DECANATURA DE INGENIERÍA INDUSTRIAL

MAESTRÍA EN INGENIERÍA INDUSTRIAL

FORMATO DE ENTREGA TRABAJO DE GRADO

Fecha de entrega: 27 de julio de 2021

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El presente documento avala la entrega del trabajo de grado por parte del director y codirector.

Documentos anexos: copia digital del Trabajo de Grado (1).

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Publicado en 2021 por la Escuela Colombiana de Ingeniería Julio Garavito. Avenida 13 No 205-59 Bogotá. Colombia
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Acknowledgments

To my mother, Lucila, for being my unconditional support throughout my professional process, for giving me the example and the strength to fight for my dreams, for supporting me in the most difficult moments, and for the sacrifices she has made to give me the opportunity to complete my master's degree.

To my aunt, Cristina, for her accompaniment, her advice, and her support during the development of my career since it provided me with bases for developing my master's degree.

To my father, Rafael, my sister, Dayana, and my family, for always being there when I need them, for the confidence and motivation they give me daily.

To my boyfriend, Diego, for supporting each of my decisions, for motivating me when I needed a word of encouragement, for sharing his knowledge, helping me, and advising me during the development of the master's degree.

I am immensely grateful to my thesis directors, the engineers Ivonne Castiblanco and Joan Paola Cruz, for their patience, their assertive orientation, their willingness at each stage of this process, for trusting me and making the initial idea of this research come true and culminate it in the best way.

To Juan Sebastián Gómez, who was a co-author in the development of the research article, for his advice and for the knowledge he contributed to obtain the results of this study.

To the engineer Sonia Jaimes, for giving me the opportunity to be a graduate research assistant and for the example she gave me as a professional and as a person.

To the Escuela Colombiana de Ingeniería Julio Garavito, because it allowed me to train as a professional, complete my master's degree with a full scholarship and be a graduate research assistant.

I thank God, for my life, my family, the opportunities I have had and for being my strength.

Abstract

The COVID-19 emergency forced educational institutions to adopt measures that would allow them to continue their educative processes in a virtual environment. The various obstacles that students have had to face have affected their engagement and motivation. Identifying factors such as student cognitive engagement in distance learning allows make timely decisions that favor the learning process. In this study, an exploratory investigation was carried out to identify student cognitive engagement in distance lessons, through heart rate, using heart rate bands in university students of the industrial engineering program in Colombia. With the data treatment and the use of a quadrant model, which related a non-self-report method (heart rate) with a self-report method (questionnaire), we obtained the following results: the heart rate has a significant variation during an active learning activity, which can be positive or negative, this indicates that the students experience cognitive engagement; the trend of the heart rate during a lesson depends on internal factors that are directly related to the active learning activities developed, and passive learning activities like the projection of a video can cause an increase in heart rate if students are instructed to do an activity after the video. We expect this study provide input for future research assessing student cognitive engagement using physiological characteristics as a tool.

Resumen

La emergencia del COVID-19 forzó a las instituciones educativas a adoptar medidas que les permitieran continuar sus procesos educativos de forma virtual. Los diversos obstáculos que los estudiantes han tenido que afrontar han afectado su compromiso y motivación. Identificar factores como el compromiso cognitivo estudiantil en clases remotas permite tomar decisiones a tiempo que favorezcan el proceso de aprendizaje. En este estudio se realizó una investigación exploratoria para identificar el compromiso cognitivo estudiantil en clases remotas, por medio de la frecuencia cardiaca, utilizando pulseras inteligentes para la medición del ritmo cardiaco en estudiantes universitarios de un programa de ingeniería industrial en Colombia. Por medio del tratamiento de los datos y el uso de un modelo de cuadrante, el cual relacionó un método de no autoinforme (ritmo cardiaco) con un método de autoinforme (cuestionario) se obtuvieron los siguientes resultados: el ritmo cardiaco tiene una variación significativa durante una actividad de aprendizaje activo, la cual puede ser positiva o negativa, esto indica que los estudiantes experimentan compromiso cognitivo; la tendencia del ritmo cardiaco durante una clase depende de factores internos que están relacionados directamente con las actividades de aprendizaje activo desarrolladas y las actividades de aprendizaje pasivo como la proyección de un video pueden generar un incremento en el ritmo cardiaco si los estudiantes tienen la instrucción de realizar una actividad luego del video. Esperamos que este estudio proporcione información para futuras investigaciones que evalúen el compromiso cognitivo de los estudiantes utilizando características fisiológicas como herramienta de medición.

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1 Introduction

Education has allowed society and its territories to be transformed. As society changes, the education style must adapt to its demands (Bertel-Narváez et al., 2019). Educational institutions focus their resources to achieve quality teaching and professional development for their students, who expect the pedagogy of education to be more suitable, reasonable, interactive, agreeable, and practical (Markopoulos et al., 2020). Achieve these expectations directly impact student engagement and become a matter of concern for teachers and institutions; therefore, measuring student engagement becomes a valuable and necessary tool for institutions (Markopoulos et al., 2020). Student engagement has been defined as the physical or mental energy and effort students apply and invest in their academic environment (Bedenlier et al., 2020). Also, student engagement envelops the disposition and energy that students maintain in a learning process, persistence in the face of obstacles, and the value given to learning (Zhou et al., 2021). A higher level of student engagement generates a deeply learning, active participation, and positive response to challenges (Zhou et al., 2021).

The interest in raising student engagement has led to the importance of its measurement (Whitehill et al., 2014; Zhang et al., 2019). Its measurement can be used to establish the best way to implement teaching methodologies, assess the quality of education, and give feedback to teachers (Bikanga Ada & Stansfield, 2017; Ma et al., 2018). So far, in Colombia, student engagement has been measured using self-report methods, such as questionnaires, in which students directly report their perceptions; sometimes, these methods can be subjective and divert attention (Darnell & Krieg, 2019). Furthermore, according to the literature review, a different approach has not yet been implemented in this country.

Higher education has been affected by the pandemic of COVID-19, generating impacts on education systems. Institutions have had to adapt their methodologies to a virtual environment and implement new teaching and online assessment strategies (García-Alberti et al., 2021), this transition has received different terms like: remote teaching, online learning, or distance learning (Gelles et al., 2020). Some obstacles that students have had to face with this situation are an unstable internet connection, restricted access to technological tools, and inadequate space to take classes (Gelles et al., 2020). Lassoued et al. (2020) have classified these difficulties into four categories: personal (self-imposed), pedagogical, technical, and financial obstacles.

This paper presents the results of an investigation conducted in Colombia to measure cognitive student engagement by measuring students' heart rate during the COVID-19. In the United States, Darnell D. K. and Krieg P. A. (2019) implemented a similar method in a group of medical students; the researchers measured cognitive student engagement using wristwatch-style monitors, which detected and recorded the heart rate of the study subjects during lecture classes that applied active learning activities. In India, Senthil and Lin (2018) performed a study using a wireless wearable sensor to collect the heart rate of university students for measuring engagement, comparing the heart rate in a state of rest against the heart rate during active learning activities in lecture classes.

The present study's objective is to make an exploratory review similarly to the analysis proposed by Darnell D. K. and Krieg P. A. (2019) and adapted for this study. In this research we analyzed the cognitive engagement, measuring the heart rate through a heart rate band, in a group of university students of the industrial engineering program at Escuela Colombiana de Ingeniería Julio Garavito in Colombia.

The structure of this paper is the following: first, we introduce a background of previous works focused on the diverse methods for measuring cognitive student engagement. Next, we present the methodology, divided into three phases: (1) research preparation, which describes the instruments and tools necessaries for began the data collection, (2) execution of the research, this phase includes the collection of three types of data, quantitative data of heart rate, qualitative data of annotations took by the researchers during the development of each lesson, and the qualitative data of the questionnaire, (3) and data treatment, in this phase we proceed to the cleaning and processing of data for validating five hypotheses, as well as the comparative analysis of the non-self-report method vs the self-report method using a quadrant model. Then, we proceeded to the analysis and results of the three phases of the methodology. Finally, we reported our conclusions and future directions of research.

2 Background

Student engagement can be perceptible in the behavioral, cognitive, or affective dimensions (Bedenlier et al., 2020). Behavioral engagement occurs when students get involved in their learning, for example, selecting times or places to study (Xie et al., 2019). Cognitive engagement happens when students make a mental effort on the topic they are learning; when students use deep or superficial study methods, they can identify the type of mental effort (Xie et al., 2019). Finally, affective engagement refers to the students' emotions, such as interest, enjoyment, or frustration (Xie et al., 2019).

In the literature, the studies found have implemented different methods to measure student engagement; these methods can be classified into two categories: self-report methods and non-self-report methods (Zeng et al., 2020). One of the characteristics of the self-report methods is that the study subjects report the data directly. The most used tools are questionnaires and interviews. On the other hand, the non-self-report methods use tools that allow collecting the data without consulting directly with the study subject, such as capturing a video during class, which can later be used to analyze the emotions that the person experiences (Zeng et al., 2020).

Different countries have used self-report methods; in most cases, the researchers used questionnaires or surveys created or adapted from previous investigations. Table 1shows some studies that have used self-report methods.

Table 1. Measurement methods self-report

Author	**Study title**	**Year of publication**			**Measurement method**	**Research location**	**Level of education**	
		2010-2015	**2015-2018**	**2018-2020**	**Method detail**	**Place-Country**	**School**	**College**
Lei et al.	Engagement data of robotic students in a synchronous-hybrid course			x	Conducting a national survey of student engagement in a telepresence environment.	USA		x
Dekhane et al.	Mobile App Development to Increase Student Engagement and Problem Solving Skills			x	The students had to develop mobile games; with a questionnaire and a pre and post quiz, the researchers evaluated the variables.	USA		x
Awang-Hashim R. et al.	Malaysian University Student Learning Involvement Scale (MUSLIS): Validation of a			x	Measurement of student engagement through the MUSLIS questionnaire.	Malaysia		x

	Student Engagement Model						
Alioon and Delialioğlu	The effect of authentic m-learning activities on student engagement and motivation	x		Measurement of the student engagement and motivation through the NSSE- National Survey of Student Engagement and MSLQ- Motivated Strategies for Learning Questionnaire.	Turkey		x
Zhoc et al.	Higher Education Student Engagement Scale (HESES): Development and Psychometric Evidence		x	Development of a case study using the HESES-Higher Education Student Engagement Scale survey.	Hong Kong		x
Ma et al.	Initial Development Process of a Student Engagement Scale in Blended Learning Environment		x	Design of a survey based on the NSSE.	China		x
Balaam et al.	Exploring Affective Technologies for the Classroom with the Subtle Stone	x		By means of the "Subtle stone", a handheld orb, students inform what they feel when they press it.	United Kingdom	x	

In the USA, the researchers have used surveys and questionnaires to measure student engagement; they carried out activities different from the traditional class. In one case, Lei et al. (2019) applied the National Survey of Student Engagement in a lesson composed of six people; three of them were physically present, and the other three in telepresence. Other study, the students developed a mobile game using a tool (GameSalad) created by the researchers, and then they measured student engagement using a questionnaire (Dekhane et al., 2013).

In Malaysia, Awang-Hashim R. et al. (2012) used a survey to evaluate the scale of participation in student learning at the University of Malaysia (MUSLIS) consisting of 24 items; later, they performed the data analysis using specific software. In Turkey, Alion and Delialioğlu (2019) implemented m-learning material in a computer networks course to measure student engagement and motivation using the NSSE- National Survey of Student Engagement and the MSLQ- Motivated Strategies for Learning Questionnaire, m-learning is the method that allows students to acquire certain types of knowledge anywhere and anytime utilizing wireless technologies, here is important to state that e-learning materials are designed to be watched on computers, while the visualization of m-learning materials is better on tablets or smartphones.

In China, Zhoc et al. (2019) applied the HESES-Higher Education Student Engagement Scale survey, which allowed to evaluated five facets of student engagement: academic engagement, cognitive engagement, social engagement with classmates, social engagement with teachers, and affective engagement. Other study applied a survey to measure student engagement, Ma J. et al. (2018) used a guide for the formulation of projects of innovation and technological development in a mixed environment, that is, the combination of face-to-face and virtual class; the survey evaluated three modules: behavioral, cognitive and emotional behavior.

Although questionnaires and surveys are the most common tools, some researchers have used other tools; for instance, in the United Kingdom, Balaam et al. (2010) developed a hand-held orb named Subtle Stone for implementing an interactive method with the students, study subjects had to press the Subtle Stone to indicate the emotion that they were experimenting in a class.

Table 2 presents some studies that have used non-self-report methods in different countries. These methods usually collect and analyze data on the physiological characteristics of the study subjects, such as facial expressions, eye movement, heart rate, among others.

Table 2. Measurement methods non-self-report

Author	Article title	Year of publication			Method of measurement	Research location	Student level of the study subject		
		2010-2015	2015-2018	2018-2020	Method detail	Place-Country	School	College	Not applicable
Zeng H. et al.	EmotionCues: Emotion-Oriented Visual Summarization of Classroom Videos			x	Recognize emotions by analyzing facial videos.	China/ Hong Kong	x	x	
Zhang H. et al.	An Novel End-to-end Network for Automatic Student Engagement Recognition			x	Face recognition with I3D- processing of 3D images or videos	China		x	
Alkabbany et al.	Measuring Student Engagement Level Using Facial Information			x	Detect facial actions (head posture, gaze).	USA		x	
Farrell et al.	Real Time Detection and Analysis of Facial Features to Measure Student Engagement with Learning Objects			x	An application identified the emotional state and the position of the head.	Ireland / Dublin	N/A		
Whitehill J. et al.	The Faces of Engagement: Automatic Recognition of Student Engagement from Facial Expressions	x			They collect facial expressions and analyze them with machine learning (ML), a program that detects high or low interaction.	USA		x	
Sakulchit et al.	Evaluation of Digital Face Recognition Technology for Pain Assessment in Young Children			x	A program, API (Application Programing interface), analyzed images taken of the face and identified emotions of the study subjects.	Canada			x
Herpich F. et al.	Mobile Augmented Reality impact in Student Engagement: an Analysis of the Focused Attention dimension			x	They measured student brain signals to see the impact of augmented reality on student engagement.	Brazil		x	

Hayashi et al.	A Quantitative Study on Learner Engagement Evaluation: Integrated Analysis of Biosignals Including Pulse Wave and Eye Movements	x	Measuring eye movement with three electrodes built into glasses.	Japan	x	x
Darnell and Krieg	Student engagement, assessed using heart rate, shows no reset following active learning sessions in lectures	x	They measured students' heart rate for identifying cognitive students engagement.	USA		x

Some studies conducted in China, the USA, Canada, and Ireland analyze facial expressions to determine factors such as emotions or student engagement. In Hong Kong, Zeng H. et al. (2020) developed an analytical system that recognizes emotions through facial expressions, named EmotionCues; they use a camera and software that detects which emotion a student is expressing. In another study conducted in China, Zhang H. et al. (2019) identified affective states such as boredom, confusion and engagement through a facial recognition system. In the USA, Alkabbany et al. (2019) recorded a video during a reading of 10 to 15 minutes; this video focused on the angle of the posture of the face and the gaze, after, the researchers analyzed these characteristics to identify student engagement; in another study also carried out in the USA, Whitehill J. et al. (2014) analyzed facial expressions using Machine Learning to determine the level of engagement. In Canada, Sakulchit et al. (2019) identified the emotions that children experienced before, during and after taking a blood sample through facial expressions and in the case of Ireland, using an application, Farrell et al. (2019) analyzed the subject's head posture to determine if the student was looking at the screen. Thus, they detected the person's emotional state, which finally allowed to determine the student engagement.

Other physiological characteristics analyzed in the studies presented include the study of brain signals and eye movement. In Brazil, Herpich F. et al. (2018) measured the signals emitted by the brains of students when interacting with educational technology. In Japan, Hayashi et al. (2019) used lenses with integrated electrodes to analyze the user's eye movement and thus determine the student engagement.

Finally, the heart rate is another physiological characteristic that researchers have used to measure student engagement (Darnell & Krieg, 2019; Senthil & Lin, 2018). In a study performed in the United States, Darnell D. K. and Krieg P. A. (2019) measured student engagement, specifically cognitive engagement, analyzing the students' heart rate. Researchers analyzed the heart rate behavior using wristwatch-style monitors during active learning activities.

The heart rate has been a tool widely used for identifying and monitoring emotions, attention, autonomic process and mental conditions (Chen et al., 2019; Park et al., 2019; Ruiz-Padial et al., 2003; Siennicka et al., 2019; Zhu et al., 2019), heart rate is associated with the autonomic nervous system which responds to a stimulus or resting states (Forte et al., 2019; Siennicka et al., 2019). Emotions have three components: cognitive, physiological and behavior (Zhu et al., 2019). These components allow researchers to use the heart rate to measure more advanced factors like cognitive engagement (Darnell & Krieg, 2019; Forte et al., 2019). The advantages of using heart rate include it is non-invasive, easy, and cheap to get (Siennicka et al., 2019; Zhu et al., 2019), experiments with heart rate are simple to set up and can be used in conjunction with other biometric measures like facial expressions and respiration (Monkaresi et al., 2017; Yamuza et al., 2019). The disadvantages associated with the heart rate are the conditions of the environment under which happen the data collection since they are challenging to eliminate, and also the response time to a stimulus is long, these two points generate more uncertainty (Chen et al., 2019; Valderas et al., 2019; Wollmann et al., 2016).

Active learning activities allow improving and inducing student engagement (Nepal & Rogerson, 2020; Ross & de Souza-Daw, 2021). The concept of active learning refers to activities that induce students in a thinking process about the new information and connect it with past experience or knowledge (Han, 2021; Nepal & Rogerson, 2020). There is a great variety of activities that can be considered as active learning such as discussion in small groups, peer activities, individual activities that required a mental effort, interactions, study cases, problem resolution, laboratories, quizzes, and games, all of them have to guarantee that students think effectively (Han, 2021; Nepal & Rogerson, 2020; Romero et al., 2021; Ross & de Souza-Daw, 2021; Sugino, 2021). The advantages involve that students feel more secure sharing their ideas in small groups, develop critical thinking, retain new knowledge, develop communication and leadership skills, and feel more motivated and interested (Han, 2021; Hernández-barco et al., 2021; Nepal & Rogerson, 2020; Romero et al., 2021; Sugino, 2021).

In Colombia and Latin America, as some researchers stated, the investigations regarding education and student engagement have focused efforts on the following topics: study habits and motivation for distance learning (Acevedo et al., 2015), academic dropout and its relationship with the student's conditions and the organizational context of the academic institution (Hederich-Martínez C. & Caballero-Domínguez C.C, 2016) the relationship between student engagement and academic performance determined through the academic mean (Pineda Báez et al., 2014), the relationship that emotional intelligence and happiness orientation have with student engagement (Durón-Ramos et al., 2020).

Another research examines the opinion of students in schools regarding how they experience student engagement after conducting, recording, and analyzing surveys (Pineda-Báez et al., 2019). Bertel-Narváez M. P. et al. performed a literary review about education in Latin America, highlighting that the motivation of learning is a fundamental aspect of developing research in Latin America (Bertel-Narváez et al., 2019). Studies and research developed in Colombia have used traditional methods such as interviews, surveys, questionnaires, and the corresponding analysis. However, in this country, the studies developed have not yet used more advanced methods, which measure student engagement with physiological characteristics.

In Colombia, the studies performed have not implemented a method that uses physiological characteristics to measure cognitive engagement. This work developed an exploratory research, similarly to the analysis proposed in the United States by Darnell D. K. and Krieg P. A. (2019) and adapted for this study during the pandemic. We used the heart rate for measuring cognitive student engagement. For collecting data, the students used a heart rate band linked to a mobile application while participating in lessons that contained active learning activities; every student collected her or his heart rate during four lessons; the total data collection took three months. This research took place at Escuela Colombiana de Ingeniería Julio Garavito in Bogotá, Colombia, in a sample of 20 students, of which we discarded four students after data cleaning.

3 Methodology

This study adopted the methodology developed by Carrasco and cited by Viñan J.A. et al. (Viñán Villagrán et al., 2018). It consists of three phases (Table 3); the first phase entails the research preparation, the second phase the execution of the research, and the third phase regards the data treatment.

Table 3. Research methodology

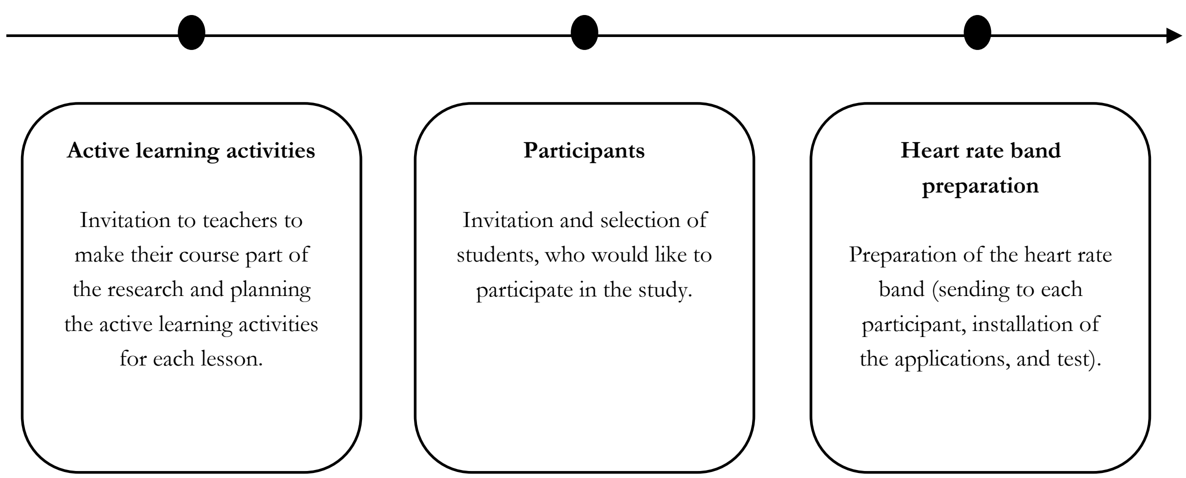
METHODOLOGY		
Phase 1	**Phase 2**	**Phase 3**
Research preparation	**Execution of the research**	**Data treatment**
• Active learning activities. • Participants. • Heart rate band preparation.	• Quantitative data (non-self-report method). • Qualitative data of annotations. • Qualitative data of the questionnaire (non-self-report method).	• Data Cleaning. • Data processing. • Non-self-report method vs self-report method

The development and detail of each phase is described below.

Phase 1. Research preparation

This phase consists of four activities to prepare instruments and tools necessary for began the data collection. Figure 1 details each activity.

Figure 1. Research preparation



Below, we explain the considerations made for developing each activity.

Active learning activities

All the activities planned with the professor include active learning activities performed in distance lessons during the situation of COVID-19 in the subject of Gerencia de Talento Humano of industrial engineering program of Escuela Colombiana de Ingeniería Julio Garavito; they developed in each lesson the method: Think Pair Share proposed by Kaddoura (Kaddoura, 2013) and adapted to this study, which we detail below:

1. Think: the professor asked a question, observation, case study, or video that induced the student to think. The student had to think and write down the answers.

2. Pair, partner or individual: students had to share the answer with one or two partners to analyze each one and reach a consensus on the best answer to the question asked. When performed individually, the student must perform an activity, as instructed by the professor.

3. Share: then, the professor asked each pair of classmates to share their answers with the whole lesson. However, in some cases, the students did not share their answers but gave the solution to the professor directly.

Participants

The following characteristics were important for selecting the participants:

1. They must be a legal age.
2. They must have a compatible cell phone.
3. They must live in Bogotá or neighboring cities.
4. Students must participate voluntarily.

We developed this study in three courses of the subject analyzed, which had between 26 and 27 students enrolled for a total population of 79 students. We measured the heart rate in a sample of twenty students, of which we discarded four students after cleaning the data, it means that we analyzed the data of sixteen students, which represents 20,25% of the population. The size of the sample was limited by the cost of the heart rate bands, the cost, and the logistical conditions for sending them, in addition, one of the main conditions for which the students decided not to participate in the study was they were in a city far from Bogotá or in areas with difficult access. On the other hand, we defined the number of participants after reviewing the sample used in similar studies carrying out non-self-report methods, which explained that a limitation of this method is that the sample is usually small in comparison with self-report methods for the cost of the tools needed in a non-self-report method (Table 4).

Table 4. Number of participants in studies of non-self-report methods

Study	Number of participants
EmotionCues: Emotion-Oriented Visual Summarization of Classroom Videos	Case 1: 15 children Case 2: 13 students
Multimodal affect recognition in learning environments	8 children
Measuring Student Engagement Level Using Facial Information	14 students
Mobile Augmented Reality Impact in Student Engagement: an Analysis of the Focused Attention Dimension	5 students
A Quantitative Study on Learner Engagement Evaluation: Integrated Analysis of Biosignals Including Pulse Wave and Eye Movements	Case 1: 6 students Case 2: 10 students
Artificial neural networks-based classification of emotions using wristband heart rate monitor data	12 individuals

Heart rate band preparation

This investigation used heart rate bands, which can measure the heart rate with a frequency of one minute; these have a Photoplethysmography (PPG) heart rate sensor, which applies low-intensity infrared (IR) light on the skin. An optical sensor measures light reflection, which changes depending on the blood flow through the illuminated spot. Since blood flow changes during a heartbeat, it is possible to measure the heart rate.

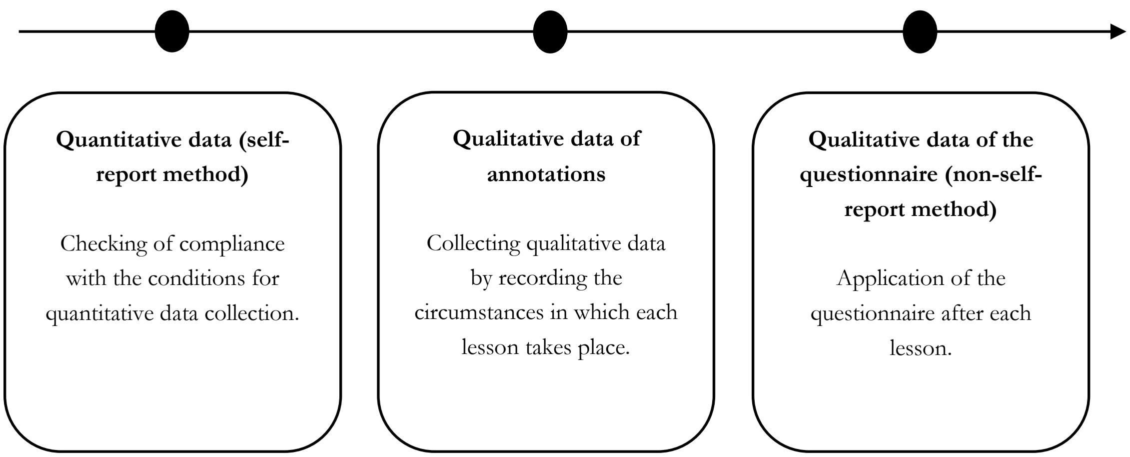
The considerations for preparing the heart rate band were the following:

1. Each course was composed of 5 or 4 students who participated in the research.
2. The heart rate band must be delivered to each participant.
3. Each participant must install the heart rate recording app on their cell phone.
4. To verify the correct functioning of the heart rate band, the students made a preliminary test.

Phase 2. Execution of the research

We divided the execution of the investigation into three categories, which composed the data collected: quantitative data, qualitative data of annotations, and qualitative data of the questionnaire. The quantitative data (obtained through a non-self-report method) refers to data of heart rate collected through the heart rate app during the development of each lesson. The annotations qualitative data refer to the data collected by the researchers while attending each lesson and taking note of the activities carried out and their respective time. Finally, the qualitative data refers to the questionnaire (self-report method) that each student filled out at the end of each lesson, which evaluated the cognitive student engagement. Figure 2 presents each data category collected in this phase. Below, we explain the conditions required in each data category.

Figure 2. Execution of the investigation



Quantitative data (non-self-report method)

The conditions verified in the quantitative data collection were the following:

1. The students must wear the heart rate five minutes before starting the lesson.
2. The students must activate and connect the Bluetooth between the cell phone and the heart rate band.
3. Participants must follow the instruction for measuring the baseline heart rate; it refers to each participant heart rate during a rest state.
4. Participants must connect to the lesson on time.
5. The participants agreed to send the data after finishing each lesson.

Qualitative data of annotations

To collect annotations qualitative data, the researchers considered the following aspects:

1. Identify when the lesson started, splitting the greeting from the main topic.
2. Recognize when active learning activities started and finished.
3. Take note of the moment when participants intervened.
4. Identify activities that can generate some emotions in the participant not planned by the research.
5. Recording the exact time when the lesson ends.

Qualitative data of the questionnaire (self-report method)

A questionnaire is a self-report tool to measure student cognitive engagement. However, using this method will allow comparing the report made by the students and the results obtained with the measurement of heart rate and helping to identify factors that may affect the student's heart rate behavior during lessons.

As described above, the participants filled out a questionnaire after completing each lesson; the main objective is to identify the students' cognitive engagement reported, allowing us to compare the participants' answers and the heart rate behavior.

To identify student cognitive engagement in different contexts, the queries in the questionnaire were selected following three studies, which applied questions focused on measuring student engagement. For the design of the questionnaire for this study, we selected questions focused on measuring student cognitive engagement. Below we show the three studies and the respective questions selected by each one.

Study one: Exploring Factors and Indicators for Measuring Students' Sustainable Engagement in e-Learning (Lee et al., 2019).

In this research through a questionnaire, they analyzed six factors in student engagement in the e-learning environment: factor 1. psychological motivation, factor 2. peer collaboration, factor 3. cognitive problem solving, factor 4. interactions with instructors, factor 5. community support and factor 6. learning management. For our study, we selected and adapted factor 3 (Cognitive problem solving), which correspond with questions 1, 2, 3, 4 and 13 (Table 5).

Study two: Examining engagement in context using experience-sampling method with mobile technology (Xie et al., 2019)**.**
They used the following measures in the survey applied: study time, study location, reasons for study, behavioral engagement, cognitive engagement, self-efficacy, academic motivation, and prior academic achievement. For our questionnaire, we adapted the measures used in cognitive engagement, which correspond with questions 5, 6, 7, 8, 9, 10, 14, 15, 16, and 17 (Table 5).

Study three: Initial Development Process of a Student Engagement Scale in Blended Learning Environment (Ma J. et al., 2018).
In this study, Ma J. et al. designed and constructed a student engagement scale framework in higher education during blended learning environment. They evaluated the three dimensions of student engagement (cognitive, behavioral, and emotional). For our questionnaire, we

selected the items used in cognitive student engagement, which correspond with questions 11, 12, 18, 19, 20, 21, 22 and 23.

Table 5 presents the final format used in the questionnaire, the complementary self-report method used in this study, which the students filled after finishing each lesson.

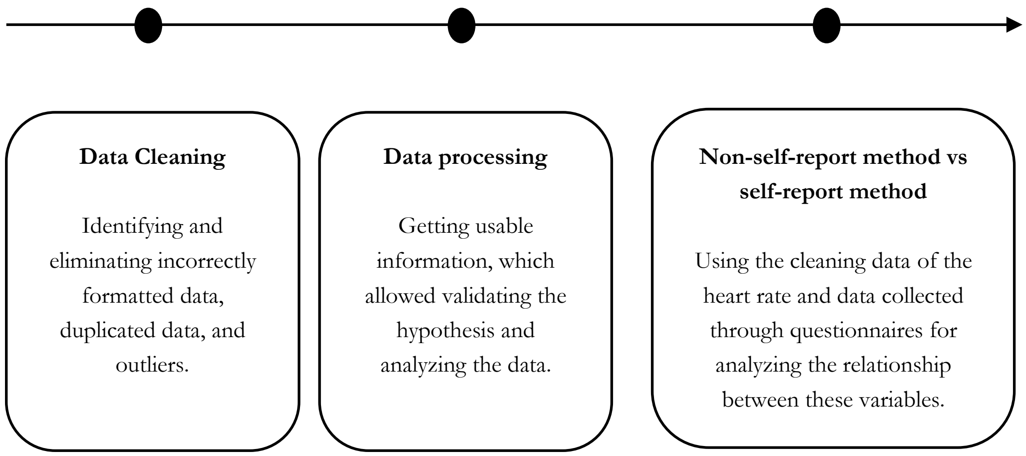
Table 5. Self-report method the questionnaire format

	SELF-REPORT METHOD: THE QUESTIONNAIRE
1	I can deduce new interpretations and ideas from the knowledge I have learned in today's lesson.
2	I can deeply analyze thoughts, experiences, and theories about the knowledge I have learned in today's lesson.
3	I can judge the value of information related to the knowledge learned in today's lesson.
4	I tried to approach the topic of today's lesson with a new perspective.
5	In today's lesson, I tried to learn new material by mentally associating new ideas with similar ideas that I already knew.
6	While learning new concepts in today's lesson, I tried to think of practical applications.
7	I made sure I understood the material I studied in today's lesson. (I am aware of what material I understood or did not understand).
8	In today's lesson, I tried to memorize the answers to the questions in the study guides for the tests.
9	To understand what the technical terms meant, I memorized the definitions provided in the texts or today's lesson notes. (I'm trying to memorize the vocabulary for this lesson).
10	I tried to write down exactly what my instructor said during the lectures in today's lesson.
11	I used what I have learned to solve practical problems in today's lesson.
12	I make connections between the things that I have learned in today's lesson.
13	I tend to apply the knowledge I have learned in lesson to real problems or new situations.
14	When I learned new material, I summarized it in my own words.
15	I mentally combined different pieces of information from the course materials in an order that made sense to me.
16	In doing the readings for the lesson, I tried to figure out what part of the reading would be on the test. (I'm studying the course materials to get the information needed for the test).
17	I study ideas exactly as they are expressed in lesson or in my readings.
18	Establish a learning plan to be able to direct my activities in the lessons.
19	I have clear learning objectives at each stage of the course.
20	I make good use of my study time for this course.
21	I connect what I have learned in this course with another subject.
22	I ask myself questions and think about a topic when I read learning materials from the course.
23	I use what I have learned from homework and tests to promote my next learning step.
24	I think about what I have already learned to understand a new course topic.

Phase 3. Data treatment

This phase included three activities that allowed us to perform the data treatment (Figure 3). The first consisted of cleaning data, the second entailed data processing, and the last compared the non-self-report method with the self-report method.

Figure 3. Data treatment



Below, we present the requirements considered in each activity.

Data Cleaning

First, we organized the data, classifying it into three categories: participants, lessons, and activities. The criteria used for cleaning the data were the following:

1. Transform the date and time data to a single format.

Table 6. Time format

Format 1	Format 2	Standard format
1:02:00 P.M.	13:01:00	1:02:00 PM

2. All participants must have data from at least three lessons; otherwise, it is discarded.

3. We normalized the data and filtered those that were greater than three standard deviations (3SD). Then, we compared the total data with the resulting data after applying the criterion of 3SD and decided to delete data that removed less than 15% of the total data. We considered this criterion and percentage under the following categories: each participant in each lesson.

4. We cleaned the data that did not have modifications in numeral 3 (the normalization with 3SD). We analyzed each activity of each participant in each lesson and eliminated the atypical data.

Data Processing

Intending to have a general view of data, we applied a clustering of all data. After, we processed and organized the data to verify the following hypothesis:

Hypothesis 1: the heart rate may increase during an active learning activity and then return to the mean level.
Hypothesis 2: the heart rate decreases from the beginning to the end of the lesson.
Hypothesis 3: the drop-in heart rate is biphasic, further decreasing during the early stages of the lesson.
Hypothesis 4: the heart rate decreases at the beginning and increases at the end of the lesson.
Hypothesis 5: the heart rate decreases in passive learning activities, such as watching a video.

For each hypothesis, we developed the following data processing:

For **Hypothesis 1:** we selected and labeled active learning activities in each lesson for each participant; we also labeled activities before and after each one, considering only those corresponding to theoretical explanation, beginning of a lesson, or end of a lesson. Subsequently, we plotted the mean heart rate before, after, and during each active learning activity using a data science platform.
For **Hypothesis 2:** for each participant in each lesson, we plotted the heart rate against time. We applied linear regression with the aim of identifying if the heart rate trend decreased or increased.
For **Hypothesis 3:** to analyze the biphasic behavior, we divided the data into two sections. We showed the first twenty minutes of each lesson against the next seventy minutes. We plotted the heart rate against time in each section; finally, we applied a linear regression.
For **Hypothesis 4:** We selected the first and last minutes of each lesson, ranging between 2 to 10 minutes, to analyze the behavior at the beginning and end of each lesson. The time range is variable since each lesson started or finished the topic and activities at a different time. Then, we graphed each time range and applied linear regression to identify the behavior at the beginning and end of each lesson.
For **Hypothesis 5:** We performed the same processing of the first hypothesis, with the difference that at this phase, we selected and labeled the passive learning activities.

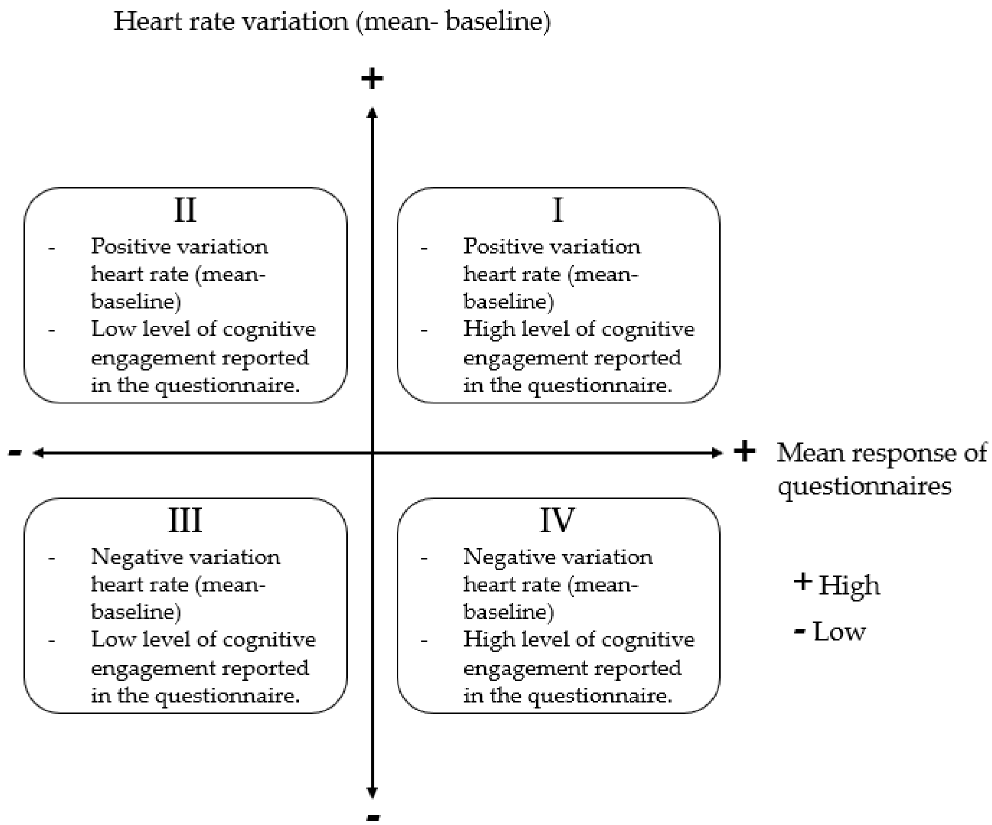
Non-self-report method vs self-report method

In research developed by Nonis et al. suggested combine two types of methods for measuring the engagement, they combined the User Engagement Scale questionnaire with a facial expression recognition system (Nonis et al., 2020). In this section, for analyzing the behavior of quantitative data of the heart rate (non-self-report method) against qualitative data of the questionnaire (self-report method), we performed a quadrant model to show the variation of these two data types (Figure 4).

For quantitative data, we calculated the mean heart rate for each participant and subtracted the heart rate baseline to identify whether there was a positive or negative variation. For the qualitative data of the questionnaire, we calculated the mean response to the questions of questionnaires filled out in each lesson; each question indicates a high or low level of student cognitive engagement, thus if the student's mean response was below 3, it indicated a low engagement, and if it was above 3 it indicated a high cognitive engagement. Quadrant I represented a positive variation of the heart rate and a high level of cognitive engagement reported in the questionnaire by students, quadrant II indicated a positive variation of the heart rate and a low level of cognitive engagement reported in the questionnaire by students, quadrant III represented a negative variation of the heart rate and a low level of cognitive engagement reported in the questionnaire by students, finally, quadrant IV indicated a negative variation of the heart rate and a high level of cognitive engagement reported in the questionnaire by students.

To perform the analysis of the qualitative data, we made a preliminary review of the methods used in the studies that we took as a reference to design the questionnaire and studies focused on measure student engagement with a self-report method, in these studies they used basic statistical measures as: mean, median, mode and, overall standard deviation, also, they used complex methods like: Pearson's correlations of key variables, moderated regressions, moderated hierarchical regression, exploratory factor analysis (EFA), confirmatory factor analysis (CFA), Turker-Lewis index (TLI), root mean square error of approximation (RMSEA), adjusted goodness of fit index (AGFI), relative fit index (RFI), and Standardized RMR (SRMR) (Delfino, 2019; Lee et al., 2019; Xie et al., 2019). After analyzing the methods used in these studies, we discarded complex methods because their application requires having a large amount of data and they are used mainly when analyzing a self-report method as the main measurement method, additionally, in our study, we focus on a dimension of student engagement (cognitive). In the studies described, student engagement was analyzed in its three dimensions (cognitive, behavioral, emotional), with all associated factors and measures. Finally, we applied the arithmetic mean as the method for analyzing the qualitative data based on two criteria, first, in the study of Delfino A.P. (2019) the mean is the statistical method applied for identifying the level of engagement using a Likert scale, a condition that corresponds with the scale used in our study, and the second criterion, the arithmetic mean is the measure that allows made a relation and connection with the data of non-self-report (heart rate) in the quadrant model, a condition that is not possible with the others basic statistical measures for the condition of the heart rate data, which is analyzed with the arithmetic mean in each hypothesis.

Figure 4. Quadrant model of heart rate variation vs mean response of questionnaires



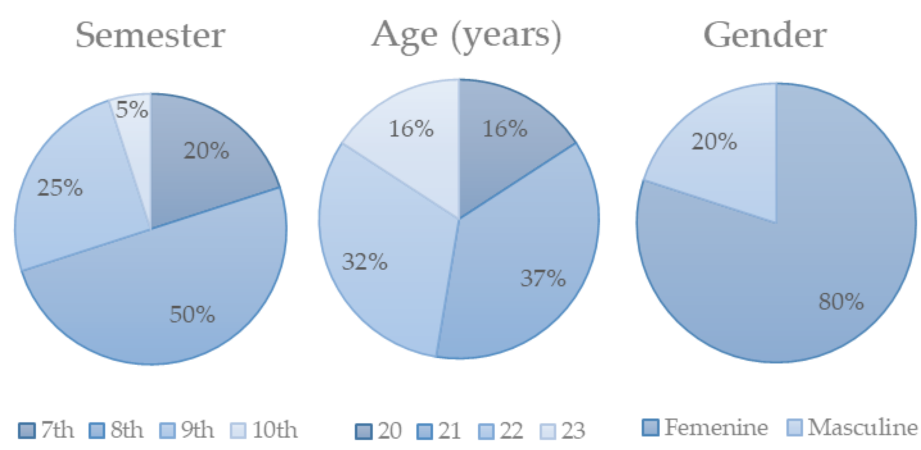
4 Analysis and Results

Phase 1. Research preparation

Four groups of five students of the subject Human Talent Management participated in the research, which were led by two professors. The activities planned and developed in each lesson followed *the method: Think Pair Share* (Kaddoura, 2013). Also, other activities considered were online quizzes, group activities, activities in pairs and individual activities. The lessons were in distance learning using a virtual platform for communication and online programs for the development of the activities.

The twenty participants belong to the industrial engineering program; Figure 5 presents the characteristics associated with them:

Figure 5. Information participants



The participants followed the instruction and conditions for the preparation of the heart rate band. Due to compatibility issues and connection issues, we discarded the data from participant 0 and 19.

Phase 2. Execution of the research

Using the heart rate band, we measured the heart rate of each participant during the lessons. We took note of different conditions that could alter the student's heart rate and the moment in which the professor developed active learning activities. Also, we collected the baseline heart rate of each participant (Table 7). In this study, we used the baseline for identifying the response of the heart rate to activities developed in each lesson; the difference between the baseline and the heart rate could be negative or positive depending on the engagement of each participant. The behavior of the heart rate compared with the baseline is the response to a stimulus, according to the study of Siennicka et al. (Siennicka et al., 2019). We do not show the baseline heart rate of four participants (participant 0, participant 9, participant 18, and participant 19) in Table 7, due to the reasons explained above. In the cleaning data section, we will explain the reason why participants 9 and 18 were also discarded.

On the other hand, we applied the questionnaire described in the methodology, we used a Likert scale to rate each item, as follows: (1) totally disagree, (2) in disagreement, (3) partially agree, (4) I agree, and (5) totally agree. In Table 7, also we show the mean according to the response given by participants in the questionnaire.

Table 7. Mean response in the questionnaire and baseline heart rate for each participant

Participant	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**
Baseline Heart Rate (bpm)	77.2	74.8	70.3	73.3	72.9	77.8	76.9	74.8	78.9	86.0	77.3	71.2	70.7	80.4	75.0	75.0
Mean Questionnaire	3.95	2.72	2.50	4.68	3.83	3.17	3.58	3.42	4.26	3.13	4.42	3.51	3.10	3.94	3.83	3.99

Phase 3. Data treatment

Data cleaning

Applying the criteria described in the methodology, we transformed the data into the same time format in such a way that the data science platform could read it; we used this tool to perform some steps of data cleaning and data processing. We discarded two participants because they had data from less than three lessons (participant 9 and participant 18). Then, we applied the normalization criterion to the participants and lessons show in Table 8. Finally, we analyzed the behavior of each participant in each activity and eliminated the outliers.

Table 8. Data normalized and discarded under the criteria of 3SD

	PART 1	PART 2	PART 3	PART 4	PART 5	PART 6	PART 7	PART 8	PART 10	PART 11	PART 12	PART 13	PART 14	PART 15	PART 16	PART 17
LESSON 1	X	X		X	X		X									
LESSON 2		X					X			X		X	X	X		
LESSON 3						X							X			
LESSON 4			X	X	X						X	X	X			X

Data processing

Before analyzing each hypothesis, we performed a clustering of all the data divided in each group to identify the general and predominant behavior of the heart rate. First, we applied the elbow method, in all groups, we obtained that the better K was of seven, and then we proceed to the data clustering.

Table 9 shows the cluster for each group, the number of items classified in each cluster, and the centroid based on the heart rate. According to the centroid, we presented the table organized in descending order, and we highlight the two clusters with the most items.

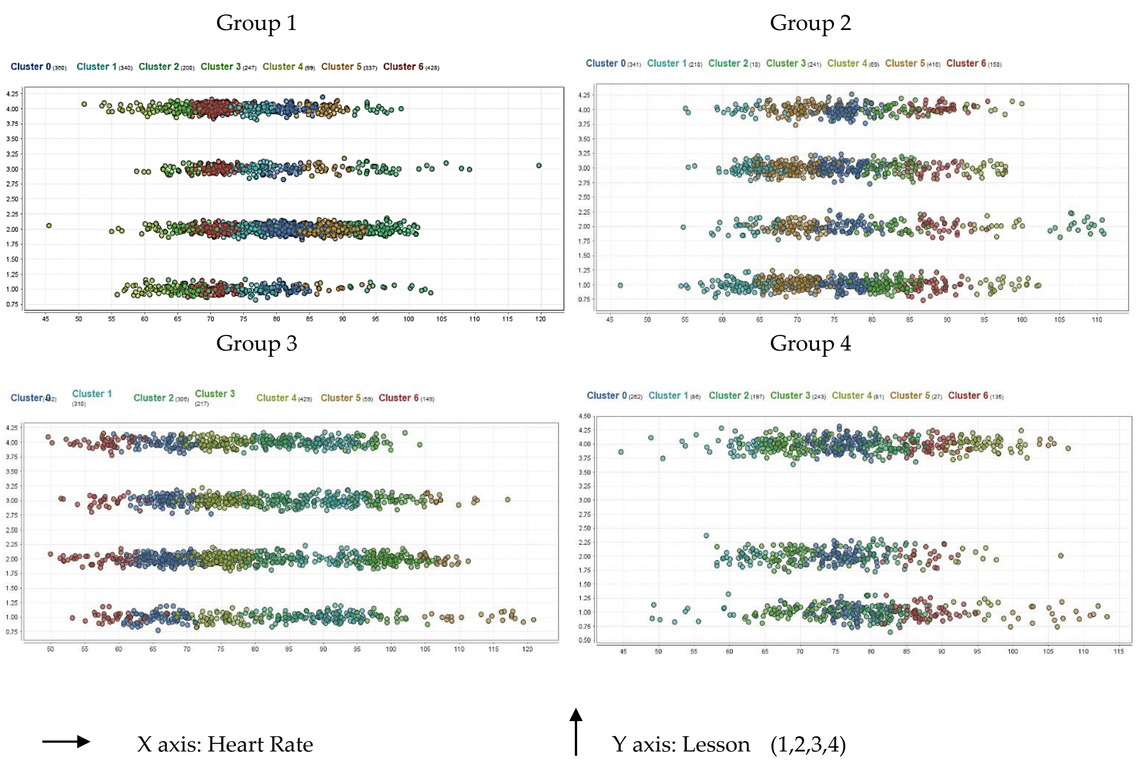
Table 9. Number of items and centroid of each cluster

GROUP 1			GROUP 2			GROUP 3			GROUP 4		
Cluster	Number of items	Centroid HR (bpm)	Cluster	Number of items	Centroid HR (bpm)	Cluster	Number of items	Centroid HR (bpm)	Cluster	Number of items	Centroid HR (bpm)
4	99	60.2	1	218	63.1	6	149	58.1	1	86	60.7
3	247	66.3	**5**	**416**	**69.9**	**0**	**402**	**66.8**	**3**	**243**	**69**
6	**428**	**70.9**	**0**	**341**	**76.4**	**4**	**429**	**74.9**	**0**	**262**	**75.8**
1	340	75.9	3	241	82.2	2	306	82.9	2	197	81.3
0	**360**	**81.6**	6	158	88.5	1	310	91.7	6	135	87.5
5	337	87.8	4	69	96	3	217	99.2	4	81	94.9
2	200	95.5	2	18	107.9	5	59	109.4	5	27	105.6

The clusters highlighted indicated the predominant behavior of the heart rate in each group, varying from between sixty-six (66) and seventy-seven (77), except for Group 1, which is between seventy (70) and eighty-two (82). This behavior shows that the predominant data was not in the extremes, which contained the minority of items.

Figure 6 presents the distribution of items in each cluster in the four groups graphically. In each graph, the behavior of each cluster is similar in each lesson. Although each participant had a different baseline, it did not alter the classification in the clustering. For this reason, we were able to perform a general analysis of data. We conducted an ANOVA test afterwards; for better data treatment, we conducted additional analysis by categorizing the heart rate according to participants, lessons, and activities.

Figure 6. Distribution of items in each cluster in the four groups



After the clustering analysis, we processed the data for analyzing each hypothesis, obtaining the following results:

Hypothesis 1 (H1): the heart rate may increase during an active learning activity and then return to the mean level.

After selecting and labeling the mean heart rate (MHR) of each active learning activity with its activities before and after, we obtained four behaviors, which described the mean heart rate before, during, and after an active learning activity. We show an example of each behavior in Figure 7.

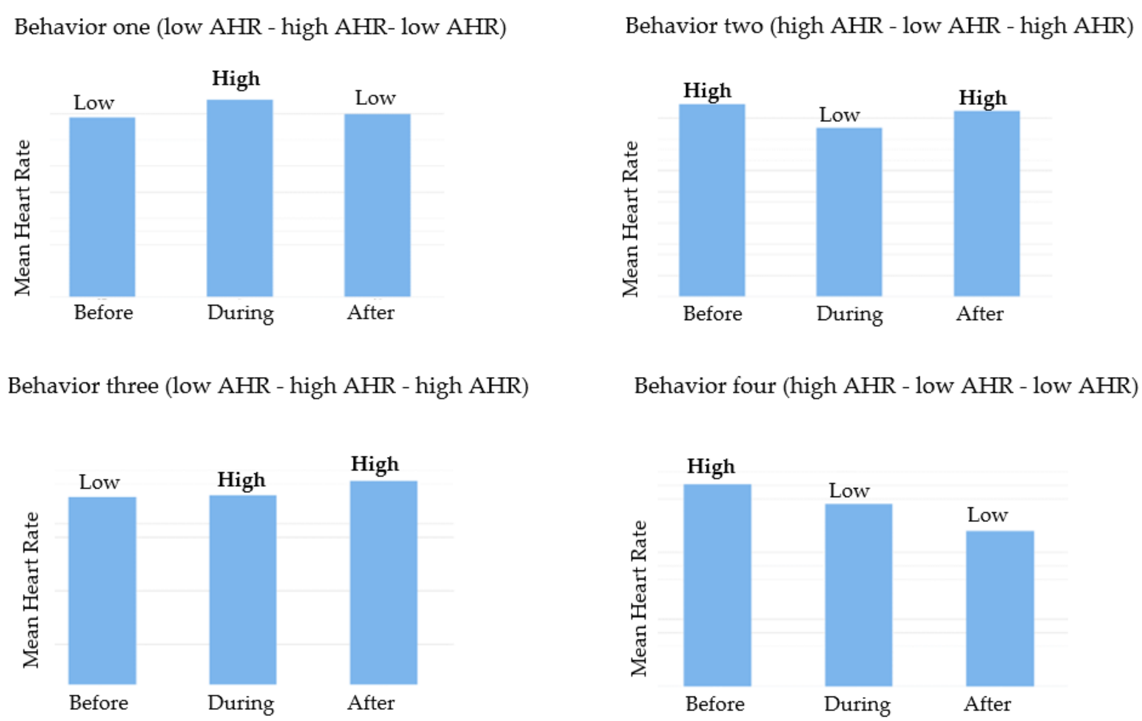
Behavior one (low MHR - high MHR- low MHR): The behavior of the mean heart rate before and after the active learning activity is lower than the behavior during this activity. This behavior coincides with H1.

Behavior two (high MHR - low MHR - high MHR): The behavior of the mean heart rate before and after the active learning activity is higher than the behavior during this activity. This behavior is contrary to H1.

Behavior three (low MHR - high MHR - high MHR): The behavior of the mean heart rate before the active learning activity is lower than the behavior during this activity, while the behavior of the mean heart rate after this activity is higher than the active learning activity. This behavior presents an increase during an active learning activity as described by H1, but then, after the MHR, it continues to increase.

Behavior four (high MHR - low MHR - low MHR): The behavior of the mean heart rate before the active learning activity is higher in comparison with the behavior during this activity, while the behavior of the mean heart rate after this activity is lower than the active learning activity. This behavior does not correspond with H1.

Figure 7. The behavior of the mean heart rate before, after, and during an active learning activity



For this analysis, we examined fifty-eight active learning activities; Table 10 presents the results obtained in each behavior. It is important to note that the activities that we considered before an active learning activity were theoretical explanation, the beginning of a lesson, or instruction given by the professor. If the activity is *theoretical explanation*, the student could be in a rest state; thus, the heart rate may be lower than an active learning activity. On the other hand, if the activity is the *beginning of a lesson*, the heart rate may vary due to external factors depending on the activity that each student was doing before starting the lesson. Finally, if the previous activity is the *instruction given by a professor*, the student can be attentive without doing any activity that involves deep learning. These three activities have in common that they are not active or passive learning activities; for this reason, they can be grouped for the analysis of H1.

Table 10. Number of active learning activities according to each behavior

Behavior	Number of active learning activities	Percentage
Behavior one (low MHR - high MHR- low MHR)	24	41.40%
Behavior two (high MHR - low MHR - high MHR)	13	22.40%
Behavior three (low MHR - high MHR - high MHR)	7	12.10%
Behavior four (high MHR - low MHR - low MHR)	14	24.10%
	58	100%

It is important to note that the activities that we considered before an active learning activity were theoretical explanation, the beginning of a lesson, or instruction given by the professor. If the activity is *theoretical explanation*, the student could be in a rest state; thus, the heart rate may be lower than an active learning activity. On the other hand, if the activity is the *beginning of a lesson*, the heart rate may vary due to external factors depending on the activity that each student was doing before starting the lesson. Finally, if the previous activity is the *instruction given by a professor*, the student can be attentive without doing any activity that involves deep learning. These three activities have in common that they are not active or passive learning activities; for this reason, they can be grouped for the analysis of H1.

The behavior one (low MHR - high MHR- low MHR) coincides with H1. As shown in Table 10, 41.4% of the activities presented this behavior, which has the highest percentage compared to the other behaviors. On the other hand, the behavior two (High MHR - low MHR - high MHR) represents the contrary situation to H1,-the main reason why this situation could happen was that we had the activity: interaction between students and professor, and it could generate an immersive state in the students that could generate a decrease in the heart rate.

The behavior three (low MHR - high MHR - high MHR) is not common and it is consistent with the results of the study of Darnell D. K. and Krieg P. A., who stated that after an active learning activity the heart rate did not continue to increase but returned to the behavior it had before this activity (Darnell & Krieg, 2019). Finally, behavior four (high MHR - low MHR - low MHR) a resting, due to the heart rate decreased during and after an active learning activity; this result indicate that the participant did not need to make a significant cognitive effort since previous knowledge and clarity regarding the discussed topic.

Due to the behavior of the MHR during an active learning activity is the most relevant factor in this study, we applied an ANOVA (Table 11) with $p<0.05$ between two variables: the baseline heart rate and the mean heart rate during active learning activities. If the value F is greater than the critical value for F, it implies that the means of the two variables are significantly different.

Table 11. ANOVA of active learning activities

Active learning activity	***F***	***Critical value for F***	***Had heart rates statistically significant differences?***
Quiz	0.18139836	3.88983922	No
Discussion of a topic in group or pair	37.492232	3.8645791	Yes
Share responses to an activity	11.8336654	3.9097293	Yes
Individual activity	24.3411839	3.85669815	Yes
Interaction between students and professor	6.80149811	3.85954326	Yes

Except for the quiz, all active learning activities had statistically significant differences in heart rate when participants developed these activities compared to each participant's baseline. The case of the quiz had a particularity, a set time was given to finish it, but some participants could finish earlier, so they could carry out other activities in the remaining time, such as taking a break; this condition could be the main reason why in the ANOVA this activity was not statistically significant.

Overall, we accept partially H1 adapting the initial approach to the following: the mean heart rate has a significant variation with an active learning activity, indicating students experiment cognitive engagement. This approach, also, is supported by the statement made by Mayson and Oleksy, "heart rate is useful in the detection of cognitive attention because it changes when cognitive attention is directed to a particular situation" (Maison & Oleksy, 2017).

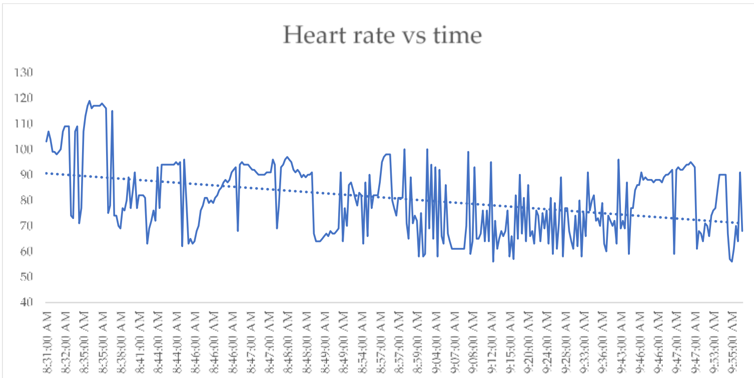
Hypothesis 2 (H2): the heart rate decreases from the beginning to the end of the lesson.

For this hypothesis, we graphed the heart rate values of each lesson and applied a linear regression. In each graph was possible identified if the heart rate trend (HRT) increased or decreased during each lesson (Figure 8). We were able to identify two behaviors:

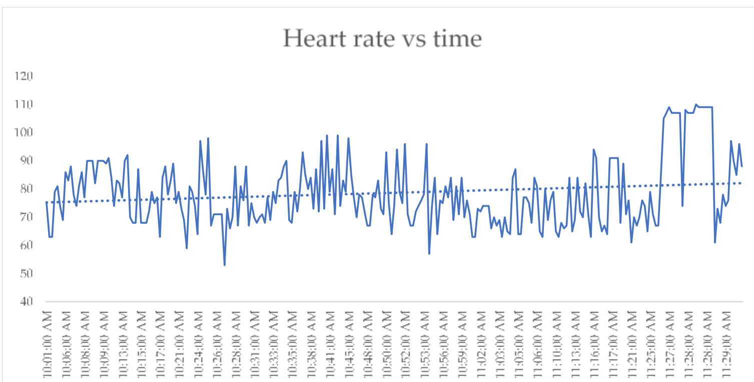
Behavior one (HRT decreased): The heart rate decreased from the beginning to the end of the lesson. It corresponds with H2.

Behavior two (HRT increased): The heart rate increased from the beginning to the end of the lesson. It is contrary to H2.

Figure 8. Heart rate trend decreased or increased from the beginning to the end of the lesson.



Behavior 1: The heart rate decreased



Behavior 2: The heart rate increased

In total, we evaluated fifteen (15) lessons; Table 12 shows the summary of each behavior:

Table 12. Summary of heart rate trend

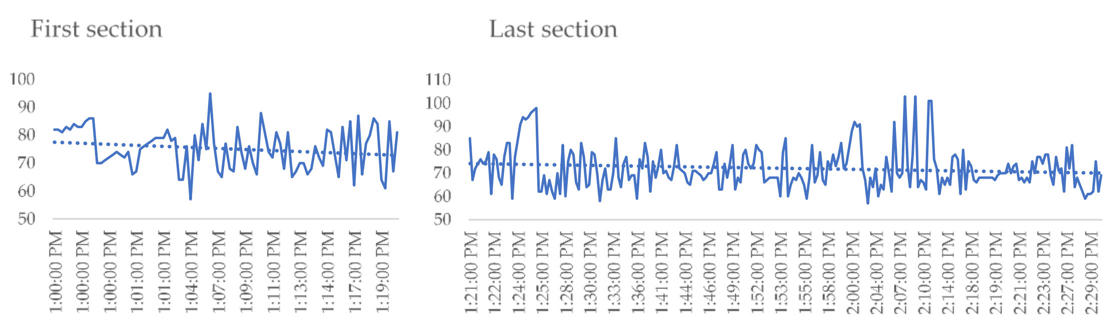
Heart rate trend	**Number of lessons**	**Percentage**
Behavior one (HRT decreased)	9	60%
Behavior two (HRT increased)	6	40%
	15	100%

The expected trend of the heart rate was not evident in all lessons; although in the study of Darnell D. K. and Krieg P. A found a decreasing trend among all the lecture lessons analyzed (Darnell & Krieg, 2019), the results we obtained in virtual lessons suggest that the trend in heart rate from the beginning to the end of the lesson may depend on external or internal factors. The external factors are related to connectivity problems or the environment in which the participant takes the lesson, the internal factors are related to the moment in which the students develop active learning activities and their duration, either at the beginning, in the middle or the end of the class. For these results we accept partially H2 with the next approach: the trend of the heart rate from the beginning to the end of the lesson depends on external and internal factors, the internal factors are linked with the active learning activities, mainly the duration and the moment in the lesson that the professor develops them.

Hypothesis 3 (H3): the drop-in heart rate is biphasic, with a further decrease during the early stages of the lesson.

For this hypothesis, we selected the lessons that presented a decrease in the heart rate trend according to H2; after that, we divided the data into two sections—the first twenty minutes of each lesson against the next seventy minutes. Figure 9 shows an example of a lesson divided into two sections with its linear regression.

Figure 9. Behavior biphasic during a lesson



A negative slope means a decrease in the heart rate trend, in Table 13 we show the slope of each section of the lessons analyzed and its correspondence with H3, for the correspondence we evaluated if the first and last section had a negative heart rate trend and if the slope in the first section was minor to the slope in the last section, which indicated a further decrease during the early stages of the lesson.

Table 13. The trend of first and last section in each lesson

Lesson	Slope			Correspondence with H3
	General	First section	Last section	
1	-0.019	-0.053	-0.017	Yes
2	-0.0055	0.028	-0.0098	No
3	-0.0027	-0.0579	0.0132	No
4	-0.0047	-0.0483	-0.0086	Yes
5	-0.0046	0.0181	0.0112	No
6	-0.058	-0.1459	0.0143	No
7	-0.0157	-0.0563	-0.0085	Yes
8	-0.0051	-0.0666	-0.0228	Yes
9	-0.011	0.3008	-0.0115	No

We show the summary of correspondence with H3 of the fifteen (15) lessons in Table 14, which has the nine (9) lessons analyzed in Table 13 and the six (6) lessons that had an increase in H2 and which do not correspond with H3 (Table 12). H3 has a strong dependency on H2 since it requires a drop-in heart rate throughout the lesson, a condition that was not met in all lessons, for this reason, we included the six lessons for the analysis in the correspondence with H3 (Table 12). Since 73% of the lesson did not show the behavior expected, we reject H3.

Table 14. Correspondence with hypothesis 3

Correspondence with hypothesis 3	Number of lessons	Percentage
Yes	4	27%
No	11	73%
	15	100%

Hypothesis 4 (H4): the heart rate decreases at the beginning of the lesson and increases at the end.

We present the behavior that occurred at the beginning and end of each lesson in Table 15. We also show the correspondence with the H4.

Table 15. Behavior of the heart rate at the beginning and end of each lesson

Behavior of the heart rate in each lesson	Slope		Correspondence with hypothesis 4
	Beginning	End	
Decreases at the beginning and decreases faster at the end	-0.2088	-0.5779	No
Decreases at the beginning and increases at the end	-0.2096	0.5495	Yes
Decreases at the beginning and decreases faster at the end	-0.1698	-0.2714	No
Increases at the beginning and increases slower at the end	0.2757	0.1136	No
Increases at the beginning and decreases at the end	0.2085	-0.6794	No
Increases at the beginning and decreases at the end	0.8469	-0.8181	No
Decreases at the beginning and increases at the end	-0.1623	0.3963	Yes
Increases at the beginning and decreases at the end	0.1784	-0.2863	No
Decreases at the beginning and decreases faster at the end	-0.1795	-0.4427	No
Decreases at the beginning and decreases faster at the end	-0.1799	-0.9221	No
Increases at the beginning and decreases at the end	0.0139	-0.0167	No
Increases at the beginning and decreases at the end	0.0699	-1.5297	No
Decreases at the beginning and increases at the end	-0.0914	0.9825	Yes
Increases at the beginning and increases slower at the end	1.4176	0.6167	No
Increases at the beginning and increases slower at the end	0.8603	0.1399	No

The heart rate decreased at the beginning and increased at the end in twenty percent (20%) of lessons; for that reason, we reject H4.

We analyzed each heart rate behavior presented at the beginning and the end of the lessons (Table 16), the percentage for each behavior is similar between them, so it is possible to conclude that there is not a standard pattern. In another study, the researchers verified a standard heart rate behavior during various lessons, however, they evaluated it during lecture classes and the students were physically present (Darnell & Krieg, 2019). In our study, the lessons were virtual, with different factors that could influence the heart rate of the participants, like connections problems, the influence of external factors by the place where they take the lessons that could affect their level of attention, among others.

Table 16. Summary of each behavior at the beginning and the end of lessons

Behavior of the heart rate	Number of lessons	Percentage
Decreases at the beginning and increases at the end	3	20%
Decreases at the beginning and decreases faster at the end	4	27%
Increases at the beginning and decreases at the end	5	33%
Increases at the beginning and increases slower at the end	3	20%
	15	100%

Hypothesis 5 (H5): the heart rate decreases in passive learning activities, such as watching a video.

In this hypothesis, we applied a process similar to H1, considering the activities before, during, and after passive learning activities, in this case, a video projection. We obtained four behaviors, which described the mean heart rate (MHR) before, during, and after a passive learning activity.

Behavior one (high MHR - low MHR - high MHR): the behavior of the mean heart rate before and after the passive learning activity is higher than the behavior during this activity. It corresponds with H5.

Behavior two (high MHR - low MHR - low MHR): the behavior of the mean heart rate before the passive learning activity is higher in comparison with the behavior during this activity, while the behavior of the mean heart rate after this activity is lower than the passive learning activity. It corresponds with H5.

Behavior three (low MHR - high MHR - high MHR): the behavior of the mean heart rate before the passive learning activity is lower compared to the behavior during this activity, while the behavior of the mean heart rate after this activity is higher than that of this the passive learning activity. It is contrary to H5.

Behavior four (low MHR - high MHR- low MHR): the behavior of the mean heart rate before and after the passive learning activity is lower compared to the behavior during this activity. It is contrary to H5.

However, this hypothesis focuses on the behavior before and during a passive learning activity since that the first two behaviors represent a decrease and the last two an increase in heart rate during a passive learning activity. Table 17 presents a summary of the combination of these behaviors and their percentage.

Table 17. Correspondence with hypothesis 5

Behavior	Number of activities	Low/high	Percentage	Correspondence with hypothesis 5
Behavior one (high MHR - **low MHR** - high MHR) Behavior two (high MHR - **low MHR** - low MHR)	2 3	5	45%	Yes
Behavior three (low MHR - **high MHR** - high MHR) Behavior four (low MHR - **high MHR**- low MHR)	1 5	6	55%	No
	11	11	100%	

The increased in the heart rate could occur because, before each video, professors instructed their students to pay attention and to make an activity after the video projection, which could prevent students from entering a resting state during the video projection. These results allow rebuild H5 with this approach: if students are previously advised that they will have to develop an activity after a passive learning activity (such as a video projection), their heart rate could increase and consequently, also their cognitive engagement. Overall, we accept partially H5 with the exposed approach.

We present a summary of the results of each hypothesis in Table 18.

Table 18. Summary of results of hypotheses

Summary of results of hypotheses	
Hypothesis	**Results**
Hypothesis 1 (H1): the heart rate may increase during an active learning activity and then return to the mean level.	We accepted partially H1 adapting the initial approach to the following: the mean heart rate has a significant variation with an active learning activity, indicating students experiment cognitive engagement.
Hypothesis 2 (H2): the heart rate decreases from the beginning to the end of the lesson.	We accepted partially H2 with the next approach: the trend of the heart rate from the beginning to the end of the lesson depends on external and internal factors, the internal factors are linked with the active learning activities, mainly the duration and the moment in the lesson that the professor develops them.
Hypothesis 3 (H3): the drop-in heart rate is biphasic, with a further decrease during the early stages of the lesson.	The drop-in heart rate was biphasic, with a further decrease during the early stages of the lesson in only 27% of them, for that reason, we rejected H3.
Hypothesis 4 (H4): the heart rate decreases at the beginning of the lesson and increases at the end.	The heart rate decreased at the beginning and increased at the end in twenty percent (20%) of lessons; for that reason, we rejected H4.
Hypothesis 5 (H5): the heart rate decreases in passive learning activities, such as watching a video.	We accepted partially H5 with the next approach: if students are previously advised that they will have to develop an activity after a passive learning activity (such as a video projection), their heart rate could increase and consequently, also their cognitive engagement.

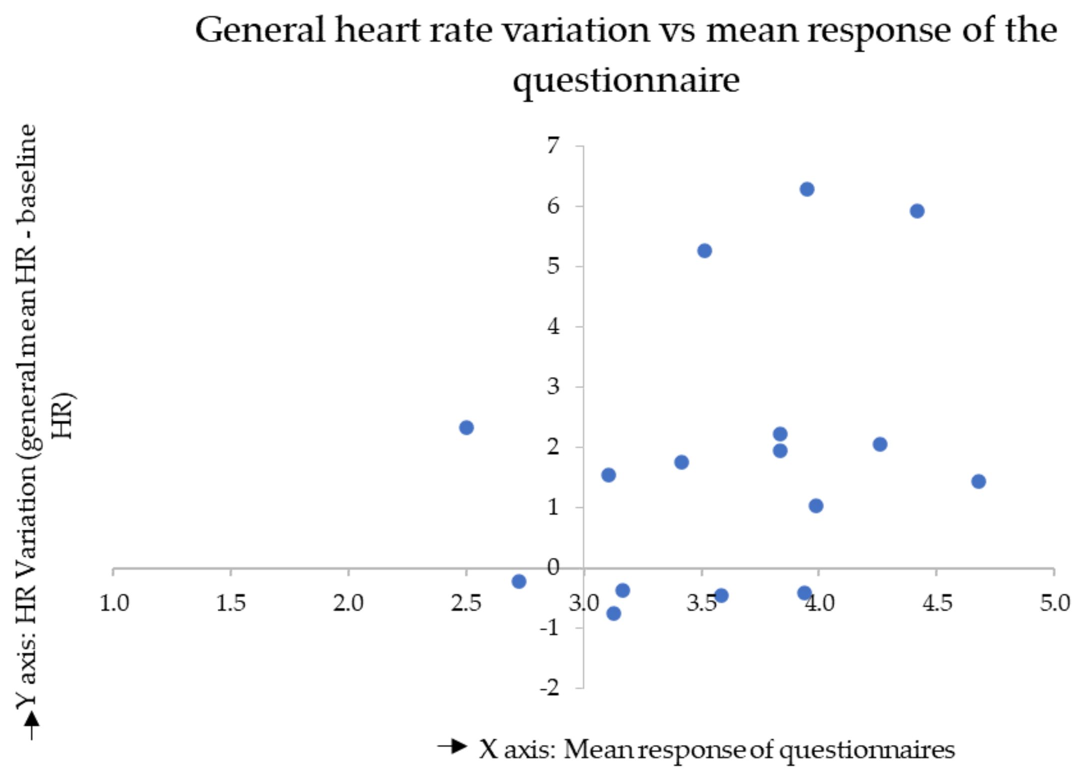
Non-self-report method vs self-report method

In this section, we constructed a quadrant model for relating the non-self-report method with the self-reported method. We analyzed two scenarios, the first related the mean responses of the questionnaire with the general heart rate variation (HRV); in this last variable, we took the data of heart rate during whole lessons, that is, all activities. In the second scenario, we analyzed the same relationship of variables with the difference that in the second variable, we only considered the HRV of active learning activities (ALA).

First scenario: general heart rate variation vs mean response of the questionnaire

In this analysis we evaluated the sixteen participants classifying them in the four quadrants (Figure 10). Ten were in the quadrant I, one in the quadrant II, one in the quadrant III, and four in the quadrant IV.

Figure 10. First scenario: quadrant of general heart rate variation vs mean response of questionnaires



The classification of the ten participants in the quadrant I indicates that they had a positive HRV, that is, an increase in the general mean heart rate (MHR) concerning the baseline, also these students reported a high cognitive engagement in questionnaires. This quadrant is the best scenery in this study because it proved that a positive HRV is related to a high engagement.

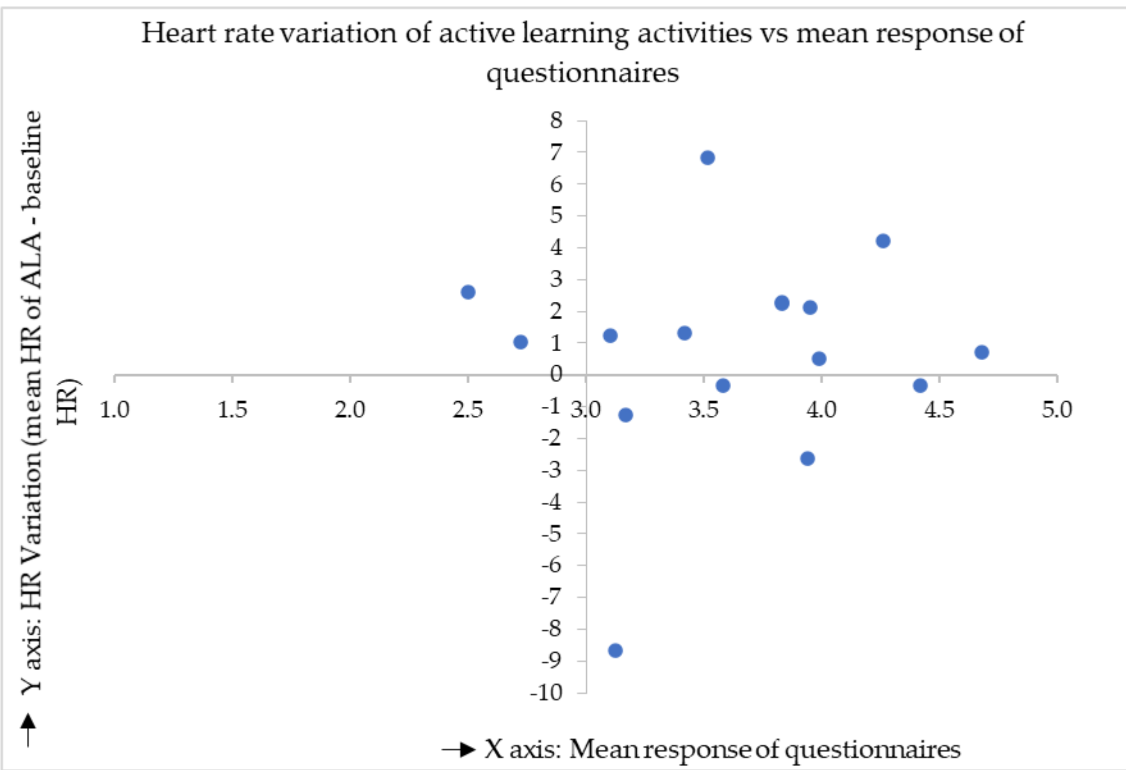
One participant was in the quadrant II; she/he had a positive HRV but reported a low level of engagement in the questionnaire. This result indicates that the student did not feel a high cognitive engagement during the whole lessons, but he could have moments or activities that caught their attention, increasing their heart rate. Also, a participant was in the quadrant III, she/he had a negative HRV, and in the same way, the student reported a low level of engagement in the questionnaire.

Finally, four participants were in the quadrant IV; they reported a high engagement in the questionnaire. However, the general MHR decreased with respect to the baseline, a circumstance that may indicate that students were in an immersive state and not necessarily a low level of attention or a low level of cognitive engagement; this affirmation coincides with the results of the study made by Ronney et al, who analyzed the behavior of the participant's heart rate while watching a film; the results demonstrated that a drop in the heart rate might suggest an immersive environment followed by an increase in the attention to the film (Rooney et al., 2014).

Second scenario: heart rate variation of active learning activities vs mean response of the questionnaire

In the same way as in the first scenario, we evaluated the sixteen participants with the difference that here we related the HRV during active learning activities (ALA) and the mean responses in the questionnaire (Figure 11).

Figure 11. Second scenario: quadrant of heart rate variation of active learning activities vs mean response of questionnaires



Nine participants were in quadrant I, seven of them presented a positive HRV below three points when an ALA was developed, this behavior is similar to the first scenario, which indicates that ALA had a great influence on the behavior of a whole lesson. The quadrant I represents that participants were making a mental effort for acquiring a high level of attention, a circumstance that resulted in a positive variation of the heart rate. The other two participants had a positive HRV greater than three points. This quadrant represents the best scenario; with these results, we can affirm that a positive HRV is linked to a high cognitive engagement.

Two participants were in the quadrant II, unlike the first scenario where we found one participant in quadrant II and the other participant in quadrant III. This behavior indicates that although the participant in quadrant III reported a low cognitive engagement in the questionnaire, the ALA developed by the professor caught her/his attention, which meant an increase in the HRV and generated that in the second scenario she/he was in the quadrant II.

Five participants were in the quadrant IV; as we had explained, this quadrant represents an immersive state of the participants. The participant who was in the quadrant I in the first scenario, now she/he is in the quadrant IV in the second scenario, this change means that she/he was in an immersive state when the professor carried out ALA. On the other hand, one of the participants had a significant negative HRV, below eight points, which indicates that her/his concentration was higher during ALA.

Overall, with the analysis performed and illustrated in the first and second scenario, the study shows that although there were heart rate variations (causing location changes for some participants inside the quadrant), the number of subjects for each quadrant is similar; a condition that allows us to suggest that ALA developed by professors determine the behavior of the MHR throughout the whole lessons.

Using the quadrant analysis was possible to ascertain that combining a non-self-report method (heart rate) with a self-report method (questionnaire) is advantageous for measuring cognitive student engagement, since the comparison of the heart rate against the report given by each participant provides more information about the influence of ALA on the heart rate.

5 Discussion

In this study, we conducted an exploratory research implementing a non-self-report method to measure the cognitive student engagement, with a physiological characteristic, the heart rate. We have measured and analyzed this variable, using a heart rate band, in sixteen (16) participants from the Industrial Engineering program, in a Colombian University located in Bogota. With the collected data, we evaluated five hypotheses. Below, we will present and discuss the results of each hypothesis.

***Hypothesis 1 (H1)*:** the heart rate may increase during an active learning activity and then return to the mean level.
For analyzing H1, we evaluated the behavior of the heart rate before, during, and after an active learning activity (ALA); we found that 41.4% of data correspond with H1. Since ALA was an important matter in this study, we applied an ANOVA test to evaluate the heart rate during an ALA against each participant's baseline, an analysis that demonstrated a statistically significant difference between these variables. We accepted partially H1 adapting the approach to the following: the mean heart rate has a significant variation with an active learning activity, indicating students experiment cognitive engagement.

Hypothesis 2 (H2): the heart rate decreases from the beginning to the end of the lesson.
We evaluated H2 with the heart rate trend; if it was negative indicated a decrease and if it was positive indicated an increase in the heart rate from the beginning to the end of the lesson. From a total of fifteen (15) lessons, sixty percent (60%) presented the behavior expected by H2. For these results we accept partially H2 with the next approach: the trend of the heart rate from the beginning to the end of the lesson depends on external and internal factors, the internal factors are linked with the active learning activities, mainly the duration and the moment in the lesson that the professor develops them.

Hypothesis 3 (H3): the drop-in heart rate is biphasic, further decreasing during the early stages of the lesson.
H3 had a strong dependence on H2, because H3 needed that the trend during a lesson to be decreasing. After evaluating the fifteen (15) lessons, we found that only 27% of them had the behavior expected in H3, for this result we rejected H3.

Hypothesis 4 (H4): the heart rate decreases at the beginning and increases at the end of the lesson.
After analyzing the behavior of the heart rate at the beginning and the end of each lesson, we found that only twenty percent (20%) of the lessons achieved H4. After the analysis we concluded that here is not a standard pattern related to this hypothesis, for this reason we rejected H4.

Hypothesis 5 (H5): the heart rate decreases in passive learning activities, such as watching a video.
We analyzed eleven (11) passive learning activities and found that forty-five percent (45%) of them presented the behavior described in H5. All activities were a video projection; however, before students watched the video, the professor indicated to them that there would be an activity after the video, a factor that could influence the results. We accepted partially H5 with the next approach: if students are previously advised that they will have to develop an activity after a passive learning activity (such as a video projection), their heart rate could increase and consequently, also their cognitive engagement.

In addition to the analysis of the hypotheses, we made the relationship between the quantitative data vs qualitative data from the questionnaire.

Non-self-report method vs self-report method

We related the heart rate variation (HRV) of whole lessons and the HRV during the active learning activities (ALA) against the response that participants gave in the questionnaire; the VHR refers to the difference between mean heart rate and the baseline, we explored the behavior of the sixteen (16) participants.

We used a quadrant model (figure 10 and 11); two quadrants stood out over the others; Quadrant I reflected that the HRV was positive and the responses in the questionnaire indicated a high level of cognitive engagement, the majority of data was located in this quadrant; the first stage, HRV of whole lessons, had ten (10) participants, and the second stage, HRV during ALA, had nine (9) participants. Quadrant IV was the second predominant one. It represented an HRV negative, but the questionnaire's response indicated a high level of cognitive engagement; this situation reflected that participants could be in an immersive state during the ALA, and not necessarily a low level of engagement. Finally, the results suggest the behavior of the heart rate during a whole lesson might be determined for the ALA that professors developed in each lesson.

6 Limitations, recommendations, and future research

We used the heart rate as a tool for measuring student engagement in distance lessons during the COVID 19, and we had limitations regarding the difficulty of eliminating environmental and external influences generated by the inconveniences of having access to resources and tools necessary for the development of the lessons, such as internet connection problems, unstable electricity, lack of an appropriate space without interruptions, a computer without the required capacity to run several programs and software at the same time (lesson connection software and programs to develop activities during class), and inconvenience with the phone that collected heart rate data (reason to remove some data from the study). These limitations affected the level of attention of the participants and sometimes caused them to carry out other activities in parallel to the lessons. The difficulty of eliminating environmental and external influences is a known limitation in the use of heart rate as a tool for identifying engagement; for this reason, we recommend for future research to use the heart rate as a non-self-report method in combination with a self-report method such as a questionnaire that allows identifying external factors that could affect the participant's attention in addition to the perception that she/he had of the lesson and the activities developed.

Another alternative we recommend reducing the influence of external factors is to use supplementary biometric measures that allow identifying additional characteristics to which the heart rate gives, like emotions, motivation or level of concentration, factors that have a strong influence on student engagement. The supplementary biometric measures we suggest are detection of facial expression, breath rate, skin temperature and conductance or brain signals.

In this study, we made an exploratory investigation limited to the number of participants, the quantity of heart rate bands; and to a subject (human talent management). The sample number of participants was between the ranges of other studies in the sector; however, we recommend that for future studies the researchers increased the sample and evaluate the student engagement in other engineering subjects. We hope that our study can serve as the basis and input for future research related to the analysis of cognitive student engagement using heart rate as a non-self-report method.

Using the heart rate for analyzing the student engagement has the advantage that data is collected in real-time, however, the data processing and the analysis require additional time, this limitation means that teachers do not receive feedback in real time to make the necessary decisions to modify or adapt the methodology of the course. For this reason, a future challenge could be the development of a model that processes and evaluates the data of the heart rate in a shorter time or even in real-time, which can be used by all students in a lesson and provide feedback to the professor.

7 Conclusions

Student engagement allows educational institutions to make better decisions regarding teaching methodologies, methods for evaluating the quality of education, and allows timely feedback to professors. The methods to determine student engagement are divided into two, self-report methods, such as questionnaires, surveys and analysis of these, and non-self-report methods, which use physiological characteristics such as heart rate, brain signals, analysis of facial expressions, among other. In Colombia, the investigations carried out have only used self-report methods.

In this study we develop an exploratory investigation to determine the level of student cognitive engagement through heart rate, during the development of active learning activities. We used heart rate bands and a mobile application to collect the data, in a sample of 16 students who were taking the subject of Gerencia de Talento Humano of the industrial engineering program of a higher education institution in Bogotá, Colombia. After executing the proposed methodology and analyzing the behavior of the hypotheses raised, the following results were obtained:

1. The results confirm that heart rate can be used as a tool for measuring cognitive student engagement in distance learning, mainly if the professor develop an active learning activity, since statistically, the heart rate has a significant variation with respect to the baseline heart rate during the development of these activities, at this point, it is important to clarify that this difference could be positive or negative, a positive variation implies an increase on the heart rate because the study subject is making a mental effort, and a negative variation means an immersive state, it means, the active learning activity captured the student's attention and immersed her/him in this environment, causing her/him to isolate herself/himself from any other activity around. In the development of virtual lessons, one of the main concerns of the professors is to identify the activities that encourage the participation of students, capture their attention and allow the transmission of knowledge, in this study, we found that active learning activities achieve these objectives, because spaces are generated within the lessons that allow students to concentrate on the activities developed, resolve doubts and connect their past experiences with new knowledge.

2. Using a quadrant model, we confirmed that combining a non-self-report method and a self-report method allows analyzing the engagement in a broader perspective. This association of technics allows to relate the engagement reported by the students with the results obtained from the physiological characteristic. In our study, one of the results suggested that during an active learning activity, most participants reported a high level of cognitive engagement, and the heart rate variation had a difference significative respect to the baseline, a result that was evident in the ANOVA, however, in this analysis was possible to identify that this difference could be positive or negative.

3. In the development of this research we found that students feel more comfortable, feel less pressure and are more willing to participate in a study if factors such as student engagement are measured using a non-self-report method, because they sent us the heart rate data immediately after the end of the lesson without having to remind them to send the data, however, the opposite happened with the self-report method, because we had to ask them to fill out each questionnaire at least twice and sometimes up to four times. The above shows that students are interested in participating in non-self-report methods and shows the importance of rethinking the way self-report methods are implemented.

4. We confirm that the heart trend from the beginning to the end of the lesson depends on external and internal factors, the external factors regarding to instability in the internet connection and activities that students may be developing in parallel to lessons, and the internal factors, which professors can control, are linked with the active learning activities. The internal and external factors that are presented in a face-to-face lesson are very different from those that are presented in a virtual lesson, in a face-to-face lesson the external factors that affect the concentration of students are reduced due to the learning environment that a classroom provides. However, in a remote environment, the external factors are greater and variable, for this reason, the active learning activities that professors develop become more relevant, mainly the duration and time of the lesson in which they are performed, in a way that these activities provide a balance at the beginning, in the middle and at the end of the lesson.

5. Concerning passive learning activities, if students are previously advised that they will have to develop a task after a passive learning activity (such as a video projection), their heart rate could increase and consequently, also their cognitive engagement. The instructions of the activities to be carried out after the video projection were focused on the topic that the students were learning and generated a discussion between the work groups or between the students and the professor, this particularity should be considered if professors want to implement a passive learning activity to promote cognitive engagement.

6. We find heart rate did not present a pattern in the biphasic analysis, neither a pattern behavior at the beginning and the end of the lesson. The four heart rate behaviors found at the beginning and at the end of the lesson allow us to deduce that the variation depends on external factors that may occur before and after the class and that the professor cannot control, for example other academic activities of other subjects or personal activities that can cause a variation in heart rate.

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9 Abbreviations

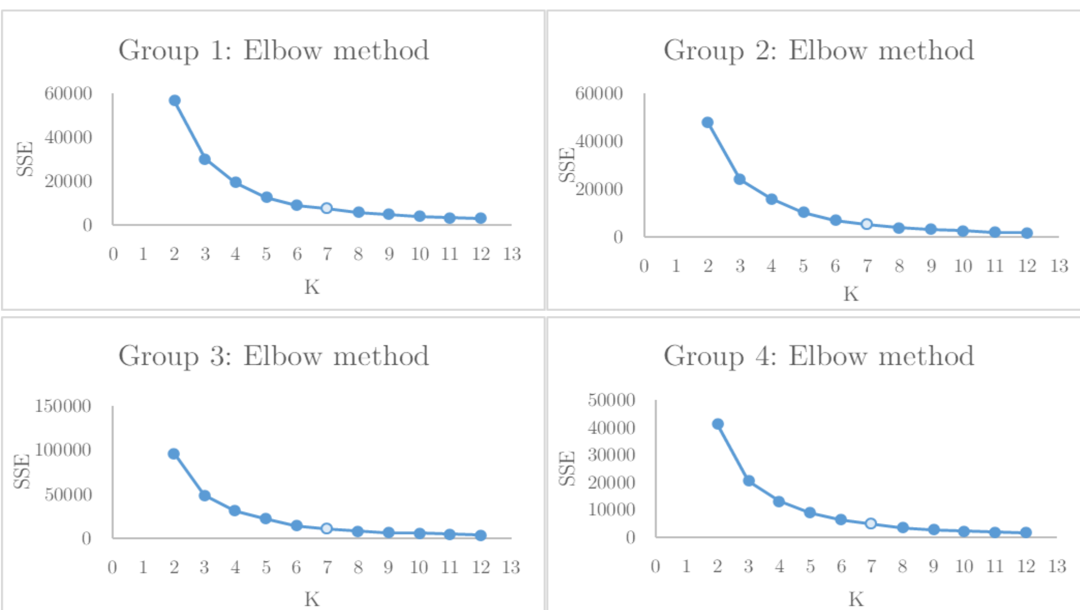
- ANOVA: Analysis of variance
- MUSLIS: Malaysian University Student Learning Involvement Scale
- NSSE: National Survey of Student Engagement
- MSLQ: Motivated Strategies for Learning Questionnaire
- HESES: Higher Education Student Engagement Scale
- ALA: Active learning activities
- PPG: Photoplethysmography
- 3SD: Three standard deviations
- MHR: Mean heart rate
- H1: Hypothesis 1
- H2: Hypothesis 2
- H3: Hypothesis 3
- H4: Hypothesis 4
- H5: Hypothesis 5
- HRT: Heart rate trend
- HRV: Heart rate variation

10 Appendices

Appendix 1: Modifications and complements made regarding proposal thesis

N	Proposal thesis	Modifications and complements made regarding proposal thesis
1	Carry out two questionnaires, a specific questionnaire that students filled out after finishing each lesson session and a general questionnaire that they filled out at the end of data collection.	We carried out a single questionnaire unifying the questions from the two questionnaires proposed. Students filled out this questionnaire at the end of each lesson and then we calculated the arithmetic mean response. This modification was made since a single questionnaire allowed a better visualization and analysis of the data in the quadrant model (which related the questionnaire data and the heart rate data).
2	Record the data for a minimum of two weeks, which represented 4 lessons in each of the students, estimating a total of 3 months for all data collection.	We recorded two-week data, equivalent to 4 class sessions for each student, and the total data collection was 2 months. Additionally, it was complemented with respect to the proposal, establishing as a criterion that the students have data from at least 3 lessons to be able to analyze the participant's data.
3	Invite 15 students to participate in the research.	We invited 20 students, and we discarded 4 students because they had problems with the compatibility of the application, or they had data from less than 3 lessons. In total, we analyzed the data of 16 students.
4	Organize 3 groups, each with 5 participants, to collect data.	Because we invited 20 students, we organized 4 groups each of 5 students.

Appendix 2: Elbow method



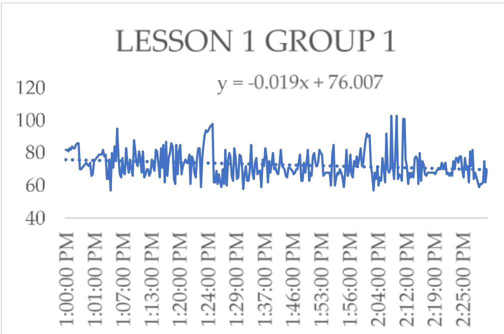
Appendix 3: Data of quadrant model for each participant during the whole lesson.

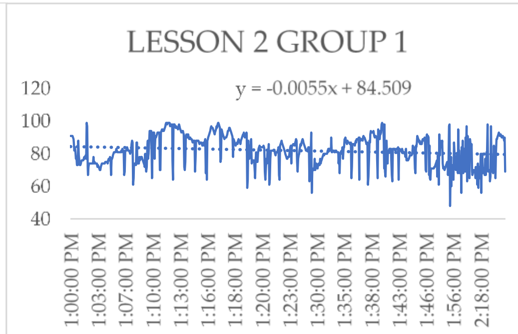
	Mean Questionnaire	HR
Participant 1	3.95	6.28
Participant 2	2.72	-0.23
Participant 3	2.50	2.33
Participant 4	4.68	1.45
Participant 5	3.83	2.22
Participant 6	3.17	-0.36
Participant 7	3.58	-0.45
Participant 8	3.42	1.76
Participant 10	4.26	2.05
Participant 11	3.13	-0.76
Participant 12	4.42	5.92
Participant 13	3.51	5.27
Participant 14	3.10	1.54
Participant 15	3.94	-0.41
Participant 16	3.83	1.94
Participant 17	3.99	1.04

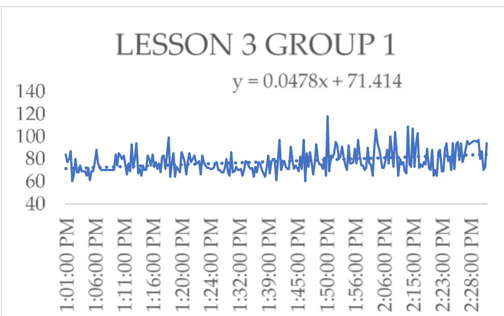
Appendix 4: Data of quadrant model for each participant during active learning activities.

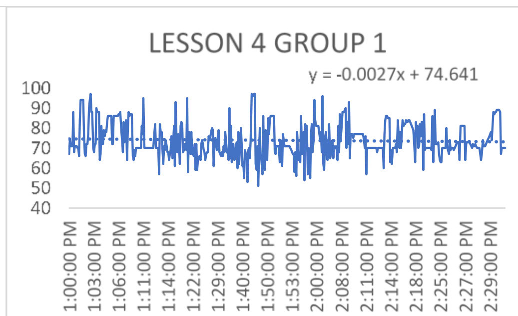
	Mean Questionnaire	HR
Participant 1	3.95	2.14
Participant 2	2.72	1.06
Participant 3	2.50	2.60
Participant 4	4.68	0.70
Participant 5	3.83	2.28
Participant 6	3.17	-1.24
Participant 7	3.58	-0.34
Participant 8	3.42	1.31
Participant 10	4.26	4.24
Participant 11	3.13	-8.68
Participant 12	4.42	-0.35
Participant 13	3.51	6.85
Participant 14	3.10	1.26
Participant 15	3.94	-2.61
Participant 16	3.83	2.23
Participant 17	3.99	0.50

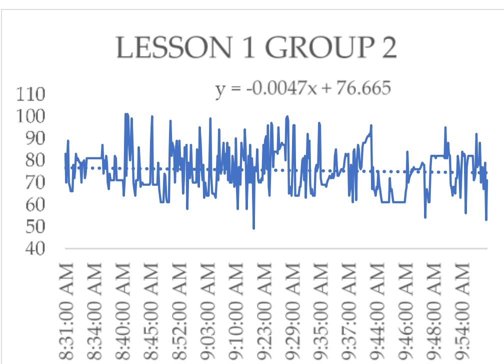
Appendix 5: Heart rate trend in each lesson

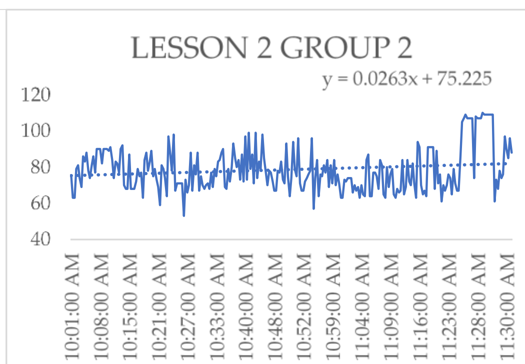


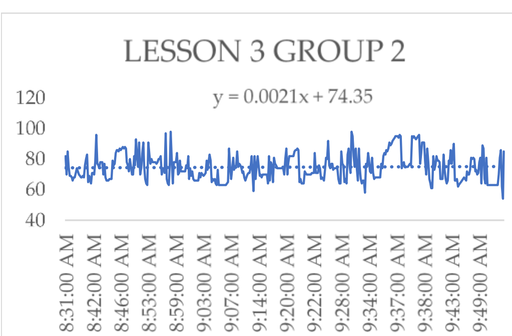


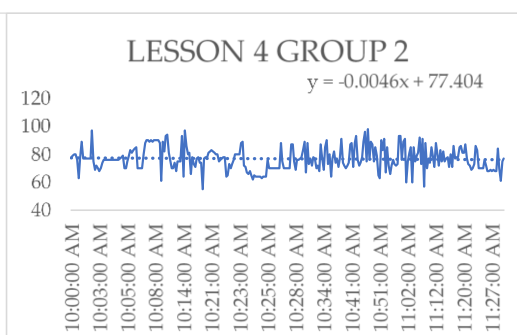


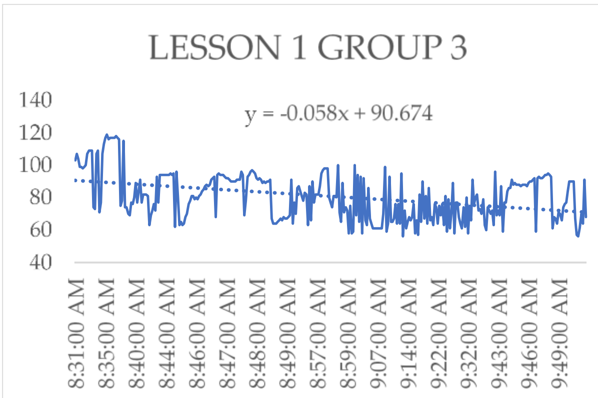











LESSON 1 GROUP 3
y = -0.058x + 90.674
140
120
100
80
60
40
8:31:00 AM
8:35:00 AM
8:40:00 AM
8:44:00 AM
8:46:00 AM
8:47:00 AM
8:48:00 AM
8:49:00 AM
8:57:00 AM
8:59:00 AM
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9:14:00 AM
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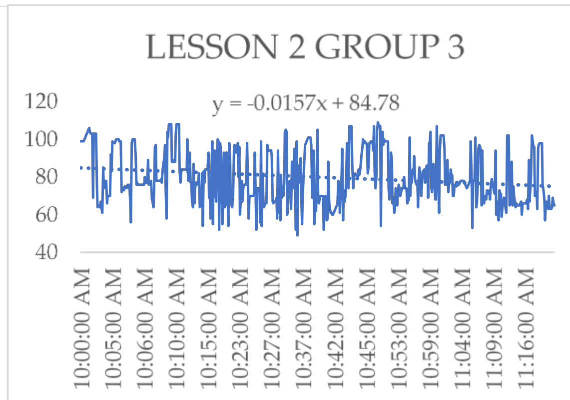
9:43:00 AM
9:46:00 AM
9:49:00 AM


LESSON 2 GROUP 3
y = -0.0157x + 84.78
120
100
80
60
40
10:00:00 AM
10:05:00 AM
10:06:00 AM
10:10:00 AM
10:15:00 AM
10:23:00 AM
10:27:00 AM
10:37:00 AM
10:42:00 AM
10:45:00 AM
10:53:00 AM
10:59:00 AM
11:04:00 AM
11:09:00 AM
11:16:00 AM


LESSON 3 GROUP 3
y = 0.0022x + 80.145
120
100
80
60
40
8:30:00 AM
8:31:00 AM
8:31:00 AM
8:32:00 AM
8:35:00 AM
8:39:00 AM
8:42:00 AM
8:45:00 AM
8:51:00 AM
8:55:00 AM
8:58:00 AM
8:59:00 AM
9:02:00 AM
9:06:00 AM
9:09:00 AM
9:12:00 AM
9:16:00 AM
9:19:00 AM
9:23:00 AM
9:27:00 AM
9:31:00 AM
9:34:00 AM
9:38:00 AM
9:42:00 AM
9:45:00 AM
9:48:00 AM
9:51:00 AM
9:53:00 AM
9:54:00 AM
9:56:00 AM
10:00:00 AM
10:03:00 AM
10:07:00 AM