# Hybrid Educational Environments – Using IoT to detect emotion changes during student interactions

Giacomo Nalli, Georgios Dafoulas, Ariadni Tsiakara,
Bahareh Langari, Kajal Mistry, Farzad Tahmasebi Aria

Computer Science, Science and Technology, Middlesex University London,
The Burroughs, NW4 4BT London, United Kingdom
g.nalli@mdx.ac.uk, g.dafoulas@mdx.ac.uk, a.tsiakara@mdx.ac.uk,
b.langari@mdx.ac.uk, k.mistry@mdx.ac.uk, f.aria@mdx.ac.uk

**Abstract.** The use of hybrid educational environments, especially after COVID-19 pandemic, has intensified leading to new pedagogic challenges as the integration of biometric sensors into learning processes. Instructors must adapt their methods so that teaching and its quality are not negatively affected. The aim of this study is to enhance the understanding of students' learning experiences by analysing biometric data during different learning activities. This paper focuses on the use of an Internet of Things (IoT) device, to collect Galvanic Skin Response (GSR) and Heart rate (HR) levels, in addition to biometric data. The quantitative analysis of the collected data shows a correlation between the data extracted that allow us to detect changes on students' emotions. Subsequently the data analysis is used by instructors to provide formative feedback to enhance student learning, benefiting learners in terms of self-directed learning and motivation which can help them to improve their performance. The paper illustrates a case study of a hybrid learning university learning activity adopted in undergraduate programmes.

**Keywords:** Internet of Things, hybrid learning, emotion detection

## 1 Introduction

Information technology (IT) plays a crucial role in improving educational development by creating a new learning environment called distance learning or e-learning [1]. Following the COVID-19 pandemic across the world, the entire learning process has shifted to online and hybrid learning environments. Despite the many advantages distance learning offers, some limitations, such as the lack of interest from some students and the need for frequent direction from a professor, make distance learning down [2]. This is a key concern of our research, as we focus on creating hybrid educational environments with the use of augmented reality (AR), internet of things (IoT), gamification and social learning networks (SLN).

Hybrid learning, which combines both face-to-face and e-learning environments brings the best features of regular face-to-face learning with technology-based online learning [1, 2, 3], in order to overcome those disadvantages.

The integration of IoT tools and hybrid interaction pedagogies in education is at the core of our research work. IoT devices we developed complements our studies in hybrid environment pedagogies and frameworks that led to implement MineCraft worlds to provide gamification support in formative assessment (CarCraft project). The game scenarios are aligned to specific learning tasks and allow students to self-assess their understanding of the educational content, thanks also to the use of an open-source social learning network as part of the Sharing-my-Learning (SmL) project.

Over the past few years educational institutions put lots of effort to make hybrid learning as effective and encouraging as possible [4, 5]. One of the issues university students face is the lack of motivation that often affects their performance and prevents them from achieving their learning outcomes. We believe the solution is the effective introduction of technology in enhancing hybrid learning interactions.

There is the viewpoint that the loss of motivation in studying is closely connected to the lack of interest in the subject or to the quality of the teaching provided by the instructor [6, 7].

Some universities tried to solve this problem delivering tutoring courses with the aim to increase motivation and promote academic success, both with specific extra lectures in class [8], and using intelligent tutoring systems [9]. We believe that among the factors affecting motivational aspects of learning is the lack of an appropriate hybrid learning environment.

E-learning and hybrid learning strategies were adopted by instructors to help students to be more engaged, through the delivery of e-content in asynchronous e-learning web-based modules in a Moodle learning management system [10]. However, despite the use of valid and tested tools aimed to increase the motivation, such as SCORM packages [11] or tailored plugins [12] , it could happen that students (even if they participated in all the activities delivered) don't obtain benefits in terms of engagement and performance, contrasting the results expected by the instructor. In this paper we examine how our IoT technology and innovative learning pedagogy can lead to an effective hybrid learning experience.

Although the COVID19 pandemic forced institutions in using hybrid learning environments, our work on designing our in-house biometric sensors and AR solutions was part of our core research focus on supporting learning processes with assistive technologies.

Our main lesson was that the pandemic provided the driver for a strategy shift in technology assisted learning delivery worldwide. At institutional level, more institutions are now prepared to invest in the deployment of technologies that can be used to offer the necessary data for assessing learner experiences, individual progress and performance of modules and programmes. In our paper we present an approach that can be feasibly applied to a vast range of learning activities to collect and assess the impact of student interactions on the way learners express their emotions. The approach can assist instructors to collect data with regards to emotion expressions and proceed with descriptive and predictive analytics of educational data.

### 1.1 Students' emotions

Sometimes the reason that influences a loss of motivation that affect negatively the performance is caused by the emotions felt by the students. Indeed, affective, and emotional factors seem to influence students' motivation and, in general, the outcome of the learning process [13].

Understanding students' emotions could be beneficiary for instructors, as they can detect whether certain activities can produce some state of anxiety or stress in students that affects memory [14] and prevents them from achieving their learning outcomes. Our work provides the necessary framework, as well as associated pedagogy and tools that can collect, analyse and use emotional state data to increase awareness of both learners and instructors.

### 1.2 Aim of the work

The goal of this work is to provide accurate interpretations of emotional states during various learning activities, and use identified patterns for adopting learning support according to the forecasted stress levels of individual learners.

An IoT device was used to collect data related to HR (heart rate) and GSR(galvanic skin response) levels and a quantitative analysis was performed to detect the changing students' emotions and provide formative feedback to improve their learning.

### 1.3 Heart rate and galvanic skin response

There is a significant portion of the related literature showing heart rate (HR) increases during an in-class assessment activity can be perceived as a sign of stress and anxiety in the students involved [15]. Furthermore, the literature indicates how the high level of galvanic skin response(GSR) values, (that is a psychophysiological phenomenon exhibited by skin containing sweat glands) [16] influences the emotions felt by university students [17].

However, it's difficult to identify stress based on only a specific physiological change of body, because the values could change depending of the age in HR [18]. In some subjects, if skin conductance changes due to sweat glands which are activated by acute stress, circulatory changes as GSR do not influence emotional sweating and hence can be considered as an independent factor [19]. Results provided only using HR or GSR individually may not be sufficient to identify stress, but matching the values collected by both sensors may increase accuracy in terms of stress detection. Our work attempts to address this issue by combining two biometric sensors in assessing the emotional state of learners during different activities.

Identifying the problem that causes negative feelings during specific learning activities could be determinant for instructors who can further assist learners by adjusting activities so they are better aligned to individual learning styles, or personalize feedback accordingly. Covering these aspects could be essentials to allow students to increase motivation in the study and to improve their performance.

## 2 Data collection and methodology

Identifying the problem that causes negative feelings during specific learning activities could be determinant for instructors who can further assist learners by adjusting activities so they are better aligned to individual learning styles, or personalize feedback accordingly. Covering these aspects could be important to allow students to increase motivation in the study and to improve their performance.

The IoT device, comprises two dedicated sensors, collecting students' HR and GSR levels with the intention to detect changes in the emotional state of individuals during different learning activities. The ultimate goal of our work is to establish a framework for predicting individual stress-levels of individual learners based on their personal profiles (i.e., learning style, personality, teamwork approach and approach towards tasks). The data collection takes place during scrum simulations (individual oral reflection), coordination meeting (team discussions) and team presentations.

The IoT device used for the data collection is illustrated in figure 1, and is a result of our in-house design and implementation efforts thanks to the contribution of researchers from our computer systems engineering, computer science and business information systems programmes. The figure 2 also illustrates the use of the sensors in our innovation hub where a “smart learning” set up is deployed.

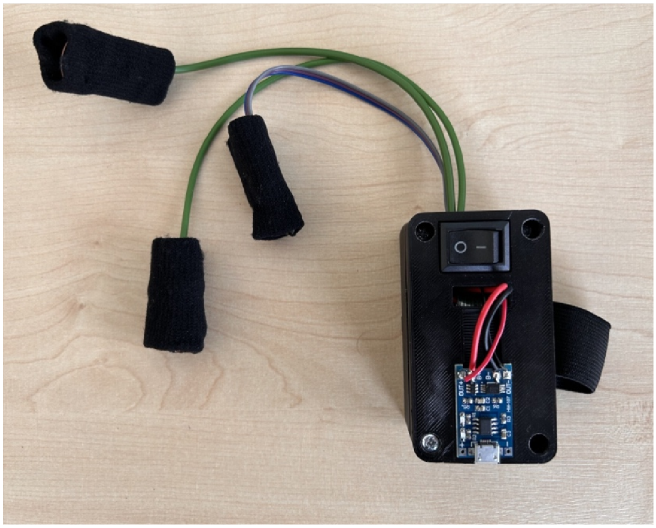

**Fig. 1.** Fully assembled IoT device for GSR and HR data extraction.

We consider a hybrid learning environment to be comprising of a collection of assistive technologies that work together with the aim to enhance learning experiences. These may include the use of AR as a mechanism of rich feedback and instruction support, or the use of affective computing methods aiming at collecting behavioural data from learners across different learning activities. The successful transition to blended or fully online learning during the pandemic, advocates the feasibility of integrating digital technologies in modern learning environments. The key lessons are that the collection of biometric and other interactions in educational contexts can help in performing both descriptive and prescriptive learning analytics.

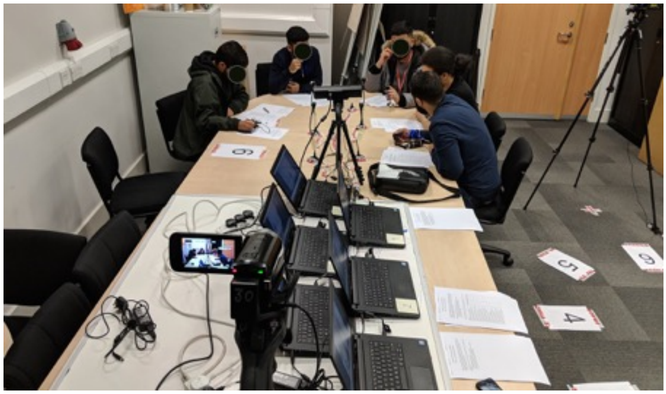

**Fig. 2.** Use of the devices in the innovation hub during learning activities.

### 2.1 Description of the Activity (Smart Lab)

The design of our hybrid educational environment included both the development of the IoT device and its alignment to a range of learning activities. Two undergraduate modules were redesigned to ensure that IoT device could be seamlessly incorporated in an integrated learning process. This involved undergraduate students of several programmes from both Computer Science (third year) and Business Studies (second year) disciplines. The study began prior to COVID-19 , but during the pandemic certain adjustments were made to ensure delivery of teaching was entirely online. During the pandemic the IoT sensor could not be used, but other aspects of the environment were supported, such as emotion detection through video tagging of video presentations.

The current study instead takes place in our “Technology, Innovation, Management and Entrepreneurship inCUBator Environment” (TIME CUBE), which students tend to refer as “Smart Lab”.

This is a space where students have the opportunity for hands-on experience with technology and tools incorporated in our teaching. The work presented in this paper includes only one year of our study and data from the delivery of hybrid learning with the participation of 484 students from different backgrounds.

The learning activities comprised both individual and group work. During 15minute-long sessions, each student is involved in (i) reflecting on his/her own work for the group project and areas of expertise that he can contribute with confidence (SCRUM simulation), (ii) participating in a brainstorming sessions where the group decides who will be responsible to present the group work, and (iii) contributing to a group presentation.

All the modules incorporating the use of the “Smart Lab” include a combination of individual and group learning activities, as follows:

- Activity 1: SCRUM meeting
- Activity 2: Team management meeting
- Activity 3: Presentation of selected topic/s

This paper focuses on the last activity for the module related to Business programme, that requires students to deliver an oral group presentation in the Smart Lab, while using the

IoT device. The “Smart Lab” is used twice during the term, as part of student formative assessment and feedback is provided during the mock presentation element.

The duration of the activity is 1-minute per group member for the presentation.

Groups are created at the beginning of the module composed by 4-6 members selected randomly, to try to get heterogeneous groups. It is indeed demonstrated the effectiveness of heterogeneous groups, in particular in helping students to achieve learning outcomes. [20]

To avoid any impact on student performance, the IoT device was tested during a preparatory mock presentation. Students held the IoT device during the “Smart Lab” session, after signing the necessary consent forms. As the device was worn throughout the learning session, students were able to opt-out at any point, not participate at all and even have their data removed.

After the presentations, students receive feedback by the module leader and lab tutors, while having access to the video recording of the session and any data demonstrating emotion changes detected by the IoT device. Students can reflect on their content presentation and communication skills. The scope of the “Smart Lab” learning experience is to increase student awareness of hybrid educational spaces and the role of data generated by IoT devices for understanding their physical state during different learning activities.

### 2.2 IoT device

During the “Smart Lab” sessions, several data collection devices are used including video recording equipment to analyse with our video tagging system body movement, cameras recording participants’ facial expression for subsequent emotional analysis and Xbox Kinect used to record contribution from each participant, and changes in voice pitch. These devices are non-intrusive in the sense that they do not physically affect the learner.

The spread of new digital devices in the everyday life, led students to feel confident using technology, comparing to the past, also during the lectures and learning activities. The benefits obtained using different technologies in higher education is demonstrated by recent studies that confirm how they can contribute to student’s motivations [21]. Students are so already immersed in technologies, having some ideas of what technologies they can expect to use in the classroom, that instructors are asked to rethink learning materials to prepare students properly [22].

This paper focuses on the IoT device that each learner wears, consisting of sensors collecting biometric data. The IoT device has the following components:

- ESP32 microcontroller with embedded Wi-Fi module
- Pulse sensor for HR detection with a voltage of 5 V, with finger cover
- GSR sensor for sweat detection with a voltage of 5 V, with finger cover
- IoT Device Case
- Elastic wristband to hang on the IoT device case
- Power Supply

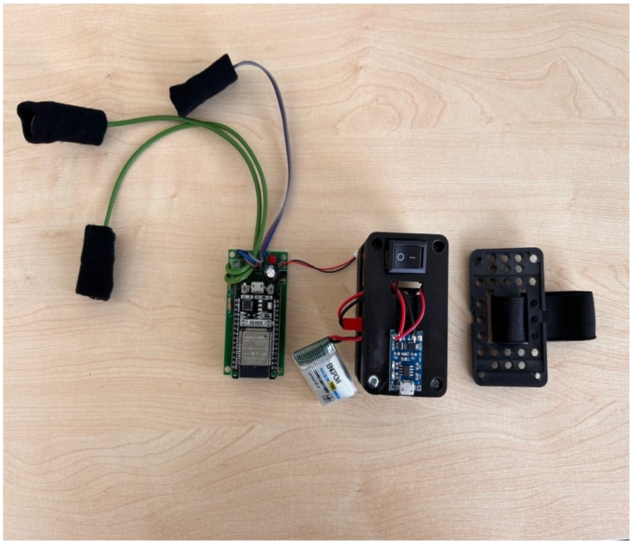

**Fig. 3.** Hardware details related to the IoT device composed by finger sensors, microprocessor with related modules and case.

The GSR sensor reads an analog voltage that ranges roughly between 0 and 512, where 0 means a low resistance and 512 a high resistance. Higher resistance reflects less sweaty fingers (about 400) while sweaty fingers have lower resistance. The HR sensor returns an analog value between 0 and 1023, where the higher resistance means the increase of HR, while a decrease of HR is linked to a low resistance. Figure 3 illustrates the hardware details of the IoT device, and the way it is constructed by our researchers. The full procedure is documented including the necessary stapes and associated images, enabling academics to adopt our proposed solution and create their own sensors to be used in their own learning sessions.

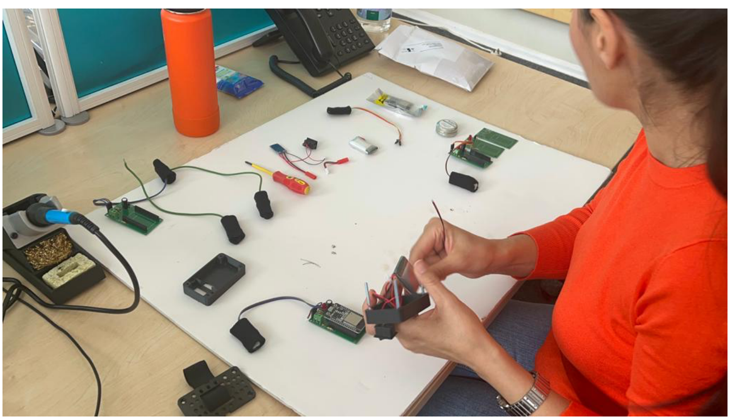

**Fig. 4.** Procedure and configuration of all hardware and sensor components of IoT devices.

The IoT device collects around 200 records per minute and stores all the data in a "mysql" database through "php" connection. The device is connected to a Database stored in a "lamp" environment.

Each learner's record includes the following fields:

- Student id
- Device id
- Timestamp
- Battery percentage
- GSR value
- HR value

The "student id" recorded is pseudonymised on collection to ensure that the privacy of the students is maintained. Furthermore, the "Smart Lab" data are held on different secure databases from any profiling data. The "device id" is a static number that is assigned to each IoT device, used to identify students during the oral presentation. Students are assigned to specific place-holders during the presentation, and timestamps represent the date and time when the data was collected while battery percentage represents the remaining battery charge.

The flow of activity during the "Smart Lab" session is illustrated in figure 5. Each student wears the IoT device during the mock oral presentation, which takes place one week before the formal presentation that is part of the module's summative assessment. The overall experience is intended for preparing students to overcome stress and become aware of their performance in a realistic scenario. The activities are also designed in such a way so students understand the concepts of IoT, hybrid work and the role of data analytics in business operations.

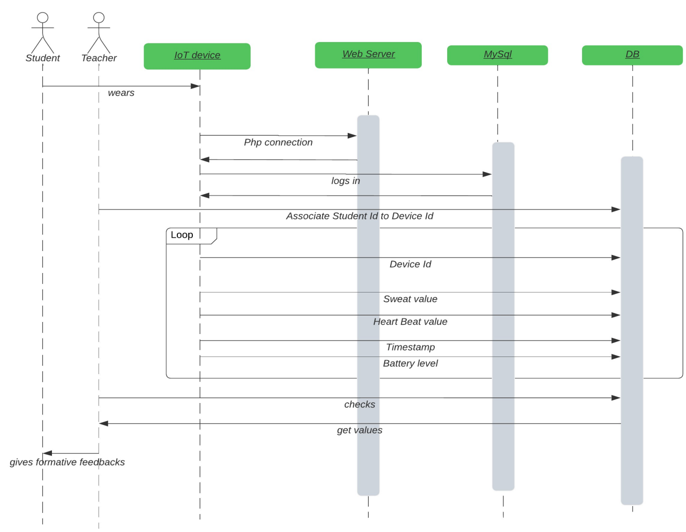


**Fig. 5.** Sequence diagram showing the flow of the activities and the data exchange between IoT device and Database.

The IoT device needs firstly to be connected to the Internet, through Wi-Fi and then it establishes an access to the webserver using “php” script. Once the IoT device access to the webserver properly, it sends the request of authentication to “mysql”, to be able to access the database. Before beginning the data collection, lab tutors assign a code number (student id) with the id of the IoT device, to match the data collected for each student. The student number that identifies each student is already anonymised at this stage, protecting student privacy. Ensuring that the database connection works properly, and the battery level is adequate, the students can start the oral presentation wearing the IoT device. A loop function was implemented that collected 200 records per minute, including “device id”, “GSR value”, “HR value”, “timestamp” and “battery level”.

### 2.5 Data Analysis

The research carried out in this work required a quantitative analysis that involved the GSR sensor and HR sensor values with the aim to identify some changing of emotions in students during the oral presentation.

The challenge was to extract useful information using the data collected by the IoT device and try to identify possible stress condition in students.

Unfortunately the dataset showed some gaps, as well as the presence of undefined values returned output as “nan” occurred when the IoT device raised some exceptions, or missed data that needed to pre-process the dataset in order to be acceptable for the analysis. The imputation, a statistical method used to replace all missing values, was used to fix all the possible anomalies found in the dataset, thanks to a specific library, performed in “python”. Specifically the python method (“fillna()”) was used , that permits to give an attribution method as a value of each feature of the dataset and replaces missing value with this data [23].

In the literature, studies affirm that the matching between the increase of HR value and the GSR level values led people to increase the stress [24].

Once collected all data related to students’ GSR level and HR, a correlation analysis was made to check the effectiveness of the device and the potential detection of emotion changing that can led students to stress.

A linear regression analysis was used to verify the possible correlation between the variables and derive the “pearson correlation,” using the equation:

$$Y= a + bX \tag{1}$$

where “X” is the explanatory variable and “Y” is the dependent variable.

The analysis was performed with Microsoft Excel using the “pearson correlation”.

The “pearson correlation” coefficient was used to measure the strength of a linear correlation between two variables. It takes a value from “-1” (negative correlation) to “+1” (positive correlation) with the value “0” that means no correlation [25].

## 3 Results

Before starting data collection, the IoT device was tested several times in order to ensure the correct working. Firstly it was needed to check the server, checking if it was reachable and in case managing the access through secure shell (ssh) protocol. Then it was essential to check not only that the IoT device was connected, but also that it sends data properly into the database. So the next step was to access to the database, verifying data and timestamp were collected adequately.

Once tested the working of "php" and "mysql" connections, particular attention was paid to the GSR and HR sensors testing if the transmitted signals were properly received.

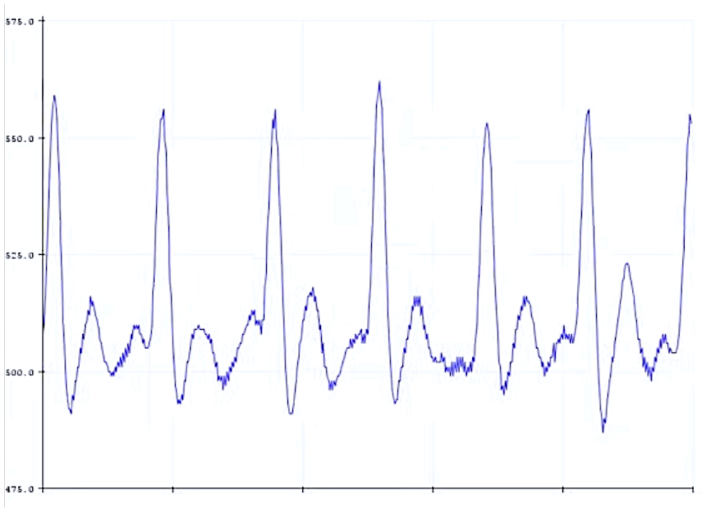


**Fig. 6.** HR graph that shows the datapoints related to heart rate measurements during a timeslot.

After different tests we checked the proper working of the sensors also using plot (figure 6) built using analog values.

However, the detection of the changing of emotion needed the use of bpm as a value for HR, so a conversion of the data from analog to bpm values was performed using the related library [26].

The statistical analysis required the extraction of different data from the database. A dataset was created selecting only the values collected during the oral presentation of each student. Indeed, in the data pre-processing, the dataset was cleaned removing all the data collected before and after each mock presentation, checking with the timestamp of the records, and processing only the data useful for the analysis.

| 1 | id | device_id | sweat_sensor_analog | timestamp | heart_beat_sensor_analog | battery_percentage |
|---|---|---|---|---|---|---|
| 166345 | 679627 | 2 | 180 | 1557676140 | 445 | 96 |
| 166346 | 679627 | 2 | 180 | 1557676140 | 447 | 92 |
| 166347 | 679627 | 2 | 180 | 1557676140 | 447 | 96 |
| 166348 | 679627 | 2 | 180 | 1557676140 | 448 | 96 |
| 166349 | 679627 | 2 | 180 | 1557676140 | 448 | 96 |
| 166350 | 679627 | 2 | 180 | 1557676140 | 448 | 96 |
| 166351 | 679627 | 2 | 180 | 1557676140 | 449 | 96 |
| 166352 | 679627 | 2 | 180 | 1557676140 | 449 | 96 |
| 166353 | 679627 | 2 | 180 | 1557676140 | 449 | 96 |
| 166354 | 679627 | 2 | 180 | 1557676140 | 450 | 96 |
| 166355 | 679627 | 2 | 180 | 1557676140 | 450 | 96 |
| 166356 | 679627 | 2 | 180 | 1557676140 | 451 | 96 |
| 166357 | 709657 | 11 | 185 | 1557684180 | 481 | 95 |
| 166358 | 709657 | 11 | 185 | 1557684180 | 484 | 95 |
| 166359 | 709657 | 11 | 185 | 1557684180 | 484 | 91 |
| 166360 | 709657 | 11 | 185 | 1557684180 | 484 | 91 |
| 166361 | 709657 | 11 | 187 | 1557684180 | 493 | 95 |
| 166362 | 709657 | 11 | 187 | 1557684180 | 495 | 95 |
| 166363 | 679627 | 2 | 183 | 1557684180 | 445 | 91 |
| 166364 | 679627 | 2 | 183 | 1557684180 | 445 | 92 |
| 166365 | 679627 | 2 | 183 | 1557684180 | 447 | 96 |
| 166366 | 679627 | 2 | 183 | 1557684180 | 456 | 96 |
| 166367 | 709657 | 11 | 189 | 1557684180 | 498 | 95 |
| 166368 | 709657 | 11 | 190 | 1557684180 | 502 | 95 |
| 166369 | 679627 | 2 | 182 | 1557684180 | 445 | 92 |
| 166370 | 709657 | 11 | 185 | 1557684180 | 488 | 91 |
| 166371 | 709657 | 11 | 186 | 1557684180 | 492 | 96 |
| 166372 | 709694 | 12 | 185 | 1557687780 | 493 | 95 |
| 166373 | 709694 | 12 | 189 | 1557687780 | 502 | 95 |
| 166374 | 709694 | 12 | 189 | 1557687780 | 502 | 92 |
| 166375 | 709694 | 12 | 189 | 1557687780 | 502 | 92 |

**Fig. 7.** Dataset after pre-processing stage, that shows data collected (analog values) by the IoT device during the oral presentation.

The dataset was then analysed using the "microsoft excel" method "correl", able to calculate the "pearson correlation" between the two columns representing the GSR and HR values for a total of 166489 values collected during the oral presentation.

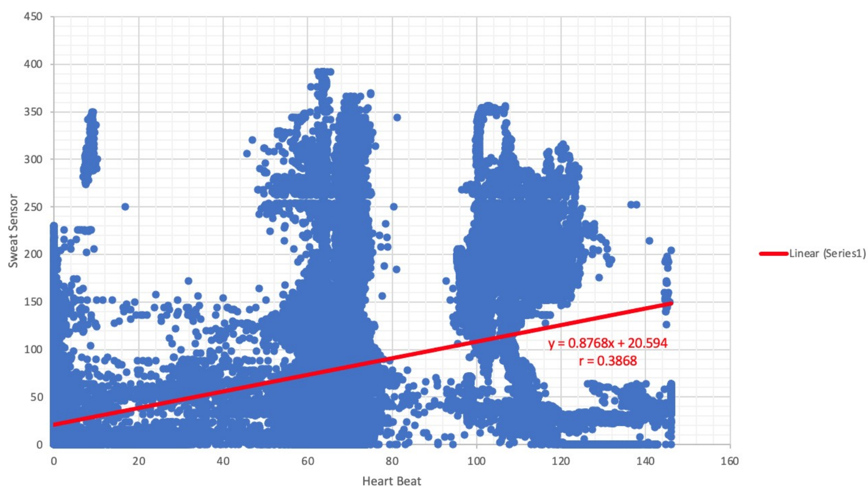


**Fig. 8.** Correlation analysis between GSR values and HR values.

In figure 8 we reported HR value on the x-axis and the GSR value on the "yaxis" for each student involved. From a preliminary analysis it was evident that there was a greater dispersion of data. To examine the data in depth, we used "y(x)=a*x+b" as a fitting function, where the parameters are "a=0.87" and "b=20". In this case, the distance between the data and the regression line (red) generated a "pearson correlation" coefficient "r = 0.38". The "pearson correlation" coefficient measures the strength of a linear correlation between two variables, where the value "r = 1" means a positive correlation and the value r = -1 means a negative correlation. In detail, when “$0 < r < 0.3$” we have a weak correlation, when “$0.3 < r < 0.7$” we have a moderate correlation and when “$r > 0.7$” we have a strong correlation. In our case the correlation coefficient “$r=0.38$” represents a moderate correlation between the variables. Indeed, as figure 8 shows, the increase of GSR level corresponds to an increase of the HR in students and this correlation led to identify stress level in students when the values of the variables overcome the threshold that consisted in the matching of a high level of GSR and a HR value greater than 100 [24].

Thanks to this correlation, we can verify the effectiveness of the IoT device as a tool to assist the instructor during the activities in providing useful feedback related to the detection of the students' emotions.

Indeed, even if the correlation that involves GSR and HR is moderate, it is important because it implies a response, supported by quantitative data, that can measure the heightened stress in students. These values are essential to monitor their changes in the emotional state during the learning activity and students can benefit from stress-reduction interventions.

Our work is in line with similar efforts aiming at using IoT devices for stress management. [27]. Our data findings demonstrate that the IoT device can be useful in detecting stress management levels during educational activities. Our findings lead to the following key reflections:

- It is feasible to integrate the use of IoT devices in learning environments, transforming most presentation and group discussion sessions into hybrid learning experiences.
- Affective computing can be applied to learning activities, making it possible to collect behavioural data from learners that can be used to reflect on individual learning experiences with the use of biometrics.
- Descriptive and prescriptive learning analytics can be used to enable forecasting of individual learner involvement, engagement and stress levels, which can lead in the provision of personalised support.

# 4 Conclusion

The loss of motivation in university students can be caused by their emotional state, that sometimes can negatively affect their performance. Detecting learners' emotions is difficult for instructors, in particular with large student numbers. Providing instructors with a method to detect emotional states, determine patterns of stress level and assess individual learners exceeding certain thresholds of biometric data can prove immensely helpful. This can lead to adaptation of learning activities in order to better fit individual learning needs, as well as personalising feedback and support according to an individual's emotional state and stress levels.

An IoT device, able to collect data related to the GSR level and HR was specifically performed in order to try to identify changes in emotion during various learning activities. A moderate correlation between the GSR level and the HR values in students highlighted the effectiveness of the IoT device as a tool to assist the instructor during the activities in providing useful feedback related to the detection of the changes of the emotions in students.

This hybrid experience not only has improved the students' learning experience, encouraging the engagement, motivation and self-directed learning thanks to feedback received, but also offered benefits to instructors, giving them an instant solution able to refine their teaching strategy during the teaching.

Thanks to this device instructors can consider sentimental aspects in learners, try to avoid that them affect negatively students' performance and give adequate formative feedback to help them to improve their soft skills and achieve their learning outcomes.

Unfortunately, the system doesn't provide a web browser interface, so it still needs a specific setting that allows to connect the IoT device to the network, but it could be useful to implement a web platform for better scalability.

The work could be extended by creating a Machine Learning model, able to predict the possible change of emotion instantly, allowing the instructor to accelerate the delivery of the formative feedback and in this way maximize the students' performance. Our next steps are to further develop our work combining Intelligent Data Analysis of biometric data generated through IoT in an effort to create smarter and optimal hybrid educational environments. We are committed in working towards the development of digital learning technologies that enhance computer mediated experiences, improve interaction design and human computer interaction in educational contexts and revising practices for collaborative learning and working. Our research contribution in the sector is aligned to the need to redefine the blurred borders between the physical and virtual learning environments, and reshaping the way digital technologies support learning activities.

**Acknowledgment.** This paper is supported by European Union's Erasmus+ Strategic Partnership programme under grant agreements No 2020-1-UK01-KA226-HE-094692 (Sharing my Learning Platform-Network-Toolkit), and No 2020-1-UK01-KA226-VET-094527 (Minecraft simulation game for Car mechanics).

**CRediT author statement. Giacomo Nalli**: Conceptualization, Methodology, Formal analysis. **George Dafoulas**: Methodology, Validation, Supervision, Project administration. **Ariadni Tsiakara**: Data curation. **Bahareh Langari** : Investigation, Resources. **Kajal Mistry:** Investigation, Resources. **Farzad Tahmasebi Aria** : Resources.

## References

1. Parsons P., Ross D.: Planning a campus to support hybrid learning, in Maricopa Center for Learning and Instruction (2002).
2. Rovai A. P., Jordan H. M.: Blended learning and sense of community: A comparative analysis with traditional and fully online graduate courses, in International Review of Research in Open and Distance Learning (2004). https://doi.org/10.19173/irrodl.v5i2.192
3. Olapiriyakul K., Scher J.M.: A guide to establishing hybrid learning courses: Employing information technology to create a new learning experience and a case study, in Elsevier, pp. 287 -- 301 (2006) https://doi.org/10.1016/j.iheduc.2006.08.001
4. Raes A., Detienne L., Windey I., Depaepe F.: A systematic literature review on synchronous hybrid learning: gaps identified, in Learning Environ Res, vol.23, pp. 269--290 (2020) https://doi.org/10.1007/s10984-019-09303-z
5. Verde A., Valero J.M.: Teaching and Learning Modalities in Higher Education During the Pandemic: Responses to Coronavirus Disease 2019, in Frontiers in psychology, vol.12 (2019) https://doi.org/10.3389/fpsyg.2021.648592
6. Li, P. The Role of Interest in Motivation and Learning. DEStech Transactions on Social Science, Education and Human Science (2018). https://doi.org/10.12783/dtssehs/ichss2017/19545
7. Dahl, D. W. Does motivation matter? Managerial Finance, vol 37(7), pp. 582-609 (2011) https://doi.org/10.1108/03074351111140243
8. Da Re L.: Promoting the academic success: the Formative Tutoring between research and intervention in the experience of the University of Padua, in Formazione & Insegnamento, vol. 16, pp. 183--200 (2018)

9. Figueiredo J., García-Peñalvo F.J.: Intelligent Tutoring Systems approach to Introductory Programming Courses, in Eighth International Conference on Technological Ecosystems for Enhancing Multiculturality, Association for Computing Machinery, New York, pp. 34--39 (2020)
https://doi.org/10.1145/3434780.3436614
10. Abou El-Seoud M. S., Taj-Eddin I. A., Seddiek N., El-Khouly M. M., Nosseir A.: ELearning and Students' Motivation: A Research Study on the Effect of E-Learning on Higher Education, in International Journal of Emerging Technologies in Learning (iJET), vol. 9, pp. 20--26 (2014) https://doi.org/10.3991/ijet.v9i4.3465
11. Sun, Y. T. A., Chiou, M. -J. Online Platform to Evolve and Develop Motivational Theories on Manufacturing Management Learning to Achieve Pandemic Curriculum Outcomes, International Conference on Education and Technology (ICET), pp. 224-227 (2020)
https://doi.org/10.1109/ICET51153.2020.9276615
12. De Almeida, L. R. Motivating attendee's participation in distance learning via an automatic messaging plugin for the moodle platform, IEEE Frontiers in Education Conference (FIE), pp. 1-5 (2016). https://doi.org/10.1109/FIE.2016.7757608
13. Shen L., Wang M., Shen R.: Affective e-Learning: Using "Emotional" Data to Improve Learning in Pervasive Learning Environment, in Journal of Educational Technology & Society, vol.12, pp. 176--189 (2009)
14. Mizoguchi K., Yuzurihara M., Ishige A., Sasaki H., Chui D.H., Tabira T.: Chronic stress induces impairment of spatial working memory because of prefrontal dopaminergic dysfunction, in J Neurosci, vol. 20, pp. 1568--74 (2000) https://doi.org/10.1523/JNEUROSCI.20-04-01568.2000
15. Elwess N. L., Vogt, F.D.: Heart Rate and Stress in a College Setting, in Bioscene: The Journal of College Biology Teaching, vol. 31, pp. 20--23 (2005)
16. Vemet-Maury E.: The cutaneous bio-electrical signals and their sources, in ITBM, vol. 12, pp. 98--111 (1991)
17. Joshi A., Kiran R.: Gauging the effectiveness of music and yoga for reducing stress among engineering students: An investigation based on Galvanic Skin Response, in Work, vol 65(3), pp.671 -- 678. https://doi.org/10.3233/WOR-203121
18. Kim J., Youn C. H., Woo J. M., Jung S., Kim D.: Association of heart rates with stress response inventory scores in different age groups, In 29th annual international conference of the IEEE engineering in medicine and biology society, pp. 5751--5753 (2007)
https://doi.org/10.1109/IEMBS.2007.4353653
19. Fernandes A., Helawar R., Lokesh R., Tari T., Shahapurkar A.V.: Determination of stress using Blood Pressure and Galvanic Skin Response, in International Conference on Communication and Network Technologies, pp. 165--168 (2014) https://doi.org/10.1109/CNT.2014.7062747
20. Nalli G., Amendola D., Smith S.: Artificial Intelligence to improve learning outcomes through online collaborative activities, in European Conference on e-Learning, Vol.21, pp.475--479(2022)
https://doi.org/10.34190/ecel.21.1.661
21. Ayari, M. A., Sahbi A, Arslan A. Effects of use of technology on students' motivation. Journal of teaching and education vol 1(2) , pp. 407-412 (2012)
22. Geer, R. Students' Voices about Learning with Technology, Journal of Social Sciences, 8, pp. 294-303 (2012) https://doi.org/10.3844/jssp.2012.294.303
23. McKinney, W. Python for data analysis: Data wrangling with Pandas, NumPy, and IPython. O'Reilly Media, Inc., (2012).
24. Basjaruddin N.C., Syahbarudin F., Sutjiredjeki E.: Measurement Device for Stress Level and Vital Sign Based on Sensor Fusion, in Healthcare informatics research, vol 27(1), pp. 11 -- 18 (2021)
https://doi.org/10.4258/hir.2021.27.1.11
25. Kotu V., Deshpande B.: Data Science (Second Edition), in Morgan Kaufmann, pp. 65--163 (2019)
https://doi.org/10.1016/B978-0-12-814761-0.00004-6
26. Pulse Sensors, https://pulsesensor.com/
27. Rodic, B., Labus, A., Bogdanović, Z., Despotovic-Zrakic, M., Radenkovic, B.: Development of an IoT system for students' stress management. Facta universitatis - series: Electronics and Energetics. 31. 329-342. (2018). https://doi.org/10.2298/FUEE1803329R