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ORIGINAL RESEARCH

Emotional characterization of children through a learning environment using learning analytics and AR-Sandbox

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Abstract

Identifying emotions experienced by students in a learning environment contributes to measuring the impact when technologies such as augmented reality (AR) are implemented in the educational field. The most frequent methods for collecting emotional metrics are questionnaires, surveys, and observations, but each of these processes lacks objectivity and veracity. For this reason, this study proposes, develops and tests a learning analytics scheme, based on the density-based spatial clustering of applications with noise algorithm, as a clustering technique with time series analysis, using the brain- computer interface device, Emotiv EPOC, as a way to collect emotional metrics. The above, in order to perform emotional behavior characterization by using AR in a learning environment through AR-Sandbox. The proposed method shows a clear inclination in the tendency of each emotion in each cluster, allowing classification of children during their interaction with the immersive environment, as well as the ability to distinguish each group of students.

Keywords Augmented reality · AR-Sandbox · Technology-enhanced learning · Learning analytics · Emotiv EPOC · Clustering · DBSCAN · Time series analysis · Emotional metrics

1 Introduction

Since its inception, technology has contributed to and changed education. Technology-enhanced learning (TEL) has had a big influence on how to learn, how to teach, and how these can be improved through the use of interactivity (Duval et al. 2017). Educational technology has evolved toward new mechanisms and means to recreate optimal environments for effective learning based on interest and motivation. At the same time, there has been an effort to analyze the impacts of these new media and the relationship between technological environments, motivation, and learning.

Augmented reality (AR) technology was used in Tarng et al. (2015) to present a virtual ecological system of butterflies. From smart devices, students could breed and observe the life cycle of butterflies, based on the premise that using this immersive environment can increase children's motivation and interest in the learning process. To validate this proposal, a quasi-experiment was carried out with a base group and a control group, in which, by means of questionnaires, it was learned that the majority of students of the base group had a greater interest in the subject when making use of the immersive environment. Another study (de Ravé

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et al. 2016) presented a mobile system of augmented reality called DiedricAR, aimed at learning descriptive geometry, recreating virtual models of figures in real space. Through a questionnaire evaluating the emotional aspect, the results showed that students had increased positive feelings by using the proposed method.

The use of learning analytics (LA) offers multiple benefits to students, teachers, and educational entities, since it allows the generation of ideas and predictive recommendations in real time (Ifenthaler 2017; Kew et al. 2018). TEL and LA were used in Kew et al. (2018) to explore the level of motivation of students in e-learning at higher education institutions in Thailand. A four-dimensional motivation survey of attention, relevance, confidentiality, and satisfaction (ARCS) obtained an average motivation value of 3.69, called medium–high. Similarly, in Papamitsiou and Economides (2014), a literature review of LA and educational data mining (EDM) was carried out, looking at a total of 40 studies. It was determined that the second most used method of data mining is clustering, focusing on the modeling of student behaviour, and the results showed the opportunities and weaknesses of research in LA and EDM.

Another study (Ati et al. 2018) focused on teaching motivation in order to reduce learning stress in children and provide them with traditional teaching methodologies; the authors presented a mobile application of AR to help children learn the letters of the alphabet, with a platform in the cloud where both parents and teachers are involved. An integration of technology with traditional school learning can be established by creating a user identification for each child. The results of each exercise are loaded on the server to evaluate how children performed on the writing activity, with help of character recognition algorithms that use applications with OpenCv. It was determined that children's experience with using the system improved their ability to learn to write at an early stage, with statistics showing an improvement after the first attempt on a worksheet.

Motivation and interest are important to evaluate in terms of the impact of educational technology on learning; however, the form of evaluation, as shown in previous investigations, has been surveys or questionnaires, which evaluate a person's emotional disposition when carrying out activities, leaving a large part of the subjectivity as addressed in some usability test cases, such as Gaona-García et al. (2016), where a search system is presented for access to academic learning objects and repositories as a visual framework, showing their results through a test that evaluates the use of the platform to search for metadata. Similarly, Gaona-García et al. (2018b) proposed a series of visual search strategies based on knowledge representation schemes, using navigational interfaces tested through perception tests and interface interaction tests. That is why it is essential to use devices such as physiological sensors, which provide an objective measure of physiological signals from emotional stimuli. Sentiment analysis and opinion mining are among the LA techniques for extraction of more relevant educational data, and can significantly improve the capacity of the actors involved in the learning process (Feidakis 2016). In this aspect, it is possible to make use of Emotiv EPOC headphones, a device for collecting signals of brain activity through 14 electrodes, which has been used in studies such as Ramirez and Vamvakousis (2012) for the detection and classification of emotions through a stimulus, in this case auditory.

The AR-Sandbox is a device that allows two-dimensional (2D) and three-dimensional (3D) visualization by projecting a digital topographic map onto a landscape of isolated space through manual manipulation (Woods et al. 2016). Additionally, this device can be related to the somatosensory system, which is associated with the largest organ of the human body, the skin, with innumerable receptors that perceive alterations of surfaces (textures). This perception is crucial for relationships between individuals and their context (Becerra et al. 2018). Based on the above-mentioned studies, the present study aims to develop a learning analytics scheme based on clustering and time series analysis, making use of the Emotiv EPOC device to capture emotional metrics in an educational environment using an AR-Sandbox, with the purpose of categorizing emotional behavior.

Additionally, our expectations of this study is that the proposed learning analytics scheme generates easily distinguishable groups as of emotional metrics, exposing a notable spectrum of dissimilarity between them.

The rest of the paper is organized as follows: Sect. 2 presents works related to the topic of this study. Section 3 presents the design of proposed experiment, along with the development of each of its components, then an analysis of the results obtained in the study. Finally, conclusions and future work are presented.

2 Related works

Technologies should be used as engagers and facilitators of thinking. Computers and different tools can play a big role in supporting learning, as they adapt to all kinds of needs (Alonso-Virgos et al. 2018). In this order of ideas, the educational technology as virtual environments (Gaona-García et al. 2018a), specifically augmented reality (AR), facilitates meaningful learning and the transfer of knowledge and satisfies the interest of the community by attracting the attention of users in the learning process (Hashim et al. 2018). In the aforementioned study, an interview was conducted with experts who pointed out the flaws of current learning systems by only including static learning materials, without involving the use of the senses, since improved learning is achieved through maximum use of the senses, which can be provided by AR systems. There are numerous studies on AR in the educational field; in Chen et al. (2019) a learning method is presented through multidimensional conceptual maps based on augmented reality and using mobile devices, applied to children at a primary school in Taiwan, with a control group. Results showed that the group who used the proposed method performed significantly better than the other group; furthermore, it was concluded that the experimental group showed greater motivation during the activity. There are also studies focusing on AR in early education. For example, in Rodríguez et al. (2019) the authors make the comparison of algorithms such as Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT) and Convolutional Neural Network (CNN) with the purpose of recognizing vowels got directly from an immersive environment based on AR, obtaining as a result that, the CNN model exposes 82.5% effectiveness being the method that presents better performance. Also Zhu et al. (2017) used an interactive educational game based on augmented reality designed for children 4–7 years old, with the main objective of learning abstract concepts, such as color mixing, mathematics, and geometric shapes. The proposal was validated through surveys of parents that allowed evaluation of their stance on the children's methods and attitudes. Results showed that it was a fun teaching environment, and there was considerably increased interest and engagement by the children. Likewise, in Cascales et al. (2013) it was proposed to implement content related to animals based on augmented reality for students 4–5 years of age using a quasi-experimental design based on nonequivalent groups, resulting in an increase in the effectiveness of learning and concluding that the use of augmented reality promotes active student behavior and develops communication skills. According to the above and with the authors (Wang et al. 2018), Interest in augmented reality to create effective learning experiences is increasing while in recent years.

With the above-mentioned studies, it is necessary to carry out an analysis of the way in which educational technology impacts learning. The learning analytics (LA) technique provides a clear way to analyze data and discover effective knowledge in large volumes of well-structured text (Feidakis 2016). Studies such as Hussain et al. (2019) have the objective of predicting the individual difficulties of students in an e-learning session using machine learning techniques and considering variables such as average time, total number of activities, average time of inactivity, average number of fluctuations, and the grades of students in each session. This study resulted in a higher level of accuracy for the artificial neural network (ANN) and support vector machine (SVM) algorithms compared to others, concluding that the teaching, learning, and success of students can be improved. Data extraction of the forum module of the learning management system (LMS) of the course of surgery at the University of Qassim is presented in Saqr et al. (2018), using social network analysis to calculate the correlation of student performance and predict performance using linear regression. The results of the correlation coefficients, linear regression, and logistic regression indicate that the student's role in the transmission of information and the student's network strength can be used as performance indicators in different environments. Moreover, Lange et al. (2018) presents a virtual training platform applying an LA approach to collect, store, analyze and visualize implicit data from the platform, in order to be gradually improved; the results show the ability of this approach to deliver data on key performance indicators.

There are also studies focused on early education. For example, in Ponticorvo et al. (2017) an agent-based model (ABM) approach is proposed for the design of a framework that allows the development of educational games using LA for the measurement, collection, analysis, and reporting of data related to the use of Montessori activities and activity books. This approach is exemplified through Block Magic and SNIFF, two functional prototypes of technology-enhanced learning (TEL) designed in accordance with these principles. The authors found that after numerous tests, the two prototypes built had very good acceptance by users, both the children playing and the adults who supported them, thanks to the complementary connection of physical materials and digital applications, taking advantage of educational potential in a motivating way and improving the teaching and learning process.

The study in Fernández-Gallego et al. (2013) relates the previous topics by presenting a learning analytics framework for virtual 3D worlds that focus on discovering learning flows and verifying compliance through data mining techniques. The authors conclude that the proposed method allows teachers to know what is happening in the students' learning process, automatically extracting the data associated with this process. In Gaona-García et al. (2014) an analysis of user interfaces was carried out for visualization of the navigation of searches of scientific bases, as part of educational technologies in digital repositories using taxonomies. The authors performed an interaction test to determine user satisfaction and the ease in performing searches, and the results showed that the perception of each participant included in the selection of digital resources allowed them to have more access options according to a theme.

On the other hand, there are studies that categorize emotional behavior in technology; Balducci et al. (2017) present the affective evaluation of a role play, through a brain-computer interface, for emotional categorization with machine learning. The results of the work confirm the good performance of the proposed guidelines, supported by subjective questionnaires, in which the emotional reactions of the players are evaluated. In Vachiratamporn et al. (2014), the player's experience with brain activity and heartbeat signals is measured, using a horror survival video game as an experimental environment, to classify the affective state of the player and his adaptation; as results it was obtained that the implicit change of time did not make a significant difference in the evaluation of the players. The same, studies have been carried out where, from the posture and position of the body captured by a Kinect, it is intended to predict the attention that a person has in a short learning process, concluding that it is possible to determine patterns when the attention has been lost (Posada Trobo et al. 2019). In addition, according to Gaeta et al. (2017), in fields such as marketing, attempts have been made to capture the interaction of customers in a shopping center through technological devices, to determine their behavior in these scenarios and implement recommendation systems in real-time. Likewise, authors such as Padilla-Zea et al. (2019) developed a gamified educational platform to enhance entrepreneurial skills with the intention of improving the motivation and engagement of the participants, obtaining as a result that around 60% of the participants indicated their intention to apply the knowledge obtained in an initiative real-life business.

The Emotiv EPOC device can be used as an instrument to measure performance metrics. In Gaeta et al. (2017) the device is presented as brain–computer interface, used to measure performance metrics such as interest, engagement, relaxation, stress, frustration, and concentration while taking a mathematics test, rehabilitating, and watching a soccer game. Results showed that, when taking the math exam, interest and engagement were similar. Strmiska and Koudelkova (2018) present an experimental framework implemented within a safe driving project compatible with the environment, using the Emotiv EPOC to obtain the level of commitment and enthusiasm while using the system, showing results of 70% and 80%, respectively, during the experimental development. Another study proposed the use of affective metrics such as enthusiasm, frustration, and commitment to evaluate multimodal dialogue systems with the use of Emotiv EPOC. The results showed that engagement was greater for tactile input, while enthusiasm and frustration were greater for voice input (Sena et al. 2016). There is also research focused on the measurement of metrics in children. In Perakakis and Potamianos (2012) a study is conducted to observe and understand the level of attention, cognition, and memory of children with attention deficit hyperactivity disorder (ADHD). A total of 15 children were invited to make use of KAPEAN through the use of a mouse and a device for recognizing manual gestures, and data were obtained through the Emotiv EPOC related to performance metrics. The results showed that when using the Leap motion, the predominant emotion was frustration, given the difficulty in mastering this gestural control device. Likewise, in Cabañero et al. (2019), this device was used to capture the brain activity of some participants, who interacted with a cognitive development game, concluding that, this type of data together with algorithms for its classification can become important to evaluate the training effectiveness of different platforms.

3 Design of the proposed experiment

The present research carried out an experimental methodology using a group of participants. The algorithms implemented in the learning analytics component were selected with the objective of characterizing groups.

Then an augmented reality device was implemented as part of the technology-enhanced learning component, whose purpose was to test the learning analytics module.

The validation of the scenario was developed with a group of 20 students between 6 and 7 years of third grade of primary school in Bogotá, Colombia. For this, it was necessary to transport the AR-Sandbox to the school facilities; a room was available for each child to interact with the scenario, individually, without disturbances. The children carried out exercises related to vowels and geometric figures in the AR environment. While doing the exercises, the students used a brain-computer interface for the acquisition of data associated with emotional metrics. Next, we present the proposed scheme and the development of each of the main components that are part of the approach.

3.1 Proposed scenario

Figure 1 presents the basic structure of the scenario that was developed, which was composed of two main components: learning analytics and technology-enhanced learning. In addition, different methods, techniques, and tools were used to develop each module. As a first step, the development of the learning analytics component was carried out by combining the density-based spatial clustering of applications with noise (DBSCAN) algorithm as an unsupervised method of clustering and time series analysis. When making use of DBSCAN, it is not necessary to provide the final number of clusters, since the algorithm generates the clusters according to the density of the data, which was why this algorithm was selected. Additionally, it is important to highlight that in order to determine the parameters of the DBSCAN algorithm, hyperparametric optimization is carried out using a grid search technique. The time series analysis is intended to perform decomposition in order to obtain the trend component and, from this, calculate the slope of the trend data, applying linear regression to determine whether the behavior of the emotional metrics captured in the educational environment increases or decreases

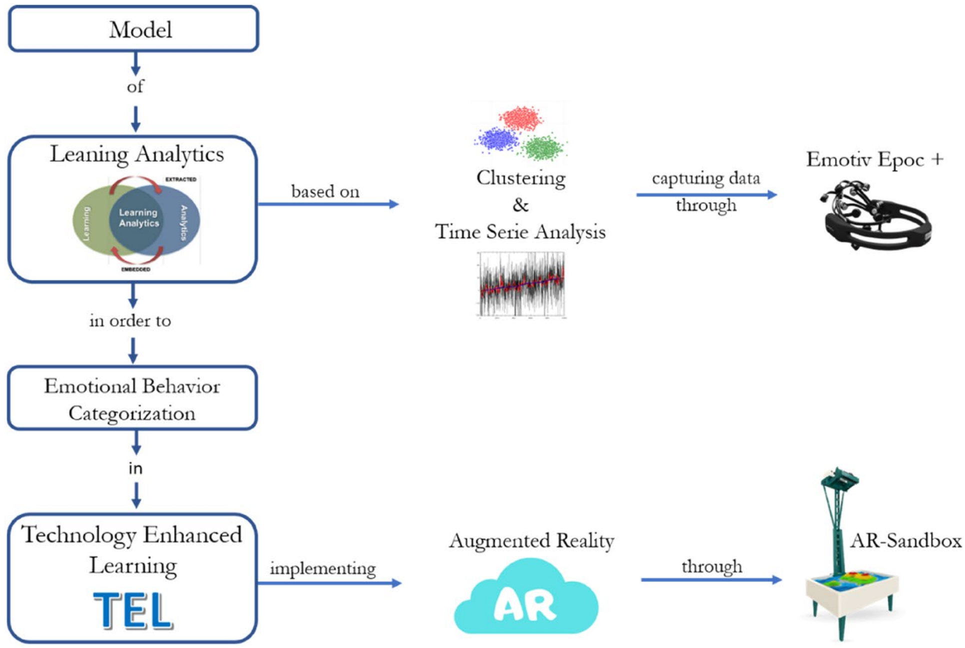


Fig. 1 Scheme proposal

over time. Finally, this component uses as a data source an Emotiv EPOC, which captures processed signals acquired from brain activity; these processed signals are represented as normalized values in a range of 0–1, determining the level of engagement, concentration, interest, relaxation, and stress experienced by an individual second by second. Implementation of the learning analytics component was carried out in Python programming language, making use of libraries such as *sklearn*, *statsmodels*, and *scipy*. The technology-enhanced learning component was developed by applying augmented reality, making use of the AR-Sandbox device, which performs real-time projections of a color elevation map on sand, capturing depths through the depth camera; the device has a first-generation 3D Kinect camera in addition to using a standard projector (Woods et al. 2016). The AR-Sandbox was used to perform exercises aimed at learning and reinforcing knowledge related to vowels and geometric figures. The purpose of implementing this scenario was to categorize the emotional behavior of students from the outlined learning analytics scheme, using the AR-Sandbox as an augmented reality device in an educational environment.

3.2 Data source

As mentioned above, the acquisition of emotional metrics is done through an Emotiv Epoc device, which is a computer brain interface. This non-invasive device has a total of 14 electrodes named as channels (Martinez et al. 2016). In addition, the Emotiv Epoc provides five basic measures of mental performance, derived directly from your mental activity. Each measure is automatically scaled to suit your normal range and base level of each condition. These measures include: Engagement, Focus, Interest, Relaxation and Stress.

To carry out this process, the Emotiv Xavier application is used making a connection with Emotiv Epoc device. From this connection, the device collects EEG biosignals from the 14 sensors around the head, these are filtered and processed by the application to provide the five basic measures of mental performance mentioned above. Additionally, the application allows the recording and visualization of the emotional metrics, to be exported later. Figure 2 presents the visualization exposed by the Emotiv Xavier App.

In this order of ideas, when obtaining the emotional metrics in their normalized range from 0 to 1 as of the filter and processing done by the Emotiv Xavier application, these data can be taken and used in the learning analytics scheme presented below, in order to make the clustering of students according to these values.

4 Learning analytics

Figure 3 presents the approach of the learning analytics module. In order to explain the development of this component, the following clarification must be made: the performance metrics data corresponds to the dataset that is captured for a student in the educational environment through the Emotiv Xavier App. The consolidated data are time, engagement, concentration, interest, relaxation, and stress, within a normalized value in a range of 0–1; values close to zero indicate that a person has a low degree of emotion, and values close to one mean that the person is experiencing a high degree

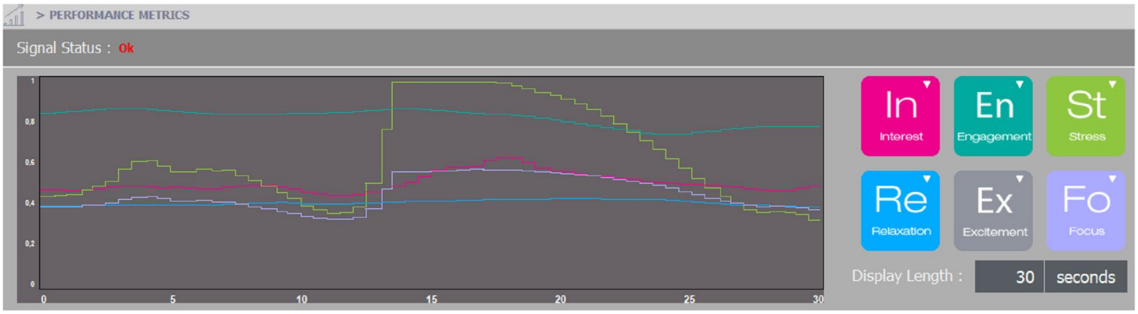


Fig. 2 Performance metrics Emotiv Xavier App

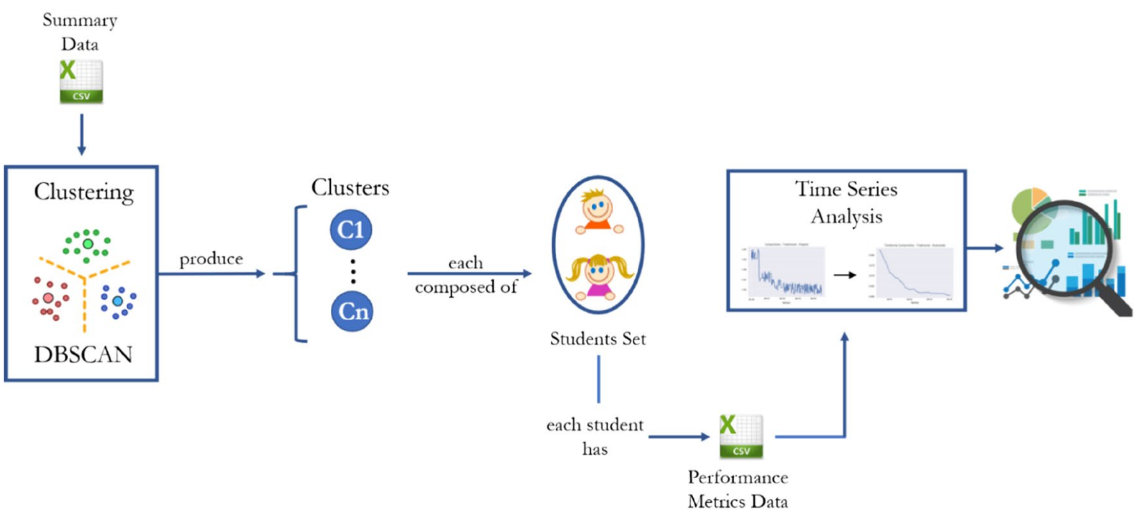


Fig. 3 Learning analytics module approach. DBSCAN, density-based spatial clustering of applications with noise

of emotion. The emotional metrics presented in this dataset were obtained from processed signals acquired directly from the electrodes in the Emotiv EPOC device, which are placed on an individual's head. It is important to highlight that, for each student, there is a performance metrics dataset. The summary dataset contains a summary of datasets corresponding to the students' performance metrics, calculating the arithmetic mean each emotion and obtaining a CSV file whose number of records corresponds to the number of students. As previously explained, this component starts by passing the summary data to the clustering algorithm, making use of DBSCAN to produce a set of clusters composed by a determined number of students.

Then, the performance metrics datasets corresponding to the students of each cluster are taken to perform time series analysis, obtaining the trend component and applying a smoothing window to perform emotional behavior categorization, determined by the percentage of increased and decreased behavior in each emotion for each cluster.

Next, the clustering subcomponent and time series analysis are presented in detail.

4.1 Clustering

The DBSCAN algorithm was selected to carry out the clustering process, since it is a deterministic algorithm, which does not require providing the number of clusters, therefore the generation of clusters is based on the density of the data, that is, for a point to belong to a cluster, it must be close to an agglomeration of similar points. When implementing this algorithm, two parameters must be defined: a positive eps number (eps), the maximum distance between points in the same group, and a natural number of minimum samples (min_samples), the minimum number of points that can be considered as a cluster (EMOTIV 2019). In order to perform hyperparametric optimization through grid search, we defined a basic scheme of DBSCAN without assigning the hyperparameters of eps and min_samples.

To carry out optimization using grid search, a dictionary of hyperparameters was defined for the proposed DBSCAN scheme with eps_values and min_samples_values. The dictionary can be seen in Table 1.

Table 1 Hyperparameter dictionary

Key	List of values
eps_value	0.1, 0.2, 0.3, 0.4, 0.5
min_samples_values	3, 4, 5, 6, 7

Table 2 Density-based cluster validation (DBCV) indices

Epsilon	Minimum samples				
	3	4	5	6	7
0.1	−0.1732	−0.3550	X	X	X
0.2	0.4771	0.4771	0.4771	−0.3462	X
0.3	X	X	X	X	X
0.4	0.3962	X	X	0.3962	0.4841
0.5	0.4247	0.4947	0.5835	0.6141	0.5414

From the proposed base scheme and the hyperparameter dictionary, 25 models were trained, assigning by grid the hyperparameters stored in the dictionary. Training of the models was carried out with a dataset consisting of 20 records, corresponding to 20 children evaluated, with each record containing the arithmetic mean of the engagement, concentration, interest, relaxation, and stress experienced during use of the AR-Sandbox. For model selection, density-based cluster validation (DBCV) was used based on (scikit-learn developers 2017), where the authors determined that the appropriate selection method for DBSCAN should be DBCV, arguing that most internal criteria are not suitable for DBSCAN since spherical groups are assumed and a key feature of this algorithm is that clusters can be found with an arbitrary shape; the exception to this set of internal criteria is DBCV. Table 2 shows the DBCV index obtained when crossing the values of eps and min_samples; boxes marked with an X represent error when trying to compile the model with those values.

From Table 2, the hyperparameter selection of DBSCAN is made, which has higher value in the DBCV index, observing that the model with eps of 0.5 and min_samples of 6 elements has the highest performance, with a total DBCV index of 0.6141. According to the above values, this schema is selected.

4.2 Time series analysis

A time series is composed of three components: trend, seasonal, and residual. To develop this module, the trend component was taken as a point of reference.

Having the defined clusters, we proceeded to review which students were in each group in order to take each time series of each child for each emotion through the ***seasonal_decompose*** function of the ***statsmodels*** library to obtain the trend component, making use of an additive model and a serial frequency value of 60, since it seeks to express time in minutes. Through these values, smoothing is applied to the trend component. Figure 4 shows the results of applying this process to the time series corresponding to student engagement during use of the AR-Sandbox.

From the trend component of each student emotion measured in the educational environment, linear regression was used to determine the slope of the data associated with the trend component; a positive slope value shows a growing tendency, and a negative value shows a decreasing trend. This process is carried out to determine the percentage of increased and decreased behavior of engagement, concentration, interest, relaxation, and stress characterizing each cluster. In order to obtain the slope of the trend component for each emotion, the ***stats*** module of the ***scipy*** library was used, using the ***linregress*** function, which calculates a linear least-squares regression for two sets of measurements (Gaeta et al. 2017; Virtanen et al. 2020). For this case, the first measure was the normalized data of performance metrics of each emotion and the second measure was the array of timestamps related to the first measure. One of the variables returned by the function is the slope of the regression line, so this value is calculated taking into account the entire time

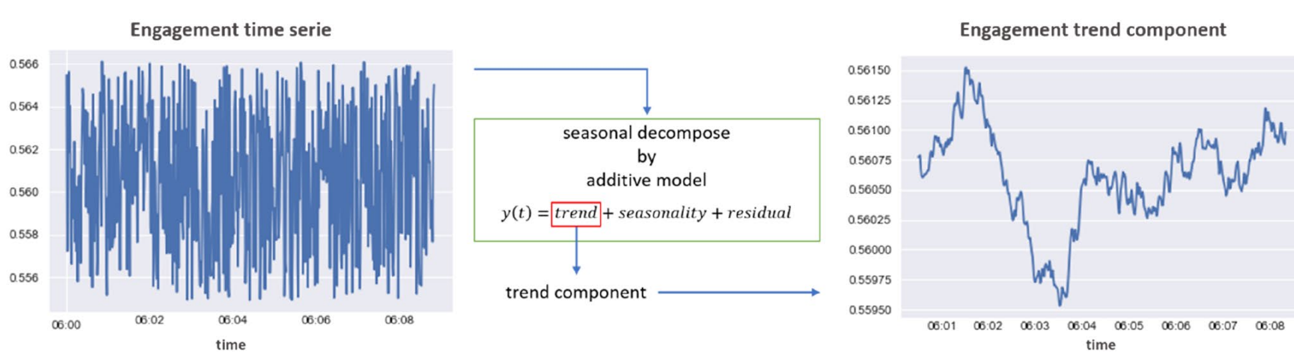


Fig. 4 Time series trend component

window, that is all the time spent by the child during the activity using the AR- Sandbox.

5 Technology-enhanced learning

Figure 5 shows the general scenario of the technology-enhanced learning component, which is composed of two main modules: (1) augmented reality and (2) learning and training. To develop the first component, an AR-Sandbox is implemented together with image recognition. An AR-Sandbox is an augmented reality device that makes digital projections of topographic maps, closing the gap between 2D and 3D visualization and improving thinking and spatial modeling skills (Virtanen et al. 2020). Image recognition is carried out by means of a convolutional neural network model applying color-space segmentation in the prediction phase proposed in a previous study (Giorgis et al. 2017). The second main component is based on the learning and formation of vowels and geometric figures in early education, more specifically, in children 5–7 years of age.

5.1 AR-Sandbox

An AR-Sandbox device allows one to make 3D figures on a surface full of sand using one's hands; when making mountains of sand, the relief becomes colored differently from the rest of the surface, determined by a color map of heights. This process is done through a first-generation Kinect 3D and a short-throw projector, where the Kinect detects the depths on the surface and the projector generates a different color for each determined height. Figure 6 shows a representation of an AR-Sandbox with geometric figures made on its surface.

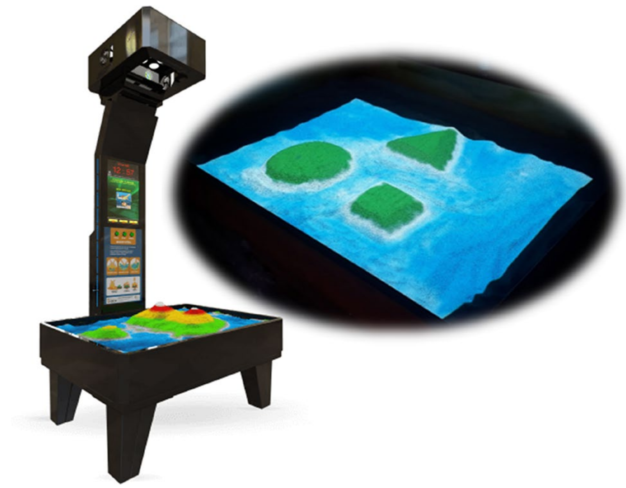


Fig. 6 Figure projection over AR-Sandbox

Figure 7 shows a model of a convolution neural network (CNN) presented in Giorgis et al. (2017), applying color-space segmentation in the prediction phase, with the aim of recognizing and classifying geometric figures from the AR-Sandbox, where the definition of the base model of the CNN was made by implementing hyperparametric optimization, through random search by means of the definitions in the hyperparameter dictionary.

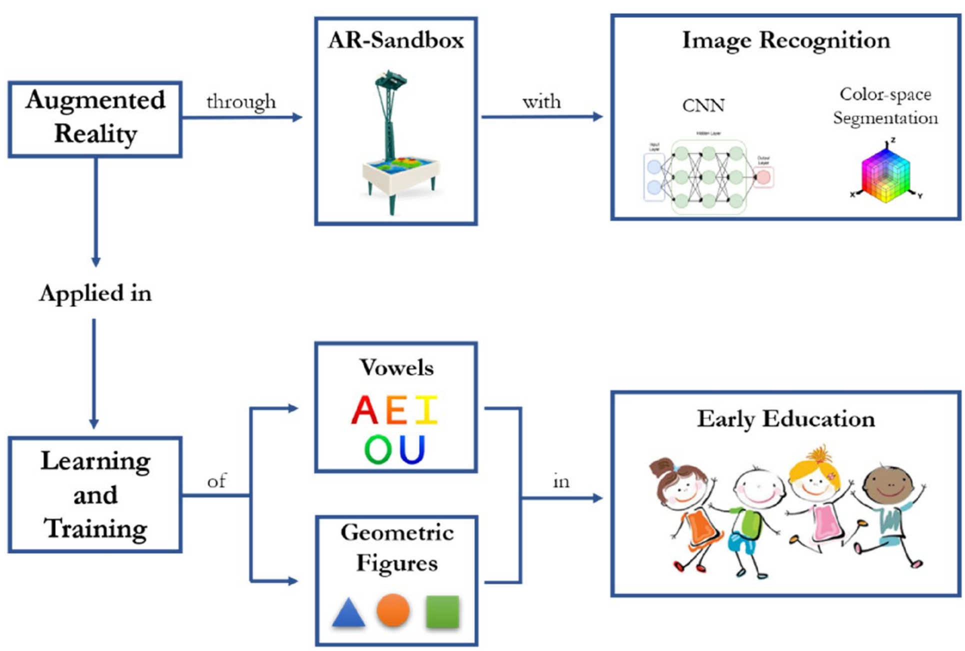
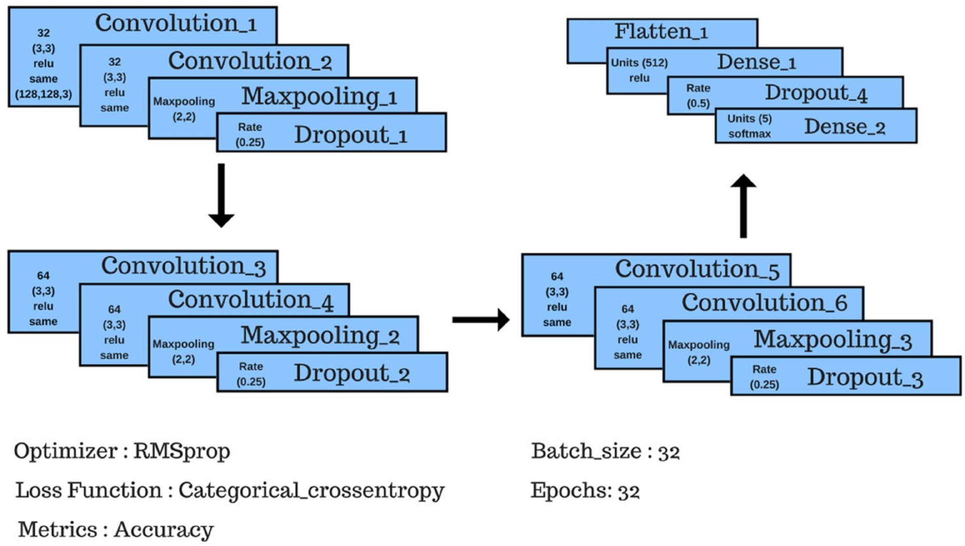


Fig. 5 Technology-enhanced learning module approach

Fig. 7 Convolution neural network (CNN) model (Giorgis et al. 2017)



5.2 Learning and training

The development of this subcomponent is aimed at setting the learning scenario in which the AR-Sandbox will be implemented along with the recognition of images. In order to test a scenario, an age range of 5–7 years was determined, given that at these ages, children are in the process of learning and perfecting their knowledge of basic geometric shapes and vowels in capital letters.

To obtain study data, we conducted a day of emotional feedback during learning. A total of 20 children were randomly chosen, where 13 were boys and 7 were girls, who already had knowledge of geometrics and vowels figures, to practice and consolidate their knowledge on these subjects by using the AR-Sandbox. The children were given a set of questions related to identifying geometric figures in real objects and vowels at the beginnings of words, so they could express their answers in the AR-Sandbox. While the children interacted with the immersive environment, they had the Emotiv EPOC device on their heads in order to capture and record processed signals acquired from brain activity through the device's electrodes second by second. The signals are expressed as emotional metrics translated into normalized values in a range of 0–1, with values close to 0 indicating a low level of emotion and values close to 1 a high level. These data were processed and used in the learning analytics component described above. To carry this out, the authors defined a hierarchy of emotions, starting with the most important: (1) interest, (2) concentration, (3) engagement, (4) stress, and (5) relaxation, given by the characteristics of the selected clustering algorithm, the order in which the data entered presents variations in cluster conformation.

6 Results and interpretation

In this section we present the results obtained from the scheme proposed in the learning analytics component and the scenario in the technology-enhanced learning module.

Table 3 shows the clusters generated from the DBSCAN algorithm: cluster 1 is made up of 12 students, and cluster 2 by 8 students. Each element of the cluster has an identifier in order to perform the emotional characterization. It is not possible to make a spatial representation, since five dimensions are being processed, corresponding to the five emotions evaluated in hierarchical order: interest, concentration, commitment, stress, and relaxation.

Figure 8 shows the distribution of genres of each of the clusters. This with the purpose of observing if the groups present difference in this aspect.

As of Fig. 8, it can be seen that according to the gender distribution it is similar, presenting homogeneity with small differences in their respective percentages.

Table 4 presents the calculated slopes for each emotion of students in cluster 1, from the trend component obtained by representing each emotion using the AR-Sandbox as a time series.

Table 5 presents the calculated slopes for each emotion in cluster 2, from the trend component obtained by representing each emotion using the AR-Sandbox as time series.

Table 3 Clusters generated

Cluster	Student IDs
1	1, 4, 6, 7, 9, 10, 11, 13, 14, 16, 17, 18
2	2, 3, 5, 8, 12, 15, 19, 20

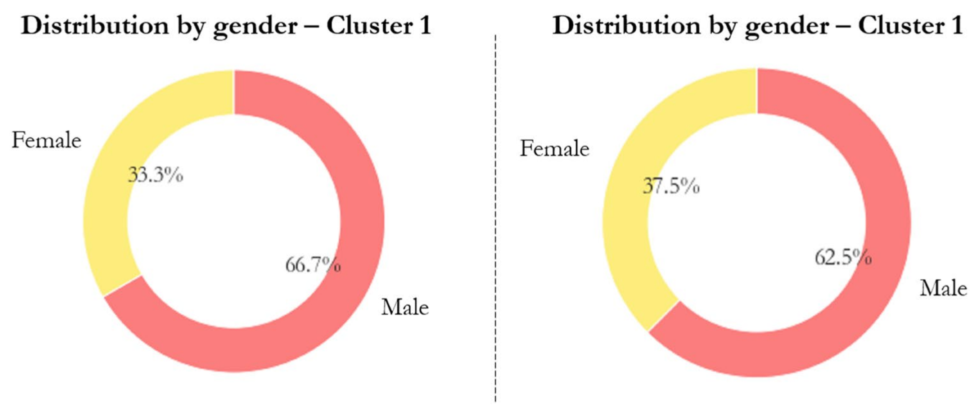


Fig. 8 Distribution by gender of the clusters

Table 4 Slopes of first cluster

Student ID	Interest	Focus	Engagement	Stress	Relax
1	0.0045	0.0032	−0.0095	−0.0015	−0.0462
4	0.0021	0.0066	0.0378	0.0144	−0.0964
6	−0.0012	0.0011	−0.0049	−0.0015	−0.0014
7	0.0064	−0.0031	0.0067	−0.0021	0.0073
9	0.0063	−0.0032	0.0030	−0.0070	−0.0072
10	−0.0016	0.0110	−0.0165	0.0345	0.0238
11	0.0011	−0.0016	−0.0598	−0.0015	0.0013
13	−0.0054	0.0015	0.0261	0.0548	−0.0154
14	0.0022	0.0053	−0.0011	0.0035	0.0175
16	0.0017	0.0495	0.0039	0.0018	0.0021
17	0.0019	−0.0031	−0.0041	0.0678	0.0029
18	0.0014	−0.0016	−0.0059	−0.0015	0.0013

Table 5 Slopes of second cluster

Student ID	Interest	Focus	Engagement	Stress	Relax
2	0.0105	−0.0076	0.0156	−0.00243	−0.0021
3	−0.0012	−0.0058	0.0242	0.0503	0.0585
5	0.0012	0.0010	−0.0057	−0.0015	−0.0013
8	−0.0002	−0.0015	−0.0011	−0.0028	0.0013
12	−0.0042	−0.0054	−0.0017	0.0036	−0.0146
15	−0.0041	0.0056	0.0049	−0.0076	−0.0137
19	−0.0054	−0.0022	0.0239	−0.0038	−0.0106
20	−0.0478	−0.0032	0.0241	0.0013	−0.0541

It is important to remember that, the consolidated values in Tables 4 and 5, is the slopes average computed in time, from applying linear regression to the trend component of the emotions of each of the students. This is why, when the value of the slope is positive the student presented an incremental behavior in this emotion while time. But if it presents a negative value, the student exhibited a decremental behavior in emotion. Additionally, each of these values will be used to define the increasing and decreasing behavior for the clusters, making a separation based on emotion.

6.1 Emotional characterization

The results of the clusters' emotional characterization for each emotion are presented below, based on the slopes obtained from the trend component.

6.1.1 Interest

Figure 9a shows the percentage of increasing and decreasing trend of interest level for cluster 1, and Fig. 9b for cluster 2.

Analyzing the consolidated data in Fig. 9a, the first cluster is characterized by a growing trend in interest level, since 75% of students in this group show a growing slope in the trend component, while only 25% show a decreasing interest. On the other hand, from Fig. 9b, it can be seen that cluster 2 is characterized by a decreasing trend in interest, given that 75% of students show a negative slope in the trend component and 25% show increasing interest. Comparing the clusters, totally different behavior can be seen: cluster 1 shows 50% more increasing behavior and 50% less decreasing behavior, meaning that students in this group had better response to the environment implemented for the criterion of interest. Possibly the children in cluster 1 had an affinity for educational material in the form of interactive and colorful representations and this may be why a majority of them showed growing interest when interacting with the AR-Sandbox, while children in the second group preferred static materials.

6.1.2 Focus

Figure 10a presents the percentage of increasing and decreasing trend of focus level for cluster 1, and Fig. 10b for cluster 2.

It can be observed that the children in cluster 1 show a slightly increasing tendency for concentration during use of the AR-Sandbox; 58.3% show a positive slope. Very close to that are the children who show a negative slope in the trend component, with 41.7%. Analyzing Fig. 10b, cluster 2 shows a decreasing trend for 75% of students, with increased concentration behavior in only 25%. Comparing the groups, cluster 1 shows a moderately positive response to use of the AR-Sandbox with respect to cluster 2, given that the former has increments and decrements of exactly 33.3% of increasing and decreasing behavior compared to the latter. Referring to this emotion, probably many children in cluster 2 found the AR-Sandbox not very showy, causing less concentration during the learning scenario with the device, while in the cluster 1, for more than half the children, the level of concentration could be increased by means of tools that involve the somatosensory system presenting a constant interaction with the environment.

6.1.3 Engagement

Figure 11a shows the percentage of increasing and decreasing trend of engagement level for cluster 1, and Fig. 11b for cluster 2.

Analyzing Fig. 11a, it can be seen that group 1 shows a slight inclination toward a decreasing tendency; 58.3% of

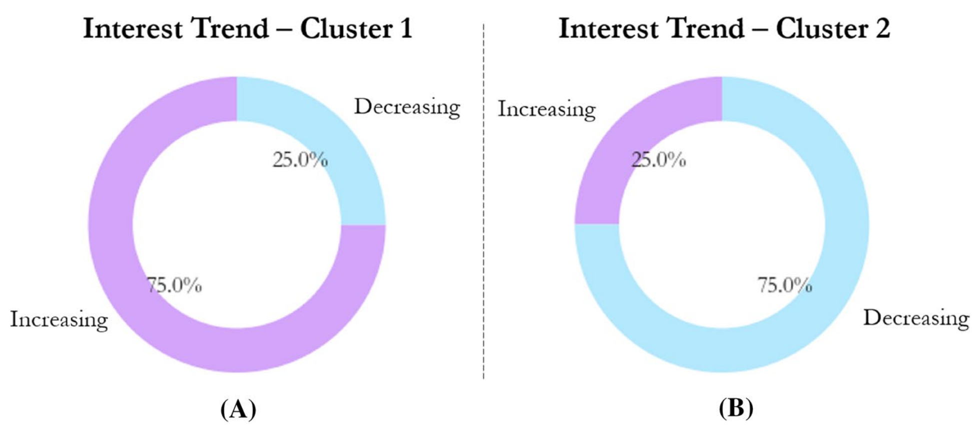


Fig. 9 Interest trend percentages

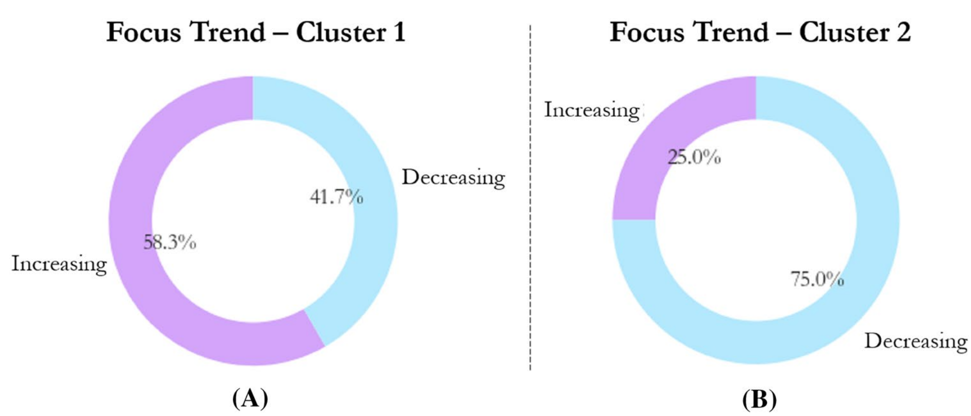


Fig. 10 Focus trend percentages

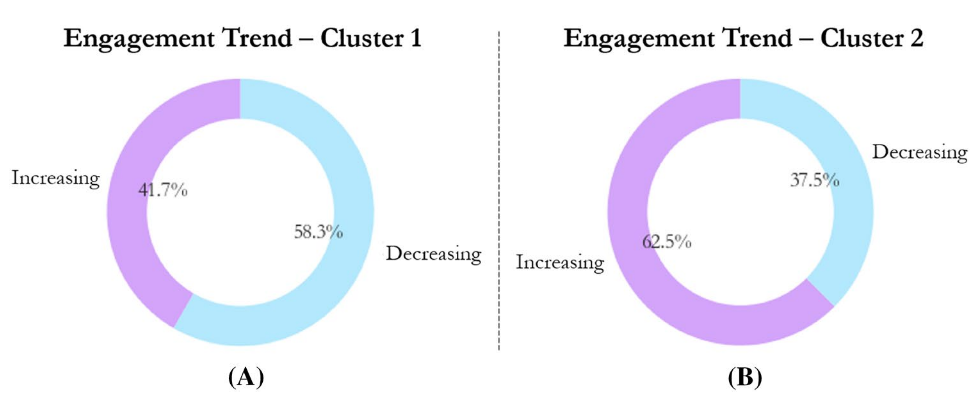


Fig. 11 Engagement trend percentages

the children show a negative slope in the analysis of the trend component of the time series. It also shows increasing behavior in 41.7%. In Fig. 11b it can be seen that cluster 2 shows a trend of increasing behavior in the level of engagement; 62.5% of children in this group show a positive slope, and 37.5% show decreasing behavior. Comparing the clusters and taking the engagement trend as a criterion, it can be determined that group 2 shows a positive impact of the immersive environment, given increments and decrements of 20.8% of increasing and decreasing behavior. In addition, it can be assumed that cluster 2 is composed mostly of children who are motivated to use tools that provide multicolored 3D projections, while children in cluster 2 show decreasing commitment when using this type of tool over time.

6.1.4 Stress

Figure 12a shows the percentage of increasing and decreasing trend of stress level for cluster 1, and Fig. 12b for cluster 2.

Based on the behavior shown in Fig. 12a, it can be seen that cluster 1 does not show an increasing or decreasing trend, given that the number of children showing a positive slope equals the number of children showing a negative slope when applying linear regression to the trend component. On the other hand, from Fig. 12b, the second cluster shows a tendency toward reduced stress, given that 62.5% of children show decreased stress levels as time progresses; only 37.5% of children have a tendency toward increased stress. When comparing the clusters, it can be seen that group 2 shows a positive response to stress, given that the percentage of decreasing behavior is greater than increasing, and group 1 does not show such a trend, that is, the percentage stays at 50%. In addition, stress in group 1 shows a duality, that is, it cannot be determined whether the use of augmented reality tools represented by the AR-Sandbox increases or decreases the tendency to experience stress, while children in cluster 2 show a trend of reduced stress by interacting with augmented reality tools involving the sensory system, in the AR-Sandbox specifically the somatosensory system.

6.1.5 Relaxation

Figure 13a presents the percentage of increasing and decreasing trend of relaxation level for cluster 1, and Fig. 13b for cluster 2.

Analyzing Fig. 13a, group 1 has a slight tendency toward increased relaxation, which corresponds to 58.3% of students, showing a positive slope in the trend component; however, 41.7% of children show decreasing behavior. On the other hand, Fig. 13b shows that children in cluster 2

Fig. 12 Stress trend percentages

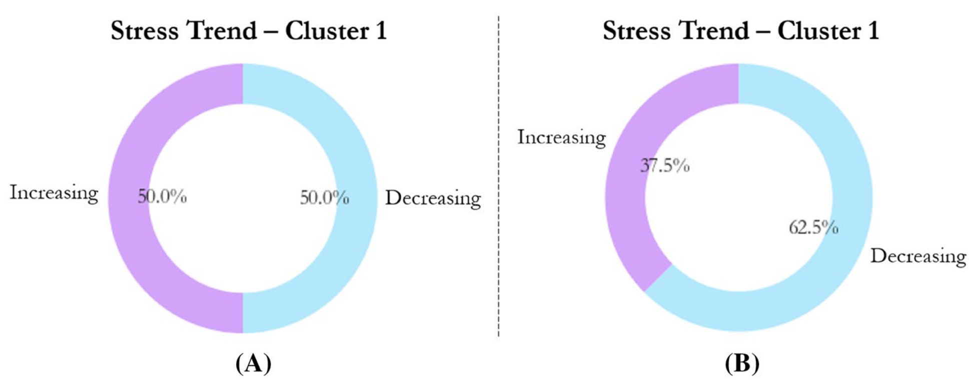
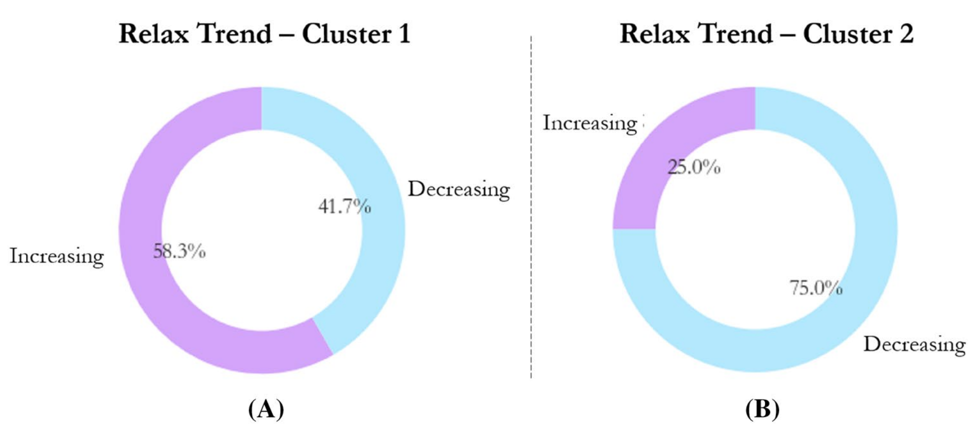


Fig. 13 Relax trend percentages



have a 75% downward trend and a 25% growing trend. Comparing behavior for the relaxation criterion, it can be seen that group 1 has a better response than group 2, since the increasing and decreasing behavior increases and decreases by 33.3%. According to the above, it is likely that children in the first group, for the most part, prefer alternative activities to the traditional education system, given that in the exercises in the AR-Sandbox, they tended to have increased relaxation levels. On the other hand, probably children in cluster 2 can increase relaxation by using traditional methods such as master classes.

6.2 Internal and relative criteria

Finally, according to studies such as Gallego et al. (2018), Restrepo Rodríguez et al. (2018), where density-based clustering validation is performed from internal and relative metrics, it is decided to validate the DBSCAN model through metrics such as: Silhoutte, DBCV, Variance Ratio Criteria (VRC) and Compose Density between and within clusters (CDbw).

As a first instance, the general validation of the DBSCAN model is performed through the scikit-learn library to calculate each of the metrics. Table 6 presents the values obtained for each metric.

Table 6 DBSCAN model internal and relative criteria

Metric	Value
DBCV	0.6141
Silhouette	0.6521
VRC	41.40
CDbw	0.5946

Making reference to the metrics such as Silhouette, DBCV and CDbw, it must be taken into account that the maximum value that can be taken is 1, where the high values indicate that the clusters are well separated according to their density. Additionally, for VRC there is no defined range of values, therefore, a high value in this index also represents a good separation of the clusters. As of the above and from Table 6, it can be seen that for Silhouette, DBCV and CDbw there are values close to or above 0.6, presenting a medium–high level of separation. In addition, referring to the VRC index, a good level of separation and differentiation between the generated clusters is presented, given that a high value was obtained in this coefficient.

On the other hand, when performing a specific analysis of the clusters based on the Silhouette coefficient, which measures how similar an object is to its own group, determined as cohesion, compared with other groups. This index varies between –1 and 1; a higher value indicates that the object fits well with its own group, and not with neighboring groups. Figure 14 presents the silhouette coefficients for each cluster.

It can be seen that most elements of the two clusters do not present a silhouette coefficient less than 0.62, so when calculating, the average silhouette coefficient is 0.6521. This indicates a medium–high level of cohesion in conformation of the clusters, since only 0.3479 is needed to indicate a high level of separation between them.

7 Conclusions

From the gender distribution of the clusters, it could be inferred that a similar emotional behavior and trend would occur. Nevertheless, from the results of the time series

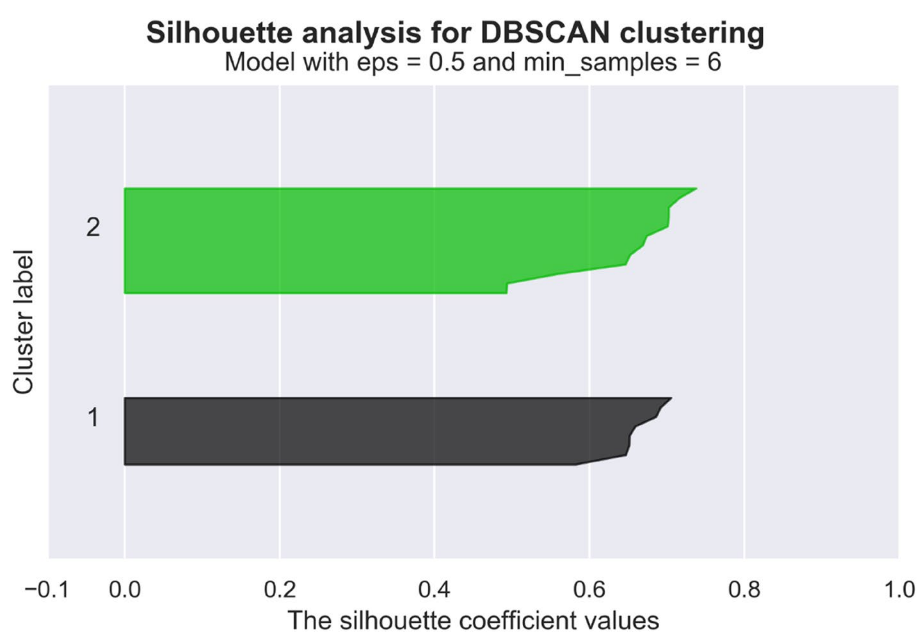


Fig. 14 Silhouette coefficient values for DBSCAN scheme selected

analysis, it can be seen that the percentages of increasing and decreasing tendency of each emotion show a clear propensity in each cluster. In cluster 1, most of them show a growing inclination for positive emotions, with percentages generally exceeding 50%; in cluster 2, there is a decreasing tendency for each emotion. This suggests a classification between children who experienced positive emotions and children who experienced negative emotions in each cluster. Therefore, the implemented learning analytics scheme generates easily distinguishable groups according to the dissimilarity determined from the time series analysis.

Consequently, since cluster 1 grouped more children, it can be said that most of the test group had a positive reaction in the exercises. However, there is a different situation with the emotion of stress; in cluster 1 there is equal increasing and decreasing inclination, and in cluster 2, there is a clear decreasing tendency to suffer stress. In this case, children in cluster 1 suffered greater stress than those in cluster 2. In general, these results allow us to recognize that children suffered from considerable stress during the activity; this may be because it was the first time they interacted with the device, and the scenario involved constant monitoring, which increased the pressure on them. That is why a progressive approach to children in the immersive environment is suggested, performing different exercises accompanied by a professional, to strengthen their confidence and familiarity with the platform.

On the other hand, the results of the silhouette coefficient allow a conclusion that the clusters are made up of members that fit well with their own group, since the coefficient is above 0.6; this is also related to previous results and affirms that the groups are classified with a medium–high percentage of cohesion and are identified by both positive and negative emotions.

In addition, from the results obtained by comparing the clusters according to their trend component for each of the emotions and the values obtained in metrics such as Silhouette, DBCV, VRC and CDbw, it can be said that the learning analytics scheme proposed generates groups easily distinguishable and separated correctly according to their density values of the emotional metrics.

Additionally, it is considered pertinent to combine the scheme proposed in this study and a cerebral dominance test, that is, to first apply a filter to the group of students in order to characterize the group so as to establish and define groupings from the learning analytics component, in order to relate the groupings with the characteristics of the brain dominance test.

In future work, we propose expanding the range of exercises according to children's level of studies and the topics related to their grade level. It is also proposed to conduct a more extensive study to determine whether there is a direct relationship between a child's emotional characteristics and learning over a long period of time; this would allow new analysis and identification of children's errors when considering new exercises that attack the problem. Additionally, we want to validate if there is a significant value of the clusters obtained as regards to the learning process outcomes of the children, involving the opinion of the teachers. Finally, comparing the DBSCAN cluster method versus other methods should be considered to determine greater reliability according to the needs of the study.

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