these challenges, the role of technology is essential. It is crucial to provide families with intuitive applications that automatically monitor children's performance and report back to the expert. In addition, the expert should be able to design the visual training sessions through the application. After designing the plan, the application presents an adaptive sequence of exercises, taking into account each child's needs.

Figure 2 shows a new framework for adaptive home-based visual training. First, the expert in low vision plans, with the child in mind, each visual training session through an exercise planner design tool. Thus, the plan will take into account the expert's criteria and the child's needs. Once the plan is designed, the runtime application executes the planned sequence of visual exercises. As a result, the child performs exercises at home under the supervision of their family. Upon completion, the expert obtains children's performance reports. Finally, from these reports, the expert can update the plan or create another one, but this time, they can take into account all the previous interactions.

There is an increasing number of applications that are developed to be used for home-based visual training, although they do not completely fit into this new framework. For instance, Matrix Game[5] consists of three applications intended to stimulate visual perception, spatial orientation, attention, concentration, classification and categorization skills. InfinityMind[6] developed EyeQ, a game-based visual training software with the goal of improving the reading skills of children and adults. These applications are intended for home-based visual training but are not suitable for young visually impaired children.

There are also visual training programs for the treatment of specific pathologies, for example, a video game for the treatment of amblyopia [8], although amblyopia is not considered low vision. This video game is a reward-based game in which the contrast of the visual rewards is changed adaptively. In this way, users must practice with their amblyopic eye. Data about users' performance in the game are stored in a database. This video game can improve the visual acuity of the amblyopic eye [8], but it is not particularly suitable for young children with severe visual impairments.

[4]https://www.visioncoachtrainer.com/

[5]https://www.myfirstapp.com/app-category/matrix-games/
[6]http://infinitemind.io/individual/

Recently, RightEye[7] launched EyeQ Trainer [13]. With EyeQ Trainer, an optometrist can diagnose visual problems and prescribe a personalized set of exercises from a full library of visual exercises to be completed at home. Once these exercises are completed, the optometrist can re-evaluate the visual functions. However, EyeQ Trainer is not particularly suitable for visually impaired children, and to our knowledge, it does not provide progress reports.

To address challenges with home-based visual training, it is desirable to develop a computer-based visual training application that (i) provides exercises for training basic visual tasks suitable for visually impaired children; (ii) monitors the child's interactions with the system; (iii) adapts the sequence of exercises as a function of the child's needs and performance; and (iv) provides suitable metrics for assessing the results.

Currently, none of the applications mentioned above meet these requirements. Therefore, we implemented EVIN [9]. In the next subsection, we present an overview of EVIN.

B. EVIN OVERVIEW

EVIN is an application created for children who have difficulties with either receiving or processing environmental visual stimuli. It provides games to support the stimulation of visual perceptual development. Children are trained with stimulating games with differing visual tasks. Each game can be adapted to the child's needs by setting up different features of the stimuli. These parameters introduce different levels of difficulty. Examples of such parameters include the size of the stimuli, the number and presentation time of the stimuli, the possibility of rotation, and the speed of presentation.

One of the objectives of EVIN is to enhance the playful nature of the material. Consequently, figures, drawings, photographs and different feedback mechanisms have been selected that are especially attractive for children between 3 and 7 years old, as this is the target age group for the games included in the platform.

The main difference between EVIN and the other applications is that our application has been designed specifically for children with low vision who have difficulty accessing most games due to their poor visual input. For example, in EVIN, we use dark backgrounds on which light-colored characters of different sizes are presented. The reason why this option is adopted is that it allows better contrast proportions [14] than its opposite, produces less visual fatigue, reduces the glare associated with many visual pathologies, and facilitates the discrimination of colors presented in shapes, drawings and photographs.

The five games currently offered in EVIN are exploration, facial expression, spatial perception, puzzles and prominent features. The main page that shows all the games available in EVIN is shown in Figure 3.

In addition, some quantitative reports are presented with the results of each session, and information about the children's session is stored in a database. An example of a report is shown in Figure 4 and includes the following information:

- Number of correct answers (a correct answer is when the child clicks on the correct stimulus);
- Number of incorrect answers;
- Percentage of correct answers;
- Amount of time to complete the exercises.

Nevertheless, the large variety of games and configurations in EVIN prevents its optimal use in home-based visual training. Recall from section II-A that in traditional training, the expert aims to choose the most suitable configuration for each child and session, for instance, the number and types of stimuli. However, because of the limitation of this approach, the expert usually entrusts the family with this step (see Figure 1). In this case, families are likely to make

[7] https://righteye.com/

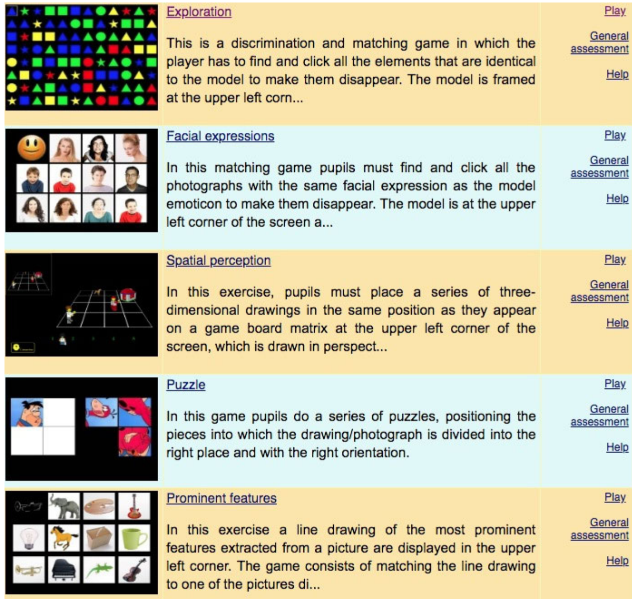
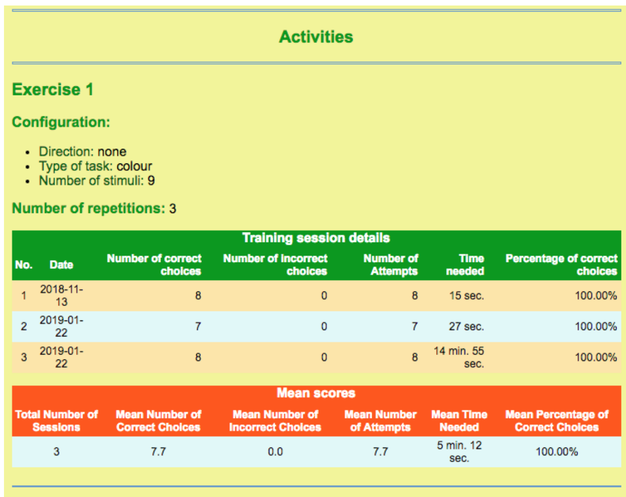


FIGURE 3. EVIN homepage: the list of the visual training games.



Activities

Exercise 1

Configuration:

- Direction: none
- Type of task: colour
- Number of stimuli: 9

Number of repetitions: 3

Training session details

No.	Date	Number of correct choices	Number of incorrect choices	Number of Attempts	Time needed	Percentage of correct choices
1	2018-11-13	8	0	8	15 sec.	100.00%
2	2019-01-22	7	0	7	27 sec.	100.00%
3	2019-01-22	8	0	8	14 min. 55 sec.	100.00%

Mean scores

Total Number of Sessions	Mean Number of Correct Choices	Mean Number of Incorrect Choices	Mean Number of Attempts	Mean Time Needed	Mean Percentage of Correct Choices
3	7.7	0.0	7.7	5 min. 12 sec.	100.00%

FIGURE 4. A screenshot with an example of a report for a particular child.

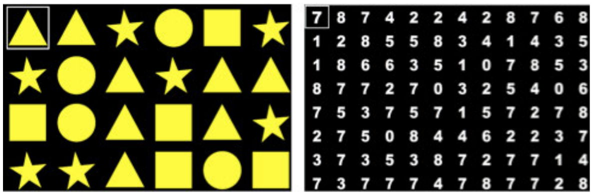


FIGURE 5. The exploration game in EVIN. Left: the game has been configured with 24 stimuli and the task of searching for a shape. Right: the game has been configured with 96 stimuli and the task of searching for a number. The test stimulus is in the upper-left corner of the screen and is framed in a square.

wrong decisions about the best configuration for their child. To address this problem, we present an adaptive version of EVIN that provides adaptive templates to support families.

As a starting point, adaptive templates in EVIN have been designed and implemented for only the *exploration game*. Among other reasons, this game was chosen because it allows the expert to train ordered scanning skills. Ferrell [1] considers the ability to perform repeated scans and fixations to observe a series of visual stimuli one of the seven basic visual skills. This ability is essential for efficiently performing many tasks, including reading. Research has shown that the search/exploration process becomes more efficient with experience because subjects require less time to locate the target [15]–[17]. It has been shown that practice improves feature search performance in subjects with severe low vision [18].

In EVIN, exploration (see Figure 5) is a game of discriminating and matching in which the child must find and click on all the elements that are identical to the test stimulus (among many nonidentical elements) to make them disappear [9]. The test stimulus is framed in the upper-left corner of the screen. Specifically, the objective of the exploration game is to perform a visual search of duplicates of the test stimulus using horizontal, vertical or horizontal+vertical saccades. Finally, to understand how we defined the metrics used in the experiment, it is important to note that in the exploration game, each element on the screen is an opportunity for each child to succeed or fail when he or she clicks on it. The higher the number of successes the child achieves, the better the skill. We detail this point in section IV.

In the next section, we describe the adaptive templates implemented in the exploration game.

III. ADAPTIVE TEMPLATES IN EVIN

A. THE NEED FOR ADAPTATION

The exploration game in EVIN must be configured according to the following variables:

- Number of stimuli: the number of elements to show on the screen from which children must choose. This parameter can take a value of 4, 6, 9, 12, 24, 48, or 96.
- Direction: the order in which the child must search for the elements (and find them). This parameter can take a value of none, horizontal or vertical.
- Type of task: the expert must choose what kinds of figures the child must search for on the screen.

For example, two different configurations of the exploration game are shown in Figure 5. Due to the large number of combinations available, there are more than one hundred ways of setting up this game. Finally, the choice of a particular configuration should also depend on the child's progress during the training session. As a result, families are not able to decide which configuration is best for each moment.

Therefore, to support home-based visual training in EVIN, experts in low vision can define templates for the game. Each template sets up the exercises and configurations that each child must perform during one or several sessions. However, the templates and their exercises should be sequenced taking into account the children's needs, among them, their behavior during previous training sessions. Additionally, this sequence must incorporate the supervising expert's criteria. For this reason, EVIN is currently designed as a knowledge-based system that adapts by means of several rules [19]. This knowledge base is composed of three elements: (i) the template model, (ii) the child's characteristics or the child's model and (iii) the adaptation rules. The last element, the adaptation rules, is directly encoded in EVIN. Particularly, they are encoded in the exercise planner runtime engine of EVIN (see Figure 2). This engine is fed with the first two elements: the template model and the child's model. In the following section, we describe these two elements of the knowledge base in detail.

B. KNOWLEDGE BASE IN EVIN

1) TEMPLATE MODEL

Each template is defined by the following attributes:

- Level of difficulty: three difficulty levels are defined (easy, medium and advanced).
- Number of exercises: the number of exercises included in the template.
- Number of repetitions: the number of times each exercise is repeated in the template.

Each exercise in a template is defined by the following attributes:

- Template: the template to which the exercise belongs.
- Number of stimuli (between 4 and 96).
- Direction (horizontal, vertical or free).
- Type of task (color, geometric shape, shape and color, or drawing or number).
- Type of reinforcement: the type of feedback that the child receives when he or she succeeds or fails. It can take the following values: visual, audio or both.
- Level of difficulty: three difficulty levels are defined: easy, medium and advanced. Although this attribute is defined by the expert in low vision, it is usually derived from the information included in the attributes (i.e., the number of stimuli, the direction and the type of task).

2) THE CHILD'S MODEL

Information on each child is also stored in the knowledge base similarly to other programs [20]. Thus, for each child, the following information is stored:

- Personal information: age, pathology, visual acuity, and visual field.
- Expert's criteria: this section contains a multitude of information, including the minimum number of sessions the child must perform in a given configuration so that the results are considered significant, and the number of sessions to be carried out in the same configuration of a game.
- Recommended initial configuration for the games: for example, the initial difficulty level and the initial number of stimuli. These parameters must be configured from the experts' experience with the child.
- Interaction data: the number of sessions, the number of attempts, the number of mistakes, the time taken to finish each game, etc.

With the information stored in these models, EVIN adapts the sequence of exercises. To reduce the complexity, we implemented this sequence in EVIN by hiding the links to those exercises that the child is not yet ready to perform [21].

C. VISUAL TRAINING WITH ADAPTIVE TEMPLATES

Currently, EVIN uses three kinds of templates in the exploration game: pretest, posttest and intervention. In particular, EVIN contains three pretest templates, three posttest templates, and thirty intervention templates. All these templates have been designed by an expert in low vision.

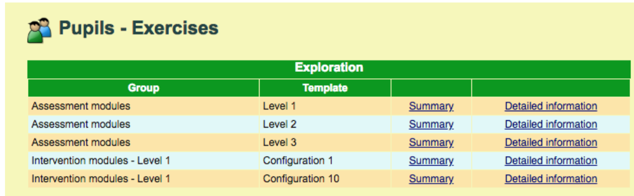
The pretest templates are intended to evaluate the visual abilities of each child in the visual exploration task before the visual training sessions. Each pretest template has a different difficulty level and has four exercises with different settings, for example, the number of stimuli varies for each exercise.

The posttest templates are intended to evaluate the visual abilities of each child in the exploration game after the visual training. In other words, these templates are for measuring the child's progress.

The intervention templates form the complete set of exercises that a child must perform during different training sessions. Currently, thirty intervention templates have been defined (i.e., ten for each difficulty level). Each template is one exercise under several configurations that are repeated 4 or 5 times.

It is important to keep in mind that these templates are customizable so that experts in low vision can modify them (see Figure 7). This adaptability is necessary because each child is different, and each case requires a different intervention. Moreover, experts can define new templates (see Figures 6 and 7).

In addition, all these templates also allow the expert to monitor and update the whole home-based visual training process comprehensively. Therefore, the expert can plan


Pupils - Exercises

Exploration			
Group	Template		
Assessment modules	Level 1	Summary	Detailed information
Assessment modules	Level 2	Summary	Detailed information
Assessment modules	Level 3	Summary	Detailed information
Intervention modules - Level 1	Configuration 1	Summary	Detailed information
Intervention modules - Level 1	Configuration 10	Summary	Detailed information

FIGURE 6. Exploration game design templates.

every phase in EVIN; the initial evaluation is performed with the pretest templates, the intervention is performed with the intervention templates and, finally, the child's progress is measured with the posttest templates.

In the next section, we show that the templates defined in this section have a prominent place in our experiment. This experiment was necessary to verify EVIN as an intervention tool for children with low vision. In addition, we detail the metrics we introduced for the accurate assessment of a child's progress.

IV. EVALUATION

In a previous work [9], we presented some early experiences with EVIN for visual training. In short, tutors considered EVIN a very useful, user-friendly and intuitive web platform for visual training [9].

In this paper, we take advantage of adaptive templates (see section III-C) as well. The pretest and posttest templates were particularly helpful. With these tools, we carried out an experiment to *evaluate the importance of an intervention with EVIN* in children with low vision. In the following sections, we describe the experimental parameters: (i) the population and sample, (ii) the metrics to accurately assess the improvement in children with low vision, (iii) the descriptive statistics used to describe the results and (iv) the methods used to evaluate the statistical significance of the results and make conclusions.

A. POPULATION AND SAMPLE

In Europe, the proportion of people with low vision is approximately 1.45% of the total population[8], and obviously, the percentage of children with low vision is even smaller. In other words, we are treating a very small number of individuals as the total population.

From this small population, we selected our sample from several schools in Spain where children with low vision are enrolled[9]. In total, twenty-three children with low vision participated in the experience. Of these twenty-three children, half were randomly selected to undergo an EVIN intervention, and the remaining children followed the standard method.

For several reasons other than those related to EVIN, only a fraction of the children finished all the tasks. Ultimately,

[8]https://uvadoc.uva.es/bitstream/10324/14293/1/TFM-M259.pdf

[9]We collaborated and signed two official ethics agreements with the Spanish Organization for the Blind (ONCE) and the Sensory Integration Center (CISEN) Foundation.

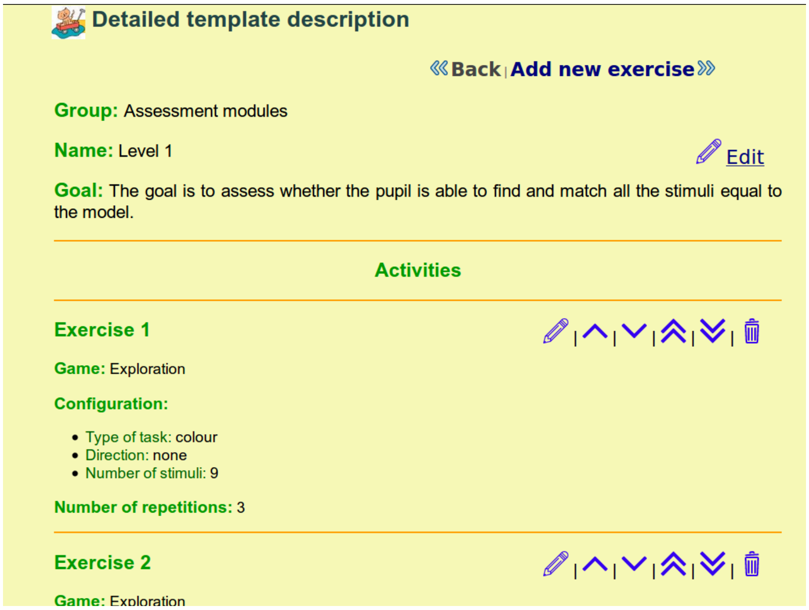


FIGURE 7. Screenshot of the authoring tool for the templates.

we obtained an *EVIN intervention group* of seven children and a *control group* of five children. The children in the control group followed a visual training program designed by the expert in low vision using traditional materials.

To check the balance of the groups, we show some baseline characteristics of each group.

- EVIN group:
  - Pathologies: aniridia, cerebral visual impairment (2 children), coloboma of the iris, retinoblastoma, and nystagmus (2 children);
  - Mean visual acuity: 0.16;
  - Mean duration of intervention: 2.9 months.
- Control group:
  - Pathologies: cerebral visual impairment, congenital cataracts, microphthalmia, nystagmus, and retinitis pigmentosa;
  - Mean visual acuity: 0.12;
  - Mean duration of intervention: 4.3 months.

In summary, 12 children completed all the pretests and posttests. In total, 7 children, the *EVIN group*, underwent an intervention with EVIN between the pretest and posttest phases. Each pretest and posttest consists of 4 exercises with 3 levels of difficulty each (see section III-B). In this paper, we consider the mean of the results of all these 4×3 exercises for each child. The results were evaluated by the metrics that will be detailed in section IV-B.

Finally, four teachers/tutors specializing in low vision helped conduct this experiment, and an additional expert in low vision oversaw the entire process.

Next, to study the effects of the EVIN intervention on children with low vision, in the next subsection, we describe how we evaluated the results.

B. METRICS

To measure the level of improvement in children with low vision, we used two main metrics based on those from earlier EVIN reports (see section II-B): the *speed* (*sp*) and the *success rate* (*sr*). *sp* measures the number of successes achieved during the time spent playing the game. Formally, we define *sp* as

$$sp = \frac{successes}{time} \tag{1}$$

sr measures the number of successes achieved out of the total number of actions the child made in the exploration game. Formally, we define *sr* as

$$sr = \frac{successes}{successes + failures} \tag{2}$$

In addition, because the main task of this experiment was the *exploration* game, we included a third to exploit the sparse data available, as we show below.

Although each metric measures different aspects of each child's interactions, we order the metrics from general to particular. For instance, although *sp* can be applied to almost any task (because we can always measure the amount of time and the number of successes), *sr* can only be applied to exercises that have both *successes* and *failures*. Therefore, *sp* is a more widely applicable metric than *sr*. Next, we focus on a more specific metric that can be applied only for the exploration game.

The exploration task can be considered a game of choosing balls without replacement from an urn with two kinds of balls: success balls and failure balls. If a child with low vision chooses the balls without any criteria, he or she would choose them with a probability that follows a hypergeometric distribution [22], [23] that assigns equal probability to success and failure balls. However, we regard this task as following a

TABLE 1. Mean of the differences between the posttest and pretest for each metric and for each group. The *EVIN* group always has a larger difference than the *control* group. This finding is clear in the right-most column, which contains $\mu_{Y.diff}(EVIN) - \mu_{Y.diff}(control)$ for each metric. The statistical significance of these differences is discussed.

	control	EVIN	$EVIN - control$
$\mu_{sp.diff}$	0.053	0.079	0.026
$\mu_{sr.diff}$	0.0033	0.073	0.07
$\mu_{p.diff}$	-0.0016	0.0032	0.0049

TABLE 2. Standard deviations for the differences between the posttest and the pretest or each metric and for each group. With such sparse data, the standard deviations (or error ranges) are so large that we cannot see significant differences at a glance.

	control	EVIN
$\sigma_{sp.diff}$	0.049	0.069
$\sigma_{sr.diff}$	0.11	0.14
$\sigma_{p.diff}$	0.0057	0.0048

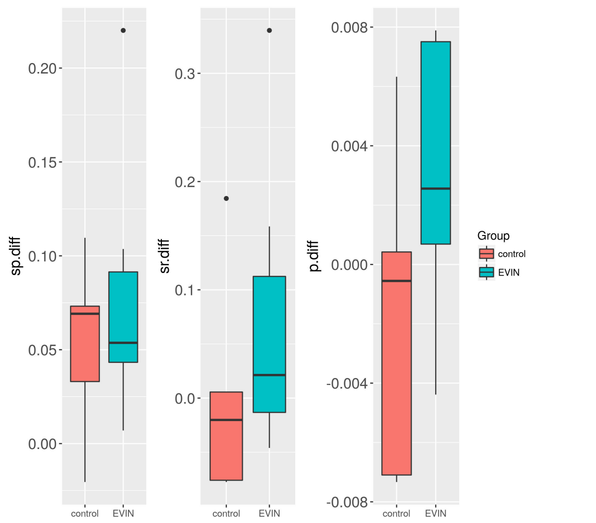


FIGURE 8. Metric boxplots. Note how the median of *sp.diff* is larger in the control group than in the EVIN group. This phenomenon does not occur in the next two more specific metrics *sr.diff* and *p.diff*. Nevertheless, the large interquartile range masks any significance, if such exists.

biased hypergeometric distribution because the children will pick up success balls at higher probability than the failure ones. Therefore, this task follows a Wallenius noncentral hypergeometric distribution [23], [24]. In this probability distribution, the higher the probability assigned to the success balls is, the more certain we are about the abilities of the child with low vision. Importantly, we can infer, from the child's successes and failures in the exploration game, the different probabilities of each kind of ball [25], [26]. Therefore, we use the probability of choosing a success ball from the urn as a metric for assessing the child's ability. We call this metric p.

Additionally, let us define $Y.pretest$, $Y.posttest$ and $Y.diff$, where Y can be sp, sr or p. The *pretest*, *posttest* suffixes are clear. The *diff* suffix stands for the difference between the posttest and the pretest: $Y.diff = Y.posttest - Y.pretest$. We mainly focus on $p.diff$, $sr.diff$ and $sp.diff$, which, we establish as the dependent variable Y of the following experiment. The independent variable X of the experiment is the group: *EVIN* or *control*.

C. DATA DESCRIPTION

This section describes the experimental data. Descriptive statistics on the three metrics introduced in the previous section are shown in Table 1 and Table 2. Recall from section IV-A that we first calculate the mean across the 4×3 exercises per child for each metric. Then, we calculate the mean for all the children in each group, that is, the sample $\mu_{Y.diff}$ shown in Table 1. A quick look at this table shows that $\mu_{Y.diff}$ for the EVIN group is always better than that for the control group. Unfortunately, if we also look at Table 2, we see that, with so few data, the standard deviations are so large for all metrics that we cannot see significant differences at a glance.

Next, we graphically display the behavior of the three metrics. Box plots of the metrics are shown in Figure 8. In this figure, the medians follow a similar pattern as the means (with the exception of $sp.diff$, as we show). Similar to the standard deviations, the interquartile ranges are so large that we cannot see significant differences at a glance. However, the more specific the metric is, the more precise the results. This pattern repeats in the paper, as we show.

Therefore, to evaluate the statistical significance of these data, we have to apply stronger statistical methods, which are described in the next section.

D. HYPOTHESIS TESTS

In the last subsection, the posttests may have shown an improvement in the EVIN group relative to the pretests. In this section, we show this conclusion more rigorously in two ways: (i) we check whether the mean of posttests is significantly higher than the mean of pretests in each group, and (ii) we check whether the magnitude of each child's improvement (also called $Y.diff$, see section IV-B or below) depends on the group in an appreciable way. To this end, we follow statistical analysis techniques [22], [27], [28]. Therefore, let us first rigorously define objectives (i) and (ii).

In section IV-B, we established the metrics as the dependent variable Y and the group of children (control or EVIN) as the independent variable X. Thus, let us specify $Y.diff(X)$ as the dependent variable that can be either $sp.diff(X)$, $sr.diff(X)$ or $p.diff(X)$. Additionally, we specify X as the group, so $X = control$, or $X = EVIN$. With all these elements, we explore whether X significantly influences each metric $Y.diff$. We define objectives (i) and (ii) as below:

(i) check whether $\mu_{Y.diff}(X)$ is significantly greater than 0, which would imply that $\mu_{Y.posttest}(X) > \mu_{Y.pretest}(X)$. Thus, we define the null hypothesis $H_0(X)$ as $\mu_{Y.diff}(X) = 0$ and the alternative hypothesis $H_1(X)$ as $\mu_{Y.diff}(X) > 0$, where $X = \{control, EVIN\}$.

(ii) check whether $\mu_{Y.diff}(EVIN) - \mu_{Y.diff}(control)$ is significantly greater than 0, which would imply that $\mu_{Y.diff}(EVIN) > \mu_{Y.diff}(control)$.

TABLE 3. **The classic one-tailed t-test for $H_0(control)$ (at the 90% confidence level) for objective (i) and for each metric. The results show the p-values and lower limits of the confidence intervals (the upper limits are ∞ because of the one-tailed test). The (*) indicates the metrics that reject H_0. □ *Additional comments:* for the metrics $sr.diff$ and $p.diff$, the large p-values (> 0.1) and lower confidence limits that are less than 0 do not allow us to reject $H_0(control)$. However, for $sp.diff$, $H_0(control)$ must be rejected, and thus, $H_1(control)$ is accepted. Therefore, we conclude that $\mu_{sp.posttest}(control) > \mu_{sp.pretest}(control)$. Finally, the third column shows Cohen's d, indicating a small effect size (∼0.2 or less) for $sr.diff$ and $p.diff$ and a large effect size (> 0.8) for $sp.diff$.**

	p-value	lower confidence limit	Cohen's d
(*) sp.diff	0.037	0.019	1.1
sr.diff	0.47	-0.07	0.031
p.diff	0.72	-0.0056	0.29

TABLE 4. **The classic one-tailed t-test for $H_0(EVIN)$ (at the 90% confidence level) for objective (i) and for each metric. The results show the p-values and lower limits of the confidence intervals (the upper limits are ∞ because of the one-tailed test). The (*) indicates the metrics that reject H_0. □ *Additional comments:* for the metric $sr.diff$, the large p-value (> 0.1) and the lower confidence limit that is less than 0 do not allow us to reject $H_0(EVIN)$. However, for $sp.diff$ and $p.diff$, $H_0(EVIN)$ must be rejected, and thus, $H_1(EVIN)$ is accepted. Recall that $p.diff$ $H_0(control)$ could not be rejected. We can see, in light of this metric, an indication about the difference between behaviors based on the group. Finally, the third column shows Cohen's d, indicating a medium effect size (∼0.5) for $sr.diff$ and $p.diff$ and a large effect size (> 0.8) for $sp.diff$.**

	p-value	lower confidence limit	Cohen's d
(*) sp.diff	0.012	0.041	1.1
sr.diff	0.1	-0.00048	0.54
(*) p.diff	0.063	0.00061	0.67

Thus, we define the null hypothesis H_0 as $\mu_{Y.diff}(EVIN) - \mu_{Y.diff}(control) = 0$ and the alternative hypothesis H_1 as $\mu_{Y.diff}(EVIN) - \mu_{Y.diff}(control) > 0$

Because we have a *greater than* alternative hypothesis, we must use one-tailed tests [28]. In addition, because of the scarcity of the data, we set the confidence level to 90%.

1) TRADITIONAL APPROACH

For objective (i), we use a one-tailed t-test for the control and EVIN groups. The results are shown and discussed in Table 3 and Table 4, respectively. The only metric for which we can reject H_0 is $p.diff$, which is not surprising because this metric is the most specific of the three metrics. However, even this metric may be insufficient when we work with this classic methodology.

Next, we focus on objective (ii). The results are shown and discussed in Table 5. In this case, H_0 cannot be rejected regardless of the metric. In fact, trying to approximate this probability distribution to Student's t distribution is optimistic. Therefore, we try another approach.

2) RESAMPLING APPROACH

In this section, we do not make any assumptions about the probability distributions as we did with the parametric approach. Because of the small samples sizes, we focus on resampling-based methods [29]. These methods are not only useful for departures from parametric assumptions and small sample sizes, but they are also more robust than their parametric counterparts [30].

TABLE 5. **The classic one-tailed t-test (at the 90% confidence level) for objective (ii) and for each metric. The results show the p-value and the lower limit of the confidence interval (the upper limit is ∞ because of the one-tailed test) of the t-test. Here, no metric can reject H_0. □ *Additional comments*: given the large p-values (> 0.1) and lower confidence limits that are always less than 0, the H_0 hypothesis cannot be rejected for any metric. Finally, the third column shows Cohen's d, indicating a large effect size (> 0.8) for $p.diff$, a medium effect size (∼0.5) for $sr.diff$ and a medium-to-low effect size (∼0.4) for $sp.diff$, which shows the much better discrimination capacity of metric p than the other metrics.**

	p-value	lower confidence limit	Cohen's d
sp.diff	0.76	-0.073	0.41
sr.diff	0.83	-0.17	0.56
p.diff	0.92	-0.0092	0.94

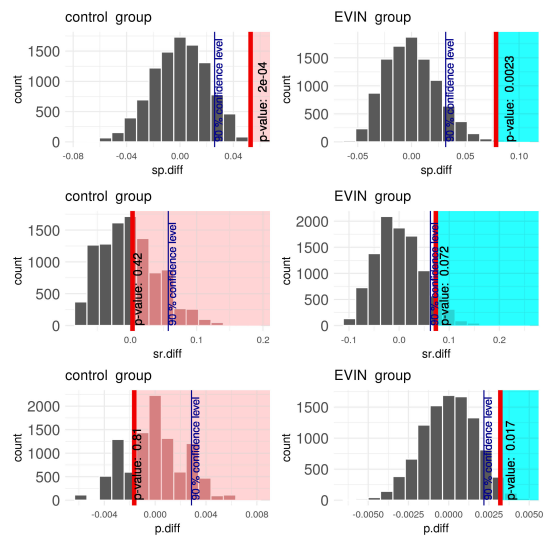


FIGURE 9. **Histogram of the three metrics (rows) and the two groups (columns) of the 10,000 children resampled with replacement, also called bootstrap sampling. In this case, sample $\mu_{Y.diff}(X)$ is represented by a red vertical line for each metric Y (row) and group X (column). Values of $\mu_{Y.diff}(X)$ are also shown in the first and second columns of Table 1. In addition, the graph shows the corresponding p-values that are also represented by the (pink or cyan) shadowed regions. The 90% confidence level is represented by a blue vertical line. Therefore, if the red line is above the blue line, we can reject H_0. Otherwise, we fail to reject H_0.**

We start by testing objective (i). We created 6 samples of 10,000 children with replacement from the original sample for each metric and group. The results are shown and discussed in Figure 9. In this figure, note that metrics $p.diff$ and $sr.diff$ allow us to reject $H_0(EVIN)$, while its counterpart, $H_0(control)$, cannot be rejected. On the one hand, we can infer at the 90% confidence level that $\mu_{sr.posttest}(EVIN) > \mu_{sr.pretest}(EVIN)$ and $\mu_{p.posttest}(EVIN) > \mu_{p.pretest}(EVIN)$. On the other hand, we cannot reject that $\mu_{sr.posttest}(control) = \mu_{sr.pretest}(control)$ and $\mu_{p.posttest}(control) = \mu_{p.pretest}(control)$. Finally, it can be inferred that sp always increases and is not dependent on the group.

Next, we focus on objective (ii). We resampled approximately 10,000 permutations of the labels "control" and "EVIN" from the original data. Then, we calculated the difference in the means of the two groups for each permutation.

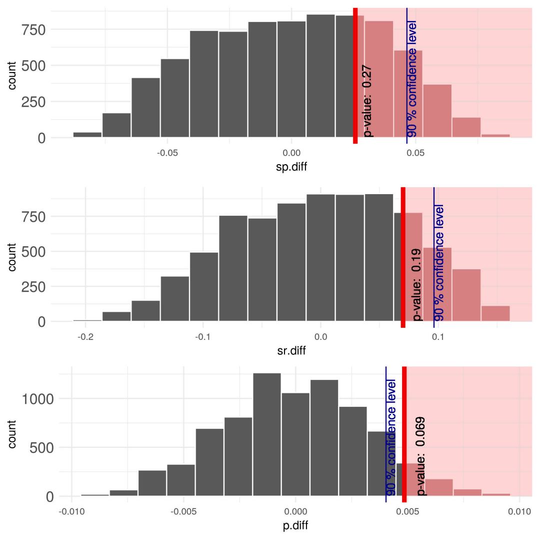


FIGURE 10. Histogram of the three metrics after permutation resampling based on the labels "control" and "EVIN". The difference in the means of the sample, $\mu_{Y.diff}(EVIN) - \mu_{Y.diff}(control)$, is shown as a red vertical line for each metric. The values of $\mu_{Y.diff}(EVIN) - \mu_{Y.diff}(control)$ are also shown in the third column of Table 1. In addition, the graph shows the corresponding p-value, represented by the pink shaded region. The 90% confidence level is shown as a blue vertical line. If the red line is above the blue line, we can reject H_0. Otherwise, we fail to reject H_0.

The histograms of the distributions and more results are shown and discussed in Figure 10. In this figure, only metric $p.diff$ allows us to reject H_0 at a 90% confidence level. In summary, we can say $\mu_{p.diff}(EVIN) > \mu_{p.diff}(control)$ with 90% confidence, and we cannot reject H_0 for the rest of the metrics.

V. CONCLUSION AND FUTURE WORK

In this work, we presented the common, traditional framework for training children with low vision and a new framework to improve it. We also presented an application –EVIN– that aims to implement the ideas that emanate from this new framework. In this new framework, an expert can plan the organization of the exercises in advance, prescribe the exercises to be performed by the children and finally assess the whole process from reports on the child's performance. This framework closes the loop that allows the expert to oversee the entire process of home-based visual training. To achieve this aim, we used adaptive templates.

We have shown how adaptive templates can support home-based visual training with EVIN. They are adaptive because the games can be sequenced according to the child's characteristics. This adaptation is performed through a knowledge base composed mainly of two models: the template model and the children's model.

Finally, we carried out a preliminary experiment to verify the significance of EVIN as an intervention tool for children with low vision. Because the population of children with low vision is very small, we had to exploit all the data we had. We (i) developed new metrics to measure very accurately the children's performance and (ii) applied parametric and nonparametric statistical methods to capture the most subtle differences in a precise way. This procedure was necessary to measure the *visual efficiency* improvement for each group.

In fact, the main goal of visual stimulation is to improve the *visual efficiency* – the process of using vision effectively [31] – but not the visual acuity or visual field in the case of children with low vision. There are no updated and scaled tests to evaluate visual efficiency. The most commonly used tests are the Diagnostic Assessment Procedure [32] and the Control List of the Look and Think Method [33]. However, we consider these tests outdated, as they have not been updated in the last forty years, and currently, many stimuli and visual tasks are not suitable for children. Therefore, our contribution is also a way to measure visual efficiency with new metrics that are possible due to real exercises on a real platform.

From the experiment, there were no significant improvements in the control group, but there were significant improvements in the EVIN group with 90% confidence. Despite the small size of the sample, the results obtained are promising and encourage us to follow this path.

Among other pending issues, we are currently working on a way to allow experts to develop templates for the other games. Having in mind that this new framework works well for visual games as important as the exploration game, we have many expectations about the other games. In addition, the ability of the experts to modify the templates has not been tested in the current stage of the project. At this time, the experts participating in our experiments were able to use this functionality without problems. However, we plan to evaluate this feature in future works.

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