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TEACHER DECISION MAKING TOOL: DEVELOPMENT OF A PROTOTYPE TO FACILITATE TEACHER DECISION MAKING IN THE CLASSROOM

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Abstract

Teaching is a complex activity that requires a combination of different knowledges, attitudes, skills and values. Teachers are continuously making decisions in the classroom to promote the teaching-learning process. This paper presents the development of a prototype that aims to facilitate teachers' decision making in the classroom in real time, considering variables related to the students, the teacher, and the environment or environmental factors in the classroom.

We used the DBR (Design Based Research) methodology for this project. We reached the first iteration when the second version of the prototype was presented. An analysis of the literature was carried out as a starting point and to establish the foundations for the first version of the prototype. A later expert judgment allowed the prototype to evolve to the second version. This is the starting point for the technological development of the designed solution.

This research is a first step towards using technology to improve teacher decision making in the classroom, and has great potential benefits for both the teacher, for improving their skills, and the student, so they can have a better and more customized learning experience.

Keywords **–** Decision making, Real-time feedback, Smart classroom, Emotion recognition, Environmental factors.

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1. Introduction

Teaching is a complex activity and requires a combination of different knowledges, attitudes, skills and values. For it to be meaningful, it needs to be a high quality and reflective practice (Pushpanadham & Nambumadathil, 2020). In the classroom, the teacher is continuously making decisions to encourage the teaching-learning process and to promote an environment that enables the physical and psychological development of the students. Decision making is relevant to the learning process because good classroom management contributes to better student behaviour as well as a better classroom climate and student-teacher relationship (Hattie, 2009).

Decision making consists of making a specific choice from within a wider group of options, taking into account the possible outcomes of any given choice and its consequences in both the present and future (Broche-Perez, Herrera & Omar-Martinez, 2016). The complexity of decision making is due to the fact that it depends on different factors, such as previous experience, values, beliefs (Ferrero & García-Doval, 2020), age, and gender (Sanz de Acedo, San de Acedo & Cardelle, 2007).

In the field of education and in the classroom, this decision making in teaching is more difficult due to factors such as high student ratios and diversity, new socializing functions that are now required of teachers (Ortiz, Castellano, Rodríguez & Agreda, 2022), and the major changes in education. These changes include new methodologies focused on active teacher learning (Palau & Santiago, 2021), student-centred approaches, and methods using digital technologies in the classroom. All this requires greater personalization of the task, and continuous reflection and evaluation of the students' everyday work (Arnaiz-Sánchez & Martínez-Rodríguez, 2018). The complexity of this task, in addition to the associated responsibilities, can be exhausting and have an impact on the teacher's health. Moreover, teaching is already one of the most stressful professional groups in our society (García, Iglesias, Saleta & Romay., 2016).

Given the new reality of the educational landscape, is it possible to develop a technological tool that would make it easier for teachers to deal with the teaching-learning process and also manage their own pedagogical practices using real time data to aid their decision making abilities?

We propose a technological tool to enhance the effectiveness of teaching and learning, with the aim of providing both teachers and students with the necessary means to achieve their educational goals. This tool would allow teachers to access information and help them make decisions in a simple and rational way. This would contribute to reducing or preventing teachers' stress and would also promote personalized learning for students. The decisions and actions taken by educators would be based on systematically collected empirical data, which would ultimately lead to more effective results for students (Ho, 2022). The goal of this proposed research is to design a tool for teaching purposes that provides real-time information and suggests possible actions to be taken in the classroom, and thus provide an effective way of improving students' learning outcomes.

To develop this prototype it was necessary to make a comprehensive analysis of various factors that have a significant impact on the teaching-learning process, including emotions, environmental factors, and technology. Based on this analysis, we chose the design-based research (DBR) methodology as the most appropriate approach because it makes it possible to carry out research that is closely aligned with the reality of the educational practice and has an applied nature, addressing practical and real-world problems (Sánchez & Prendes, 2022). The tool prototype was developed by applying this methodology, and the designed tool was evaluated by expert judgment through a questionnaire.

2. Theoretical Framework

2.1. Conditions of Students and Teachers

Educators' responsibilities are multifaceted and often demanding, making it challenging to dedicate sufficient time to personalizing the learning experience for students. This includes promoting and reinforcing the personal meaning and value that students attribute to the learning process (Engel & Coll, 2022). Digital technologies offer greater opportunities for customized learning; however, this depends less on the characteristics of the technology and more on the design and development of the activities that incorporate the technology (Coll, 2018).

Pardo, Jovanović, Dawson, Gašević and Mirriahi (2019) highlight the positive effects of combining technology-collected information with a teacher to provide frequent and personalized feedback, which is a fundamental element of student support actions (Pardo, Poquet, Martínez-Maldonado & Dawson, 2017). Therefore, education along with technology, and specifically with Artificial Intelligence (AI), are significantly improved at different educational levels (Ocaña-Fernández, Valenzuela-Fernández, Garro-Aburto, 2019). By collecting data, these technologies can support teachers in their efforts to improve student outcomes (Banihashem, Aliabadi, Pourroostaei-Ardakani, Delaver & Nili-Ahmadabadi, 2018).

The complexity of the teaching task, along with the associated responsibilities, can be overwhelming and can have a negative impact on teachers' overall wellbeing. It is already one of the most stressful professional groups in our society (García et al. 2016), and consequently, greatly affected by burnout syndrome. Different studies have analysed the relationship between burnout and teaching, highlighting the following aspects related to generators of emotional exhaustion in teachers (collected by Vicente de la Vera and Gabari (2020)): workload, time pressures, negative perception of the work environment, lack of confidence in performing tasks appropriately, and labour conflicts, among others.

Studies such as those of Sánchez-Pujalte, Mateu, Etchezahar and Gómez-Yepes (2019) and Vicente de la Vera and Gabari (2020) show that teaching experience is a protective factor; that is, the most experienced teachers have developed coping strategies and are the most emotionally protected when they face professional challenges (Ghorpade, Lackritz & Singh, 2007).

2.2. Digital Technologies in the Classroom

This project is framed within the Fourth Industrial Revolution, in which technology is used in conjunction with other disciplines, methodologies, and current pedagogical strategies to achieve more customized teaching (Mogas, Palau, Fuentes, & Cebrián, 2021). The aim is to ensure innovation and educational quality, by promoting student inclusion, the personalization of learning content to provide higher quality attention, and the use of new methodologies to achieve more meaningful learning.

There is currently an increase in the use of digital technologies in classrooms (Hassan & Geys, 2016). Different countries are investing in equipment and providing technological resources in educational environments. Lorenzo, Gallon, Palau and Mogas (2021) consider that these technologies need to be present in teaching and learning practices to satisfy the new challenges that society faces. These technologies allow data to be collected through sensors (Jormanainen, Toivonen & Nivalainen, 2018), cameras (Korozi, Leonidis, Antona & Stephanidis, 2017), computer systems or other tools (Liu, Huang & Wosinski, 2017), in order to process inputs, provide responses through feedback and actions with real time recommendations (Kinshuk, Cheng & Chew, 2016), as well as facilitate teacher decisions (Kim, Soyata & Behnagh, 2018). The use of digital devices (smartphones, touch screens, interactive tools, whiteboards, etc.) is basic for carrying out learning processes, because connectivity brings with it a large number of opportunities (Van De Bogart & Wichadee, 2016). Some other advanced systems are already being explored, such as eye-tracking systems (Ha & Kim, 2014), facial recognition systems (Aguilar, Sánchez, Cordero, Valdiviezo-Díaz, Barba-Guamán & Chamba-Eras, 2017) and motion (Negron & Graves, 2017) to determine attention and mood.

One of the most trending topics on the impact of Industry 4.0 on education is the emergence of smart classrooms. A smart classroom is the unit of a smart culture equipped with adaptive technology for a more enriching experience for the teacher and learner (Cebrián, Palau & Mogas, 2020). It uses digital and adaptive devices to promote faster and more effective learning (Koper, 2014) and incorporates technological advances such as learning analytics (Llurba, Palau & Mogas, 2022). Three dimensions need to coexist: technology, environmental factors and the processes carried out (Palau & Mogas, 2019; Cebrian et al., 2020). Exploring how technologies can promote conceptual understanding as well as the general teaching practice to improve educational success, employability, personal fulfilment and social inclusion will help us determine the technological innovations that are truly necessary for smart classrooms to support the needs and perspectives of schools (Lorenzo et al., 2021).

2.2.1. Emotion Recognition

Emotions play a crucial role in the learning process (Pekrun & Linnenbrick-Garcia, 2014). They are a key aspect of people, affecting all facets of their lives and producing physiological and behavioural changes (Jang, Park, Park, Sang-Hyeob & Jin-Hun, 2015).

Human emotions can be inferred by several modalities (Rescigno, Spezialetti & Rossi, 2020): physiological signals, including electroencephalogram (EEG), body temperature, electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), breathing (Shu et al., 2018), speech (Koolagudi & Rao, 2012), and body gestures, including facial expressions (Kleinsmith & Bianchi-Berthouze, 2013).

Technologies allow us to unobtrusively monitor and measure students' non-verbal language, such as facial expressions (Li, Gong, Li & Tao, 2016). These are expressed involuntarily and provide valuable emotional and cognitive information for teachers, who can use the information to adapt and customize the teaching-learning process. Collecting this data can improve the teaching-learning process, avoiding misunderstandings and misinterpretations, and enhance the assessment of content and the competence achieved (Horvat & Jagušt, 2020).

In recent years, automatic emotion recognition has become an important component in the fields of affective computing and human-machine interaction, and the tools for acquiring facial expression images are one of the cheapest and most natural (Rescigno et al., 2020). Many researches have relied on facial recognition for emotion recognition; however, the results are not always consistent, as people sometimes disguise their emotions (Hsu, Wang, Chiang & Hung, 2017). Moreover, establishing a generalized model is complex due to anatomical, cultural and environmental differences (Rescigno et. al, 2020). Thus, emotion recognition remains a challenge due to various reasons: blurred boundaries and differences between individuals; because emotions affect different aspects of people's lives not only the physiological domain and are therefore difficult to identify; and because emotions do not have the same physiological characteristics for all subjects (Zhao, Wang, Yu & Guo, 2018). It is worth mentioning the work carried out by Llurba, Fretes and Palau (2022) in which they also experiment with this emotion recognition in the classroom.

2.2.2. Environmental Factors

Environmental factors are not always considered in the teaching-learning process when it comes to offline classes, but Mogas et al. (2021) demonstrate their importance, providing a better understanding of what happens in the classroom. The environmental factors mentioned include the acoustics (Mogas et al., 2021), lighting (Mogas & Palau, 2021) and air quality. Similarly, the term Ambient Intelligence (AmI), according to Mogas, Llurba and Palau (2022), implies the integration and interaction of software, hardware and sensor networks to empower students and teachers through a context-aware, sensitive, adaptive and responsive digital environment. AmI makes it possible to conceptualize smart classrooms centred on environmental factors (Mogas et al., 2021), thus facilitating automated tasks (Gams, Gu, Härmä, Muñoz & Tam, 2019).

Acoustic factors in the educational environment can have an impact on the students' and teachers' perception of wellbeing and comfort (Montiel, Mayoral, Navarro-Pedreño & Maiques, 2019). These factors can affect health, increase frustration and irritability and reduce the ability to concentrate, stay motivated and keep learning. Researchers conclude that this problem should be addressed by paying particular attention to architectural redesign, the provision of technological resources and acoustic adaptation (Mogas, Palau & Márquez, 2020; 2021). Therefore, it is necessary to work on the design of the classroom and the use of technologies, such as devices and recycled and green materials, as well as advanced automation systems that enable acoustic solutions that generate smarter learning spaces.

Classroom lighting affects cognition, and therefore impacts academic performance, attention rates, work speed, productivity and accuracy, among others (Mogas & Palau, 2021). LED lighting seems to be the most suitable for improving psychological health and cognitive processes in the classroom and should be dynamic according to the different activities performed. Indoor air quality (IAQ) in the classroom refers to parameters related to indoor temperature and relative humidity, carbon dioxide concentration and air renewal rates (Krawczyk & Wadolowska, 2018). The analysis of these factors is important in the teaching-learning process, as different studies show that low IAQ levels have a physical and mental impact on teacher and student concentration and task performance (Istrate, Catalina, Cucos & Dicu, 2016).

2.2.3. Data Collection and Processing

Teachers who base their instructions and movements on systematically collected empirical data effectively improve student outcomes (Marsh, Pane & Hamilton, 2006). Similarly, when teachers engage in their own learning by recording their own sessions or sharing and discussing them with peers (micro-teaching or classroom study), the classes have a greater effect on students (Hattie, 2009).

The most common data processing tools are wearable sensors and smart devices that can facilitate decision making. Different studies propose a multisensory analysis, in which information is received from more than one channel. Research has tested combining different strategies to achieve the best form of data collection. Resources must be chosen carefully because when a small set of sensors is used, even if less information is received, the system identification process is faster and more convenient. On the other hand, multiple portable sensors can be difficult for users to carry, and it is important to assess personal space and comfort levels (Antar, Ahmed & Ahad, 2019).

Smart classrooms take advantage of experiences to create innovative tools to collect and analyse information holistically in conjunction with an AI system, providing recommendations to teachers based on different interrelated variables. This gives a more complete view of student learning, which enables easier decision making for teachers. The use of cameras, sensors and tools facilitates measuring environmental parameters and other aspects such as facial recognition of students. Voice and movement are reliable data for recognizing student satisfaction (Gligoric, Uzelac, Krco, Kovacevic & Nikodijevic, 2015). AmI systems contain devices and sensors embedded in the user's work environment. These sensors collect information about lighting, temperature, noise, pressure, object position, facial and voice recognition, bio-signal reading, and GPS (Radosavljevic, Radosavljevic & Jelic, 2019).

In terms of teacher decision making in the classroom, Data-Driven Decision Making (DDDM) refers to collecting data from different sources for improving student performance (Marsh, et al., 2006). Once the data are collected, users must make sense of them (Vanlommel, Van Gasse, Vanhoof & Van Petegem, 2017) to be able to use them to improve the educational process. Teachers may have some difficulties in analysing and interpreting data (Brown, Schildkamp & Hubers, 2017).

3. Methodology

The DBR methodology was used to carry out this project and respond to problems detected in the educational field. This entails introducing a new transforming element into a situation. This methodology aims to respond to problems detected in the educational field based on scientific theories or models of possible solutions, designing products that are tested and validated then distributed to the educational world (de Benito & Salinas, 2016). It is characterized by being iterative, pragmatic, contextual, participatory, reflective, flexible, interactive and integrated.

The DBR model has three stages or phases (Plomp & Nieveen, 2010): 1) preliminary research, in which needs and/or problems are analysed and described and a literature review is carried out; 2) design and development of the prototype, in which the prototype is revised and improved through systematic studies corresponding to the research cycles; and 3) final evaluation, in which the interventions are evaluated to identify whether the objectives set in the research process have been met.

This research proposes developing a product focused on teachers in Spain at the secondary education stage (12 to 16) and the post-compulsory stage (16-18). These stages are a problematic time period for teachers, and there is a higher incidence of disorders related to stress and teacher burnout (Vicente de la Vera & Gabari, 2019). Moreover, the Spanish Labour Force Survey (Encuesta de Población Activa) highlights that there is a 16% rate of early school drop-out.

To develop this prototype, first a systematic review was carried out using Boolean operators to search databases, such as Web of Science (WoS) and Scopus, which have a large amount of information and high quality standards. The words used for the search were "real-time feedback", "environmental factors", "acoustic" or "oxygen", and "emotion recognition" or "artificial intelligence".

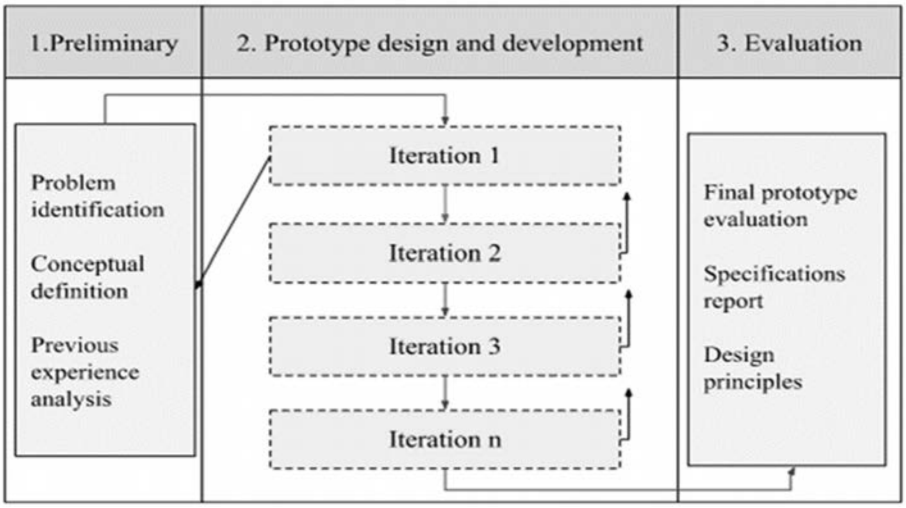


Figure 1. DBR development stages

The inclusion criteria take into account variables such as education, learning analytics, dashboard, feedback, real-time, and artificial intelligence. The exclusion criteria used include duplicity of articles, and temporality. We chose only those articles published in recent years (2011-2022), those records that did not deal with experiences or related aspects or with language limitations, and only those articles written in English or Spanish.

After searching the previously mentioned databases, 722 articles were obtained in the Scopus database and 127 in Web of Science. Once reviewed and some articles were excluded according to the previously selected criteria, we had 31 articles to review.

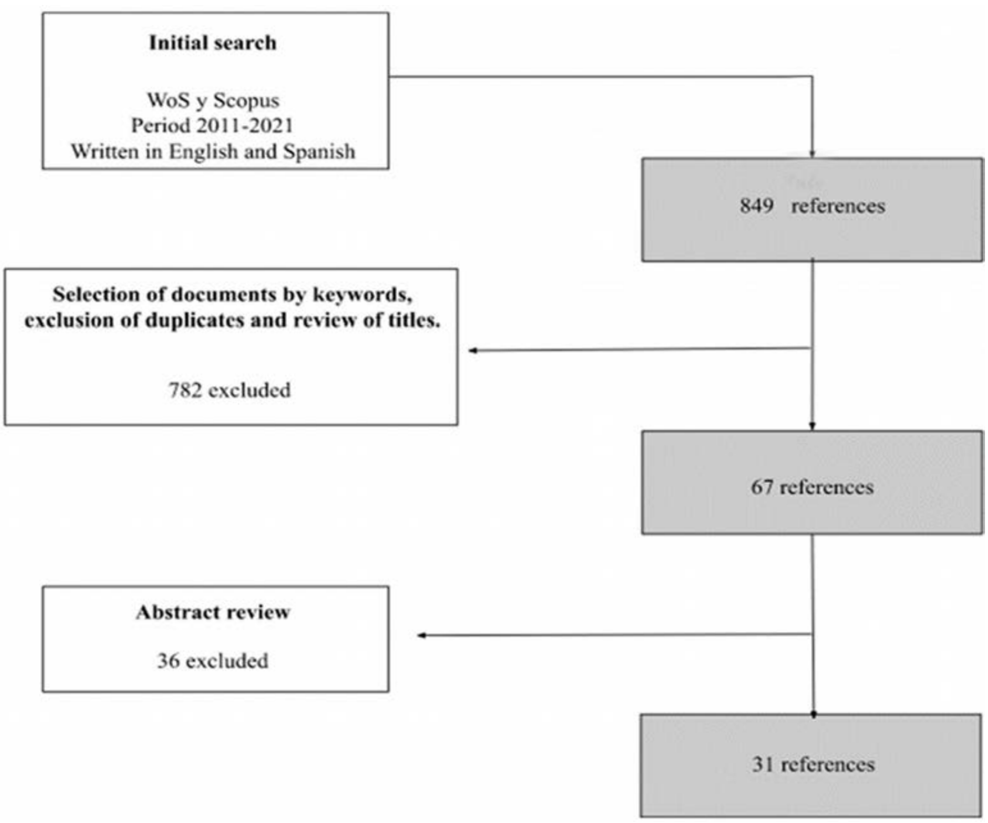


Figure 2. Graphic representation of the systematic review process

We also analysed experiences and materials related to feedback in real time and feedback for being more effective.

Once the prototype was developed, it was examined by experts, that is, different professionals related to the study topic whose purpose was to shed light on the research problem, establishing an iterative process through feedback (López-Gómez, 2018).

According to the same author, the samples of experts should be diverse and should not be less than ten professionals, which is why the proposed panel of experts is thirteen people with a minimum of four per profile, as small samples (less than seven) do not offer representative information and large samples have disadvantages related to time constraints.

Three professional profiles were selected for the expert judgment to provide a wider and more diverse perspective: researchers, computer programmers or developers of web environments, and secondary school teachers. Thirteen experts responded to the questionnaire, of which three belong to the research area, three to the computer area and four are secondary school teachers.

The prototype was designed in three phases, which increased in development difficulty, and each of these phases was evaluated in the questionnaire, which is composed of two parts, a quantitative section with a Likert-type scale and a qualitative section with open questions.

4.Results

4.1. Tool Development

Once the literature and the different experiences with this type of methodology had been reviewed, the following scheme was proposed to develop the prototype, as shown in Figure 3, including the variables collected, the tools used, and how this information is stored and made accessible.

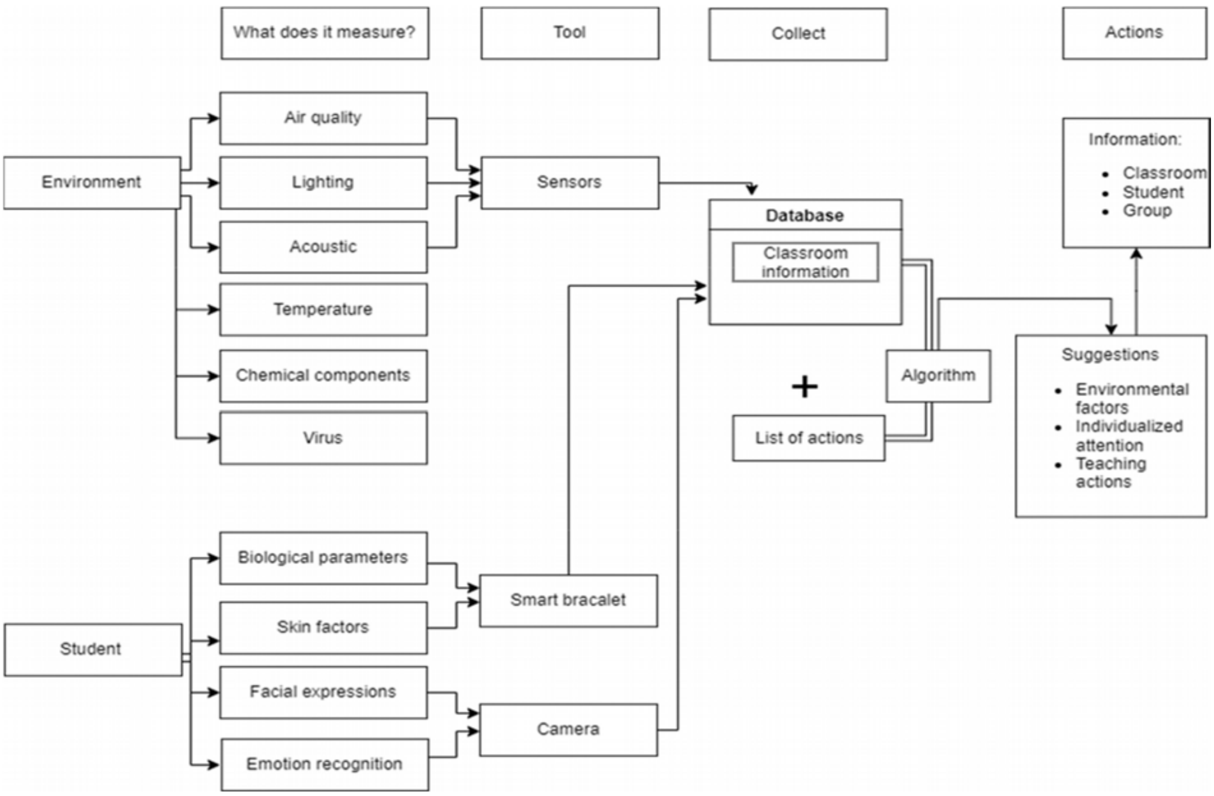


Figure 3. General description of data collection process

Teachers will have all the information provided by the tool on a portable device, which is a tablet with the single function of being using as this tool. They obtain graphic information about the students' emotions and environmental factors, as can be seen in the prototype.

The tools selected for data collection are non-intrusive. Environmental factors are measured by different sensors (Learnometer and ACTUA) located in strategic spots in the classroom. Student data are collected through facial recognition cameras (Azure) that are located in the classroom and smartbracelets (Empatica E4) that students wear on their wrists during class. This tool also enhances recording attendance in class.

Figure 4 shows how information is collected in classrooms and Figure 5 illustrates the tools used and the variables they collect.

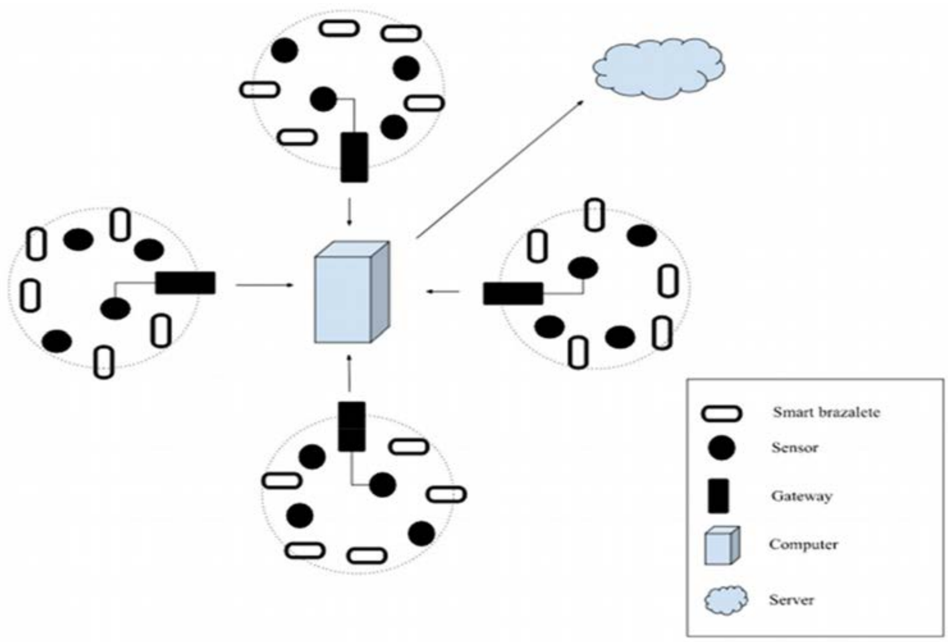


Figure 4. Collecting and processing information in the classroom

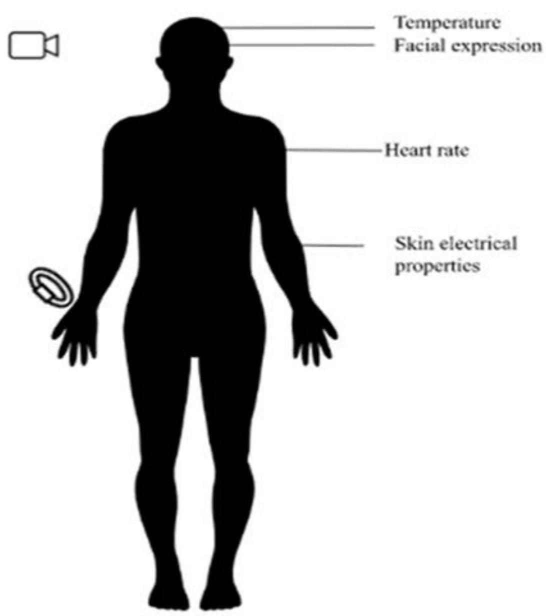


Figure 5. Student data collection: tools and variables to be measured

For the emotion classification, we use a multidimensional system with four dimensions based on the arousal and valence variables according to the research conducted by Zhao et al. (2018), who concluded that this system has high accuracy (75.56%).

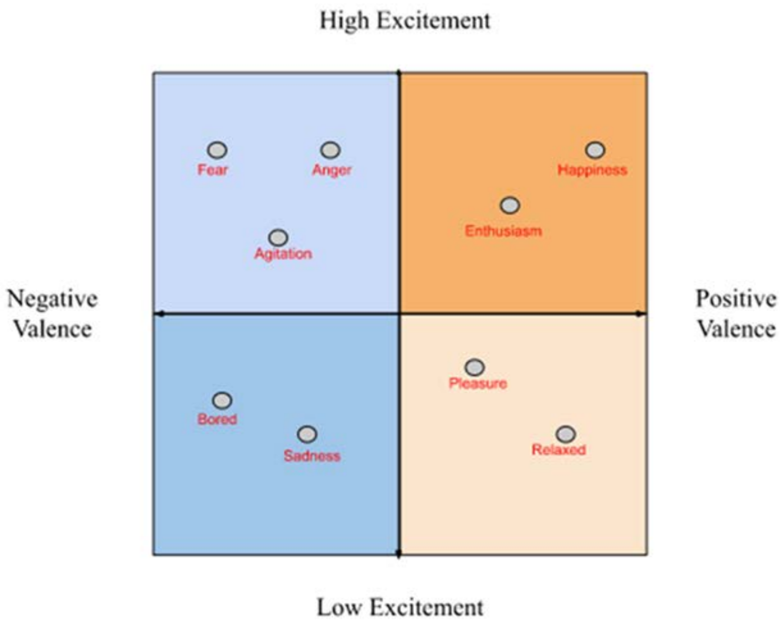


Figure 6. Multidimensional model (Zhao et al., 2018)

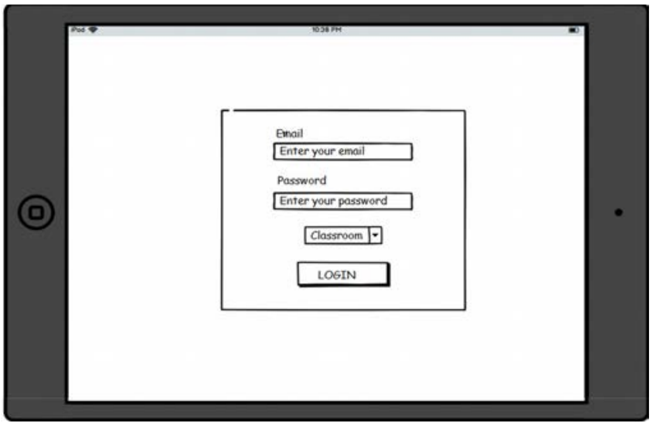
The emotions collected are shown to the teachers using colours. These colours have direct relationships with the affective sensation and are suitable for emotion detection (Kajiyama & Satoh, 2014); therefore, these colours are used to show the students' emotions in a way that is intuitive and simple for teachers.

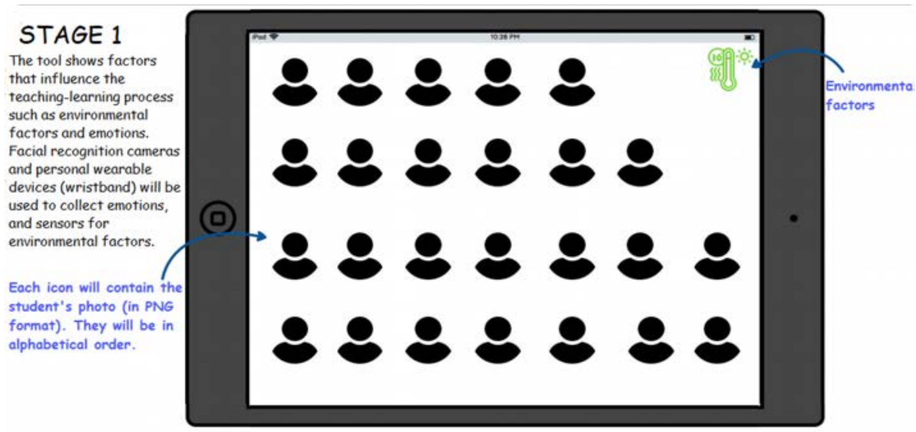
The environmental factors are monitored according to different variables that influence the teaching-learning process, with the aim of obtaining the optimal values for this process. The tool shows that the factors and favourable values are: a temperature between 20 and 26ºC, recommended to achieve thermal comfort (Muñoz, 2018); CO2 levels below 1000 ppm (Krawczyk & Wadolowska, 2018); two lighting factors are analysed, the first one is the intensity and brightness, which the European Union (EU) suggests a minimum value of 300 lux (Vera & Vidal, 2020), and the second one is the light colour, which encourages communication when it is warmer and improves attention and memory when it is cooler; the acoustics, for which the standard background noise should be around 35 dB; the chemical components should be lower than 0.3 mg/m3; and the levels related to COVID-19 should be appropriate (ACTUA research project financed by the Generalitat de Catalunya).

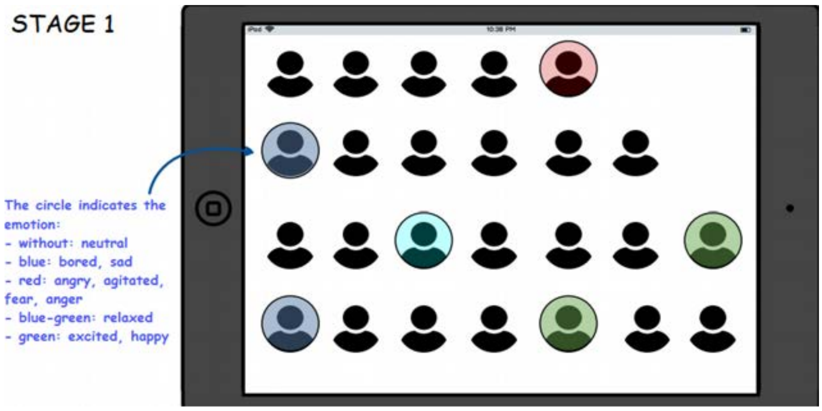
The development of this tool involves three progressive phases. In the first phase, information is collected from students and environmental factors through various devices, showing teachers the information provided so they can find out about students' emotions and those environmental factors that are affecting the teaching-learning process in a positive and/or negative way. The second phase includes, in addition to the above, suggesting actions to the teacher to be implemented in the classroom. It also distinguishes between different types of activities that can be carried out, including a expository class, or individual and group activity. In the third phase, unlike the previous one, the instructions suggested by the tool are adapted according to variables such as the group, the teacher or the time of day. The tool "learns" in relation to the data collected, which allows the instructions and the activities to be adjusted to the needs of the class.

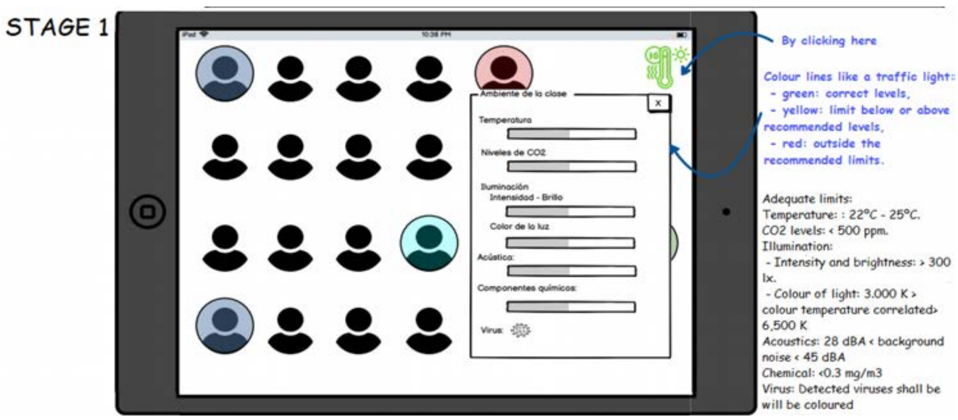
4.1.1. Prototype

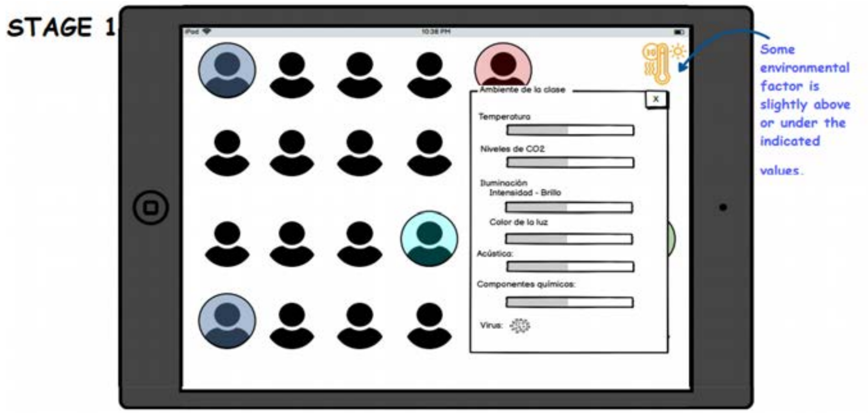
Stage 1

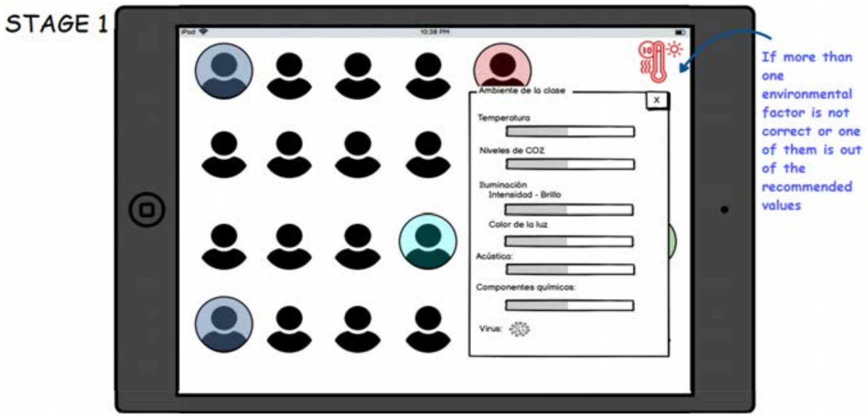




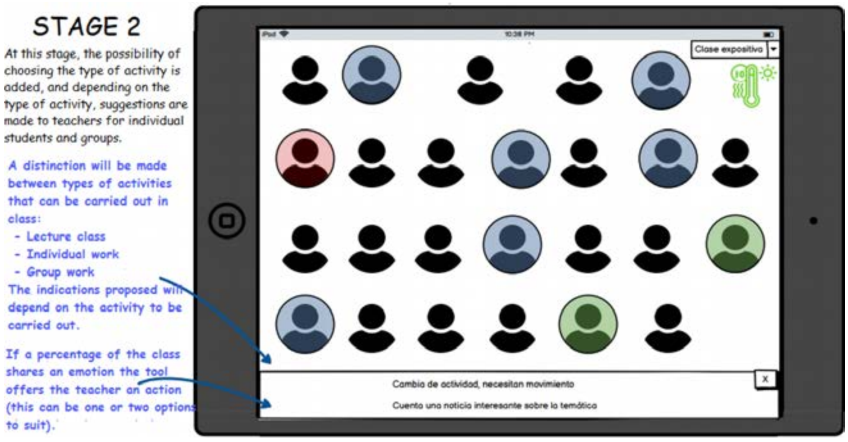


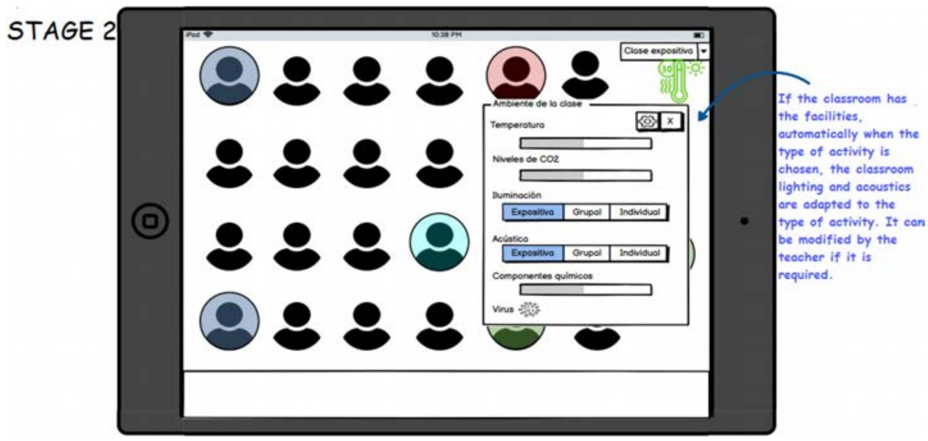


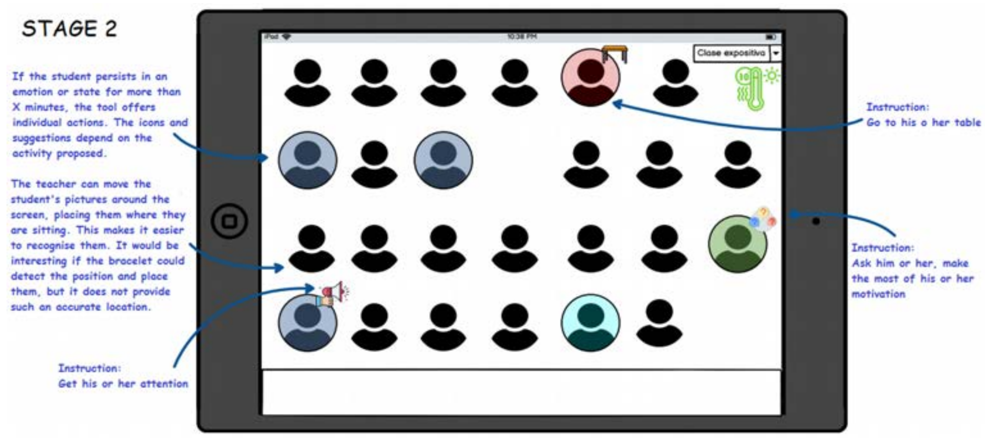

STAGE 1
Ambiente de la clase
Temperatura
Niveles de CO2
Iluminación
Intensidad - Brillo
Color de la luz
Acústica:
Componentes químicos:
Virus:
Some environmental factor is slightly above or under the indicated values.

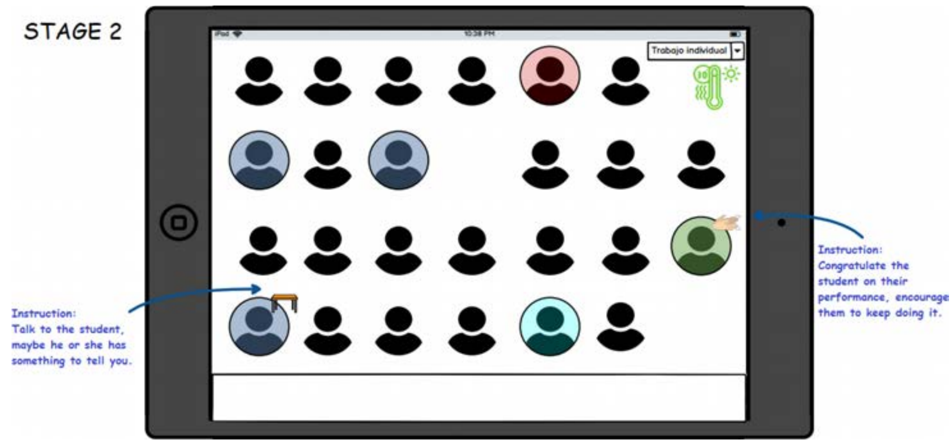

STAGE 1
Ambiente de la clase
Temperatura
Niveles de CO2
Iluminación
Intensidad - Brillo
Color de la luz
Acústica:
Componentes químicos:
Virus:
If more than one environmental factor is not correct or one of them is out of the recommended values

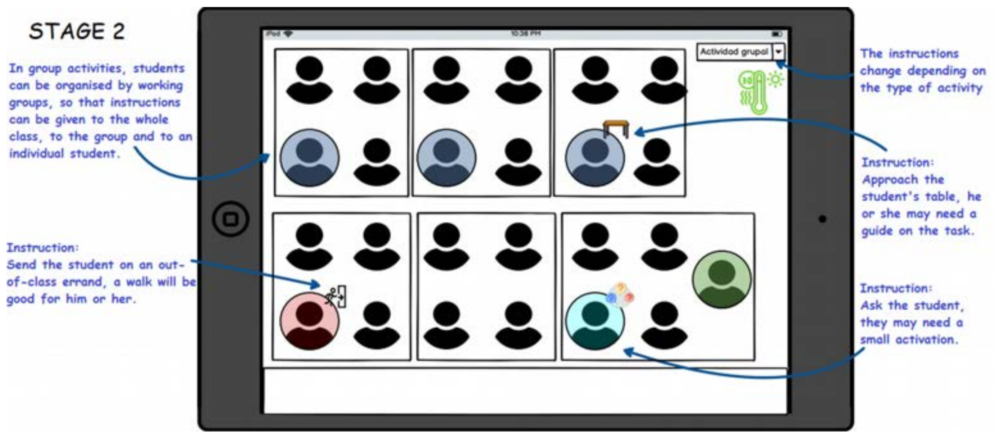
Stage 2

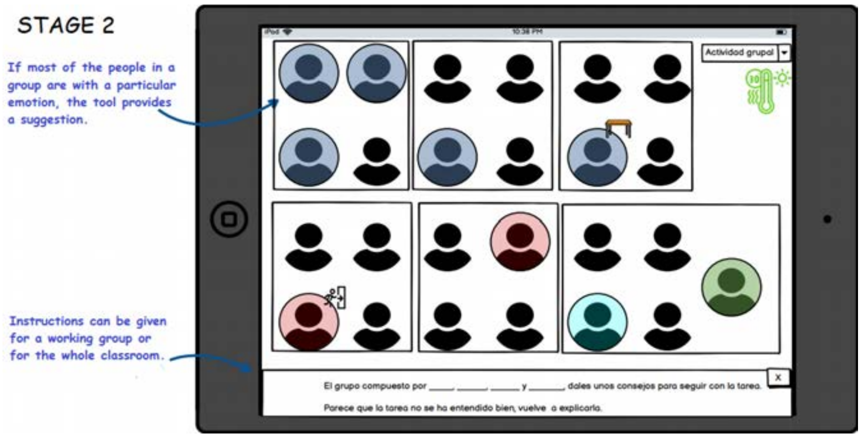

STAGE 2
At this stage, the possibility of choosing the type of activity is added, and depending on the type of activity, suggestions are made to teachers for individual students and groups.
A distinction will be made between types of activities that can be carried out in class:
- Lecture class
- Individual work
- Group work
The indications proposed will depend on the activity to be carried out.
If a percentage of the class shares an emotion the tool offers the teacher an action (this can be one or two options to suit).
Clase expositiva
Cambia de actividad, necesitan movimiento
Cuenta una noticia interesante sobre la temática


STAGE 2
Clase expositiva
Ambiente de la clase
Temperatura
Niveles de CO2
Iluminación
Expositiva
Grupal
Individual
Acústica
Expositiva
Grupal
Individual
Componentes químicos
Virus
If the classroom has the facilities, automatically when the type of activity is chosen, the classroom lighting and acoustics are adapted to the type of activity. It can be modified by the teacher if it is required.


STAGE 2
If the student persists in an emotion or state for more than X minutes, the tool offers individual actions. The icons and suggestions depend on the activity proposed.
The teacher can move the student's pictures around the screen, placing them where they are sitting. This makes it easier to recognise them. It would be interesting if the bracelet could detect the position and place them, but it does not provide such an accurate location.
Instruction: Get his or her attention
Clase expositiva
Instruction: Go to his o her table
Instruction: Ask him or her, make the most of his or her motivation

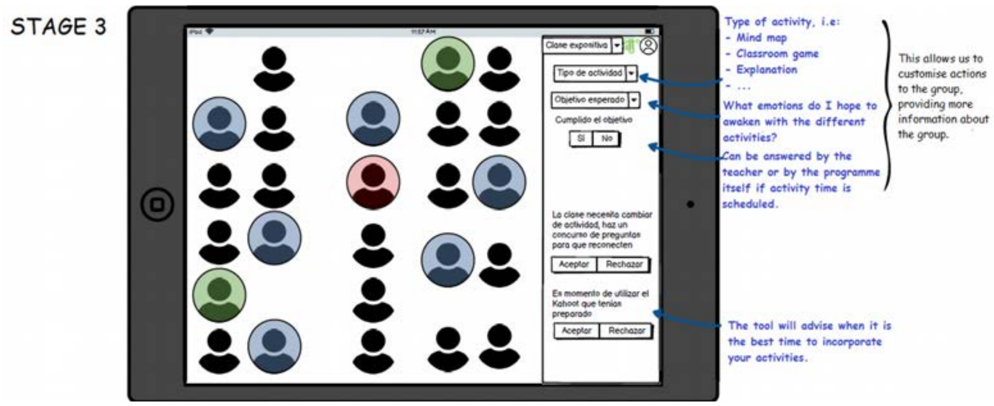

STAGE 2
Trabajo individual
Instruction: Talk to the student, maybe he or she has something to tell you.
Instruction: Congratulate the student on their performance, encourage them to keep doing it.

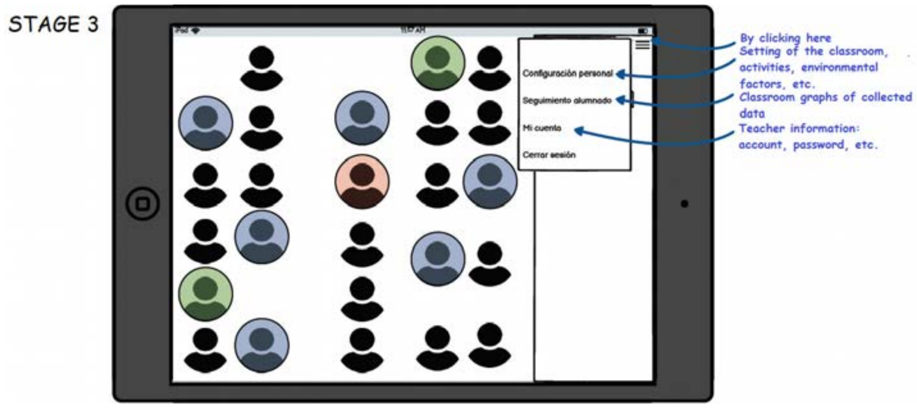

STAGE 2
In group activities, students can be organised by working groups, so that instructions can be given to the whole class, to the group and to an individual student.
Instruction: Send the student on an out-of-class errand, a walk will be good for him or her.
Actividad grupal
The instructions change depending on the type of activity
Instruction: Approach the student's table, he or she may need a guide on the task.
Instruction: Ask the student, they may need a small activation.

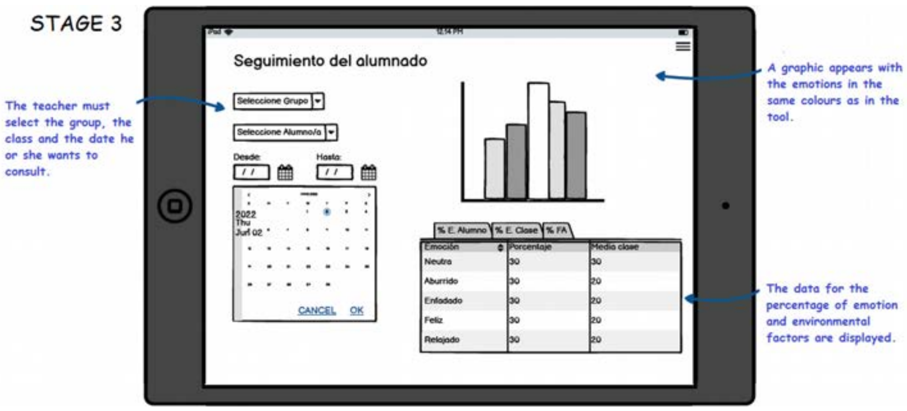

STAGE 2
If most of the people in a group are with a particular emotion, the tool provides a suggestion.
Instructions can be given for a working group or for the whole classroom.
Actividad grupal
El grupo compuesto por ____, ____, ____ y ____, dales unos consejos para seguir con la tarea.
Parece que la tarea no se ha entendido bien, vuelve a explicarla.
X

Stage 3


STAGE 3
This phase incorporates actions customised to the class
Sugerencia
La clase necesita cambiar de actividad, puedes hacer un concurso de preguntas para que reconecten
Aceptar
Rechazar
User settings
The tool suggests options to teachers that they can accept or reject. This registration is important to determine whether the actions taken have an effect on the students.
This pop-up will appear for a limited time, if the teacher does not accept or reject within a certain time it will disappear from the screen.
The software will store information about the actions taken and the effects on the learners. All actions will have a percentage, at first the actions will work randomly.If they have an effect on the students, taking into account variables such as emotions, time or type of activity, the activity is assigned with a percentage. The actions with the highest percentage will have the highest potential to be proposed.
These messages are sent to the teacher every X minutes in order not to interrupt and distract. The messages can be visual or auditory, and can be modified by the teacher. The sound messages will be a wake-up call, when the situation is considered more urgent.


STAGE 3
Tipo de actividad
Objetivo esperado
Cumplido el objetivo
Si
No
La clase necesita cambiar de actividad, haz un concurso de preguntas para que reconecten
Aceptar
Rechazar
Es momento de utilizar el Kahoot que tenías preparado
Aceptar
Rechazar
Type of activity, i.e:
- Mind map
- Classroom game
- Explanation
- ...
What emotions do I hope to awaken with the different activities?
Can be answered by the teacher or by the programme itself if activity time is scheduled.
This allows us to customise actions to the group, providing more information about the group.
The tool will advise when it is the best time to incorporate your activities.


STAGE 3
Configuración personal
Seguimiento alumnado
Mi cuenta
Cerrar sesión
By clicking here
Setting of the classroom, activities, environmental factors, etc.
Classroom graphs of collected data
Teacher information: account, password, etc.


STAGE 3
Seguimiento del alumnado
Seleccione Grupo
Seleccione Alumno/a
Desde:
Hasta:
CANCEL
OK
% E. Alumno
% E. Clase
% FA
Emoción
Porcentaje
Media clase
Neutra
Aburrido
Enfadado
Feliz
Relajado
The teacher must select the group, the class and the date he or she wants to consult.
A graphic appears with the emotions in the same colours as in the tool.
The data for the percentage of emotion and environmental factors are displayed.

4.2. Tool validation

For the expert judgment analysis, professionals in the three areas related to the tool were selected and asked to participate in the questionnaire. The prototype was designed in three phases, with increasing levels of development difficulty. Each of these phases was evaluated in the questionnaire, which is made up of two parts: Firstly, a quantitative section with a Likert-type scale in which the following criteria are evaluated: Level of suitability (Is it suitable for achieving the desired aims? Is it influential in the teaching-learning process?) and the level of viability or usability (Is it a useful tool for the teacher? Is it easy to use in the classroom?). Secondly, a qualitative section with open questions on the level of importance (Is it significant? Does it stand out from other possible factors to be considered? Does it provide important data?).

Taking into account that the tool is a new element as well as the controversy that these tools generate among professionals, in order to analyse and improve the tool, when the average is higher than 3.8 the tool is considered adequate, if the scores are between 3.7 and 2.5 small modifications should be made, and if the scores are lower, then this part should be reconsidered.

The results obtained are shown in the table, with the total arithmetic averages and also the professionals' arithmetic averages.

	Stage 1				Stage 2				Stage 3			
	Res	**IT**	**Tea**	χ	**Res**	**IT**	**Tea**	χ	**Res**	**IT**	**Tea**	χ
Convenience	4.5	4.5	4.4	4.5	4.7	3.7	4.2	4.5	3.7	3.5	3.7	3.9
Usability and feasibility	4.2	4.2	3.8	4.1	4.5	4	4.2	3.7	3.7	4	3.7	3.8
Significance	4.7	4.2	4	4.5	4.2	3.4	4.2	4.2	4.2	3.8	4.2	3.9

Note. The data collected in the "Res" box is the average from the researchers, in the "IT" box the average from the computer scientists, and in the "Tea" box the average from the secondary school teachers, and X is the overall arithmetic average

Table 1. Data collected from the expert judgement.

The qualitative data collected show that the tool is straightforward, schematic, simple and easy to use, especially in the early stages. There are doubts about whether it can become an additional workload, a distracting factor or be overwhelming for the teacher.

There are different opinions about monitoring and following the tool's instructions. Some experts are motivated by the prototype, believing that it improves student motivation and teacher performance, and that storing graphs and information can be valuable. However, other experts are concerned about the added sense of control that students may feel and the loss of connection and empathy that the teacher needs to develop. In addition, some teachers may not accept the suggested indications in a positive way.

Concerning the model used for emotion sampling, the experts propose other theories such as Ekman's seven basic emotions model.

Finally, the experts highlight the need to increase resources and training for teachers, and the importance of taking advantage of technology's potential benefits in the teaching-learning process.

5. Discussion and Conclusions

Using digital technologies can facilitate the teaching-learning process, making it customized and interactive (Yánez, Thumlert, Castell & Jenson, 2019), and have a positive effect on teachers and learners by improving their wellbeing and guaranteeing success in the process.

We are considering including other environmental factors, such as dust; however, there is no agreement on the influential factors in smart classrooms, and as Mogas et al. (2020) state, up to now only isolated or tangential studies have been carried out. According to the same authors, the most characteristic environmental factors considered are temperature, air quality, lighting and acoustics.

A multi-dimensional model is used to capture emotions. Discrete models, such as Ekman's, may be insufficient to describe emotions that require more than one word to define them, unlike dimensional models that consider a continuous space in which each dimension represents a fundamental property common to all emotions (Valenza & Scilingo, 2014). This model has been chosen due to its simplicity and the 75% accuracy that it has demonstrated (Zhao et al., 2018). Furthermore, this accuracy can be increased by working in conjunction with the Azure camera.

The results reveal the experts' concerns about monitoring emotions; however, according to Schutz and Pekrun (2007), emotions are vital for learning, motivation and identity development and health. This supports the necessity of using measurement instruments to analyse and evaluate emotions in the classroom (Pekrun, Goetz, Frenzel, Barchfeld & Perry, 2011).

The multi-sensor system serves as a data collection system without interfering with the teaching-learning process and obtaining reliable information. Accordingly, Gravina, Alinia, Ghasemzadeh and Fortino (2016) determine the advantages and motivations of multi-sensor data fusion, stating that this fusion technology has a mature foundation that provides a satisfactory performance.

The results collected show that the tool's instructions are sometimes rejected due to the differentiation between the human factor and the machine factor, rather than seeing them as two elements that work together for a better outcome. A similar and practical example is automated driving, which has the potential to reduce the number of fatal crashes, lighten the burden of daily travel, and democratize access to mobility in the wider population (Alyuz, Aslan, Healey, Alvarez & Esme, 2018). Like the vehicle, accurate and early detection is needed to carry out real-time actions (Botta, Cancelliere, Ghignone, Tango, Gallinari & Luison 2019); however, insufficient research has been conducted in the educational setting to be able to provide data in this regard. The user's trust in the instrument and the tool's intelligence is a crucial factor and one of the biggest challenges in the automotive sector today. Likewise, authors such as Koo, Kwac, Ju, Steinert, Leifer and Nass (2015) highlight the understanding of emotions and trust as key aspects for affective computing in the car. The same needs emerge in the educational field to face the lack of motivation or control over decisions.

These tools have the potential to generate information, facilitating decision making and positively enhancing the task outcomes (Albright, Winston & Zappe, 2010). This decision making needs to be based on a significant amount of information, and the actions require people who are specialized in analysing, understanding and interpreting data that could be complex and extensive (Vázquez-Ingelmo & Therón, 2020). Therefore, tools such as control panels or dashboards make it easier to analyse and generate content (Sarikaya, Correll, Bartram, Tory & Fisher, 2018), and make the tool useful for teachers, identifying the user patterns and variables related to the learning process.

However, although these tools are able to collect information continuously and truthfully, their accuracy is limited. When the focus is on emotions, as previously mentioned, it is sometimes difficult to identify them because people do not express their emotions in the same way or sometimes hide them.

During the research process, difficulties were identified that may have affected the study. One limitation was that it is a new topic with limited references, and consequently there are aspects that could not be determined, such as timing for showing emotions in a way that does not interfere as a distracting element in the teaching process. Therefore, tests should be carried out. In addition, more iterations on the product are recommended. We suggest including more items in the questionnaire, and each item should have only one question. Finally, this type of research can generate rejection and controversy. Data collection and monitoring can lead to ethical conflicts and a lack of privacy for individuals.

5.1. Implications, Impacts and Future Challenges

The following research has implications in different sectors linked to technology and education. It is beneficial and has an impact on the economy, culture, politics and other services (European Commission, Directorate-General for Research and Innovation, Flecha, Radauer & Besselaar, 2018). It promotes interdisciplinary projects, where different areas must work together to address the challenges of today's teaching, starting from designing a potential tool for improving teaching quality.

The tool provides valuable data for the educational practice. It is not intended to replace the teacher, rather it aims to be an aid for decision making according to objective data to enable academic success. However, there may be corporate, legal and/or ethical barriers to implementing this type of system in the workplace.

The use of technologies and data processing in the educational environment generate debate around privacy, confidentiality and data security and how to handle them responsibly (Mandinach & Jimerson, 2016). In addition, ethics issues may arise from the use of AmI cameras and systems that will need to be addressed with all the ethical and legal safeguards. This may generate side research about how to deal with these issues in the best possible way.

Finally, it should be noted that, historically, classroom practices have not been open to external evaluation, which has been a barrier to improving teaching practices. This line of research is seen as an opportunity to help teachers to improve their practices and at the same time enhance their work quality, which may have repercussions for the quality of their lives.

5.2. Future Lines of Research

This research is only a first phase of design, creation and implementation of this tool. The next step is to develop the tool and test and implement it in the classroom.

In future research, data collection can be extended by using other devices, such as voice or body analysis, which would make it possible to detect emotions with greater accuracy. Monsalve-Pulido and Parra-Rodriguez (2018) showed that 89.0466% effectiveness is obtained for the selected dataset by using Kinect technology and the KNN algorithm.

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