

Investigating the VR rollercoaster experience by applying AI models to biometric data

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Abstract. Detecting emotional components within a Virtual Reality is crucial for evaluating the user experience. However, it's not always easy to detect changes in emotional states during immersive scenarios. This paper investigates the use of an IoT stress detection device aimed at collecting heartbeat and galvanic skin data during the VR rollercoaster simulation, consisting of a moving chair and a synchronized visor, providing a 3D scenario with adjustable speed. The biometric data was processed by a machine learning model, accurately selected after a comparative analysis between three Clustering models, to identify the different stress levels felt by the participants during the ride. Their stress levels were then cross-referenced with their perceptions on the ride to demonstrate whether VR can have an impact on their emotions. The results show how the VR can affect the perceived levels of stress and how a VR simulation could be comparable to a real roller coaster.

Keywords: VR, AI, Clustering, Roller Coaster.

1 Introduction

Emotional components are important parts of the Virtual Reality (VR) user experience. Recently, the development of new technologies such as has led to the provision of simulations so realistic that they can be used in different fields. VR is used for instance for medical field [1][2][3][4] for its ability to see through the skins and organs making easier to visualize the areas for a surgery intervention [5]. Another VR applications refers to health care and therapy, reducing the perception of pain during medical procedures [6], or for carotid stent training[7] or for anatomy education [8].

However the medicine is not the only field faced by the new emerging technologies as VR, AI, IoT and blockchain as they cover a broader area also in the education [44], as they allow a greater engagement rather than the traditional education and training methods [9] and at the same time it provides the chance to adopt experiential learning and social constructivist approach. [10]. Thanks to these benefits, VR could fit perfectly for a training aimed to develop soft skills [11][12]. VR technologies are also largely used in the tourism sector, in particular for virtual tours in different places, allowing people to explore a new dimension of tourism by discovering new cities in a sustainable way [13][14] or visiting museums [15][16], especially during the COVID-19 pandemic [17]. Indeed, the VR technology has great potential to allow people to feel the same emotions during the simulation as they would in real life [18][19][20]. For this reason, VR simulations have also been adopted to allow people with neurodiversity to have multiple experiences and manage their emotions in a safe environment, by controlling the sensory load in the system and adapting it to the individual's sensory needs [21]. However, it's not always easy to detect changes in emotional states during immersive scenarios [22][23][24]. A validated stress device, developed entirely in-house, can be used to detect these emotional changes during the VR simulation. This study explores the potential efficacy of a VR roller coaster simulation, consisting of a moving chair and a visor, which presents a three-dimensional scenario with adjustable speed.

The aim of this research is to investigate participants' reactions during a VR roller coaster simulation by collecting and analysing biometric data to determine their stress levels and cross-referencing this data with their self-perceptions to assess the realism of a virtual reality simulation.

The study involves 38 participants, who kindly agreed by giving their consent at the stand exhibition and have been asked to ride the VR rollercoaster wearing the stress device in order to collect heart rate and galvanic skin data necessary to determine their stress levels during the experience. Clustering techniques were then used to assess participants' stress levels by analysing the data contained in each cluster returned. After the VR experience, participants were invited to complete a final questionnaire to collect their perceptions. The questionnaire aimed to investigate prior experience of roller coasters and simulations, perceptions of VR immersiveness, emotional and physical responses, usability of the technology, and awareness. The questions require answers on a scale of 1–10 or using the Likert scale. The responses were then cross referenced with the stress levels obtained to assess whether a VR experience could impact the emotional state of the user and specifically whether a VR simulation could be compared to a real experience. The quantitative analysis showed how the VR roller coaster simulation can be compared to a real roller coaster experience.

2 Related works

Identifying emotional states during immersive scenarios is a challenging task that researchers are used to face. The authors in [37] propose an analysis of the features-based recognition of emotional states by comparing multiple algorithms. The author in [38],

on the other hand, classified emotional states using a machine learning algorithm that can identify them by analysing body posture for real-time recognition. The authors in [39] analyse how EEG signals can be applied in VR environments, demonstrating good results in terms of emotion detection. The authors in [40] applied deep learning to process biometric data for emotion detection in real-time immersive activities. Despite progress in research in this field, this study had to be adapted to the roller coaster equipment (fully realized in-house). For this purpose, the use of a specific hand crafted IoT device able to collect 200 galvanic skin and heart rate records over a period of one minute was crucial to undertake the research. This approach allows us to collect thousands biometric data points and then apply machine learning algorithms to identify potential changes in emotional state, which are then cross-checked with a post-experience questionnaire to assess the impact of the experience.

3 Methods and methodology

Data collection took place during a stand event where participants had the unique opportunity to engage with the virtual reality (VR) roller coaster simulation. The 38 participants (18 females and 20 males), aged over 18, volunteered to take part in the research by giving their consent to ride the VR rollercoaster and have their biometric data collected. At the end of the ride, participants completed a perception questionnaire about their VR experience. The roller coaster simulation was characterized by a chair above a motion platform and a visor synchronized with VR software. Specifically, the motion platform (Fig. 1) was moved by a compressor-driven system that simulated the motion of a roller coaster, including the capture of 360 video and sound provided by the visor and speakers [25].

Instead, the heart rate and galvanic data were collected during the ride using an IoT device developed entirely in-house, consisting of an ESP32 with Wi-Fi module and pulse and GSR sensors that must be attached to the participant's fingers. The IoT device consists of a special case with an elastic wristband, finger covers for the sensors and a battery that allows it to be used without a power supply [26]. The pulse sensor for HR and two GSR sensors for sweat detection both with a voltage of 5 V, have been linked to the microcontroller. These sensors have been used to identify the biometric values, then processed in order to return the stress levels.



Fig. 1. The VR rollercoaster is powered by a compressor-driven system linked to a Meta Quest visor, which is able to simulate the sound and provide the roller coaster video experience. There is also a fan to simulate the air of the roller coaster.

The stress detection device collected the biometric values into a database using a php connection, recording analogue values (adc) of heartbeat and galvanic skin in the range 0-1023 (heartbeat) and 0-512 (sweat level). The extracted data was then pre-processed before being processed by the clustering algorithms.

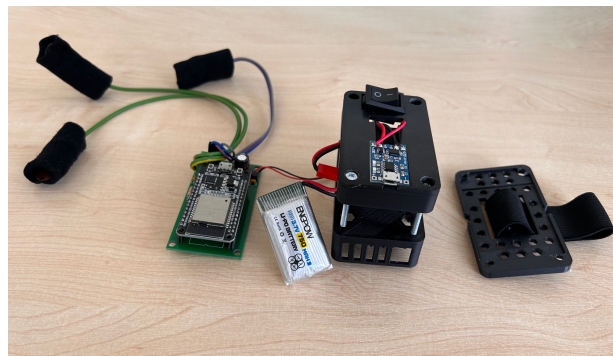


Fig. 2. The hardware details of the IoT device which include Hr and GS finger sensors, a microprocessor with Wi-Fi modules.

Clustering allows to identify similarity between data in a dataset and create clusters (groupings) [27][28][29][30] of participants with same reactions during the roller coaster. Clustering is particularly effective at determining different psychological states, and it is often used, particularly when processing heart rate data.[41] Specifically, the dataset contained the following features: id device, heartbeat min, heartbeat max, heartbeat avg, sweat level min, sweat level max, sweat level avg.

A comparative analysis of different clustering algorithms (K-means, Mean Shift and Gaussian Mixture Model) was then carried out to create clusters (groupings) of participants with similar biometric values to identify the different levels of stress they were experiencing.

The algorithms were then compared using silhouette analysis [31][32] to select the most performant and return the clusters that identify the different stress levels. The clusters were then compared with the participants' perceptions, collected via a post-activity questionnaire, based on their previous roller coaster experience and the positivity of their emotions during the VR simulation.

4 Results and discussion

Identifying changes in stress levels during the VR rollercoaster simulation required data pre-processing and data cleaning, as the IoT device returned a single csv file with 200 records per minute for each participant. Specifically, a dataset was created by associating the following features with the participant ID: minimum, maximum and average of the heartbeat and galvanic skin values. The dataset was then processed by the different clustering algorithms specifically implemented for this study. The different machine learning models were developed by adopting the Python libraries of Scikit Learn related to the algorithms K-means, Mean Shift and Gaussian Mixture Model.

The development of the models adopted the default setting provided by Scikit Learn library except for the number of clusters to create which is 3 for all algorithms. For example, the model developed using K-means was characterized by “3” “clusters number”, “k-means++” as “method for initialization”, “none” as a “random state” and “Lloyd” as “algorithm”. The model based on Mean Shift instead was characterized by parameters as “no bandwidth”, “no seeds”, “no number of jobs” and “300” as “max iteration”. The model based on Gaussian Mixture Model provided “full” as “covariance type”, “100 max iteration” and “1e-06” as “reg covar value”. The performances of the clustering algorithms were then assessed using silhouette analysis and the results compared to select the most powerful to analyse the different stress levels.

Table 1. Comparison of the performance of the different clustering models

ML models	Silhouette score
K-means	0.85050147
Mean Shift	0.83124089
Gaussian Mixture Model	0.83434980

Table 1 shows the different values of the silhouette index obtained by the three clustering algorithms, where the most powerful is K-means as the silhouette index value is closer to 1. The selected ML model was then implemented by using the elbow method approach able to select the optimal number of clusters to generate based on the dataset provided[33][34][35]. The following Table 1 gives a summary of all heading levels.

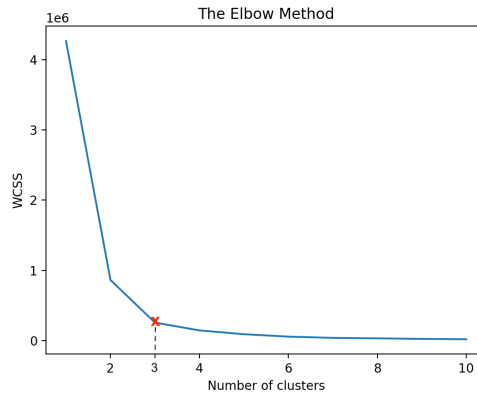


Fig. 3. Elbow method graph to identify the optimal number of clusters to create based on the participants' values in the dataset.

The model generated 3 distinct clusters using the optimal number of clusters as shown by the Figure 3 composed by 23 people (cluster 1), 12 people (cluster 2) and 3 people (cluster 3).

The clusters were then analysed to check the similarity of the items included in each cluster and the potential differences between the clusters to check the stress perceived during the VR rollercoaster simulation.

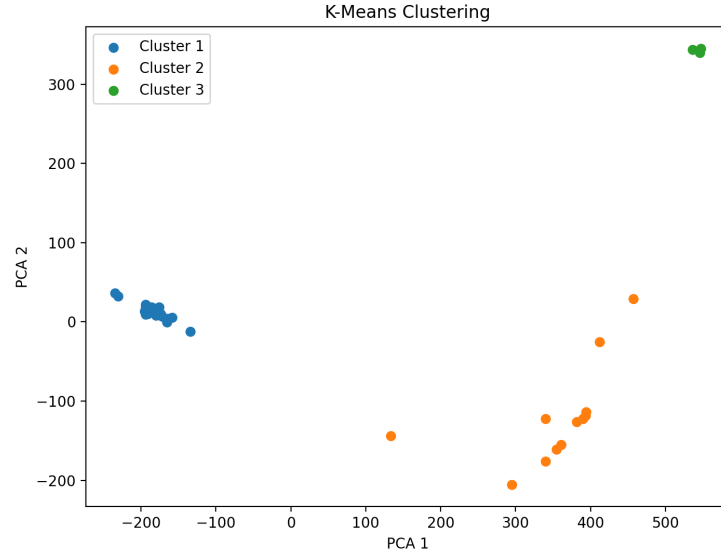


Fig. 4. K-means clustering returned 3 distinct clusters, identified by different colours.

Clustering based on biometric data indeed has been widely used in the literature for the stress detection [42], especially through the implementation of k-means clustering using heart rate and galvanic skin response. [43] The Table 2 shows that the clusters represent different reactions felt by people during the VR rollercoaster experience, as indicated by the different values for HR avg and GS avg.

Specifically cluster 1 represents students with a normal state of stress, as the HR analogue values fluctuated between 435.91 and 497.45 and GS values are low with an avg of 15.66. Cluster 2 instead can be identified as “high stress” as returns higher values compared cluster 1, with an HR values of 640.03 and GS avg values of 51.75. Finally cluster 3 groups people that felt a very high stress condition during the VR rollercoaster with an HR avg value of 906.09 and also an high score in terms of GS avg (89.31). Consequently the study aims to investigate people's perceptions by analysing the responses to the questionnaire to find possible correspondences with the state of stress returned by the clustering.

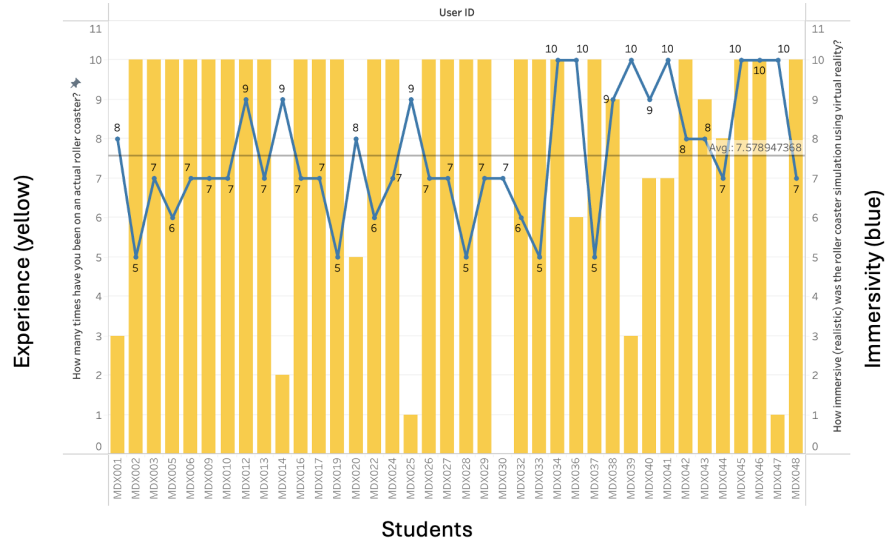


Fig. 5. Plot matching people responses to previous experience on real roller coasters (yellow) and perception of immersion on VR roller coasters (blue).

Table 2. Average features values included in each Clusters

Clusters	HR min	HR max	HR avg	Sd HR	GS min	GS max	GS avg	Sd GS
Cluster 1	435.91	497.45	464.09	78.96	3.00	41.82	15.66	17.96
Cluster 2	428.17	995.75	640.03	115.73	2.67	119.17	51.75	20.34
Cluster 3	844.67	970.67	906.09	4.58	80.00	98.67	89.31	0.40

To illustrate this point, a plot was created matching responses to previous experience on real roller coasters and the level of immersion on VR roller coasters to see how immersive the VR experience was by using a scale characterized by values from 0 to 10, where 10 is the max. Figure 5 shows an high VR immersion score, with a mean of 7.57 and no responses below 5. The trend has been also represented in a single plot at Figure 6.

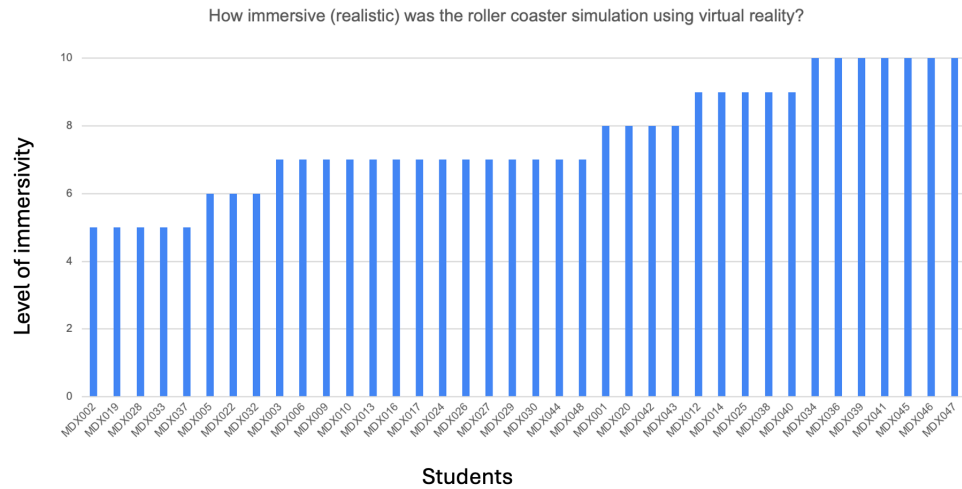


Fig. 6. Participants answers related the level of immersion on VR roller coasters.

Figure 6 demonstrates a high level of immersion and reality during the VR experience, not only for participants who had not experienced roller coasters or only a few times, but also for those who had already ridden roller coasters more than 10 times.

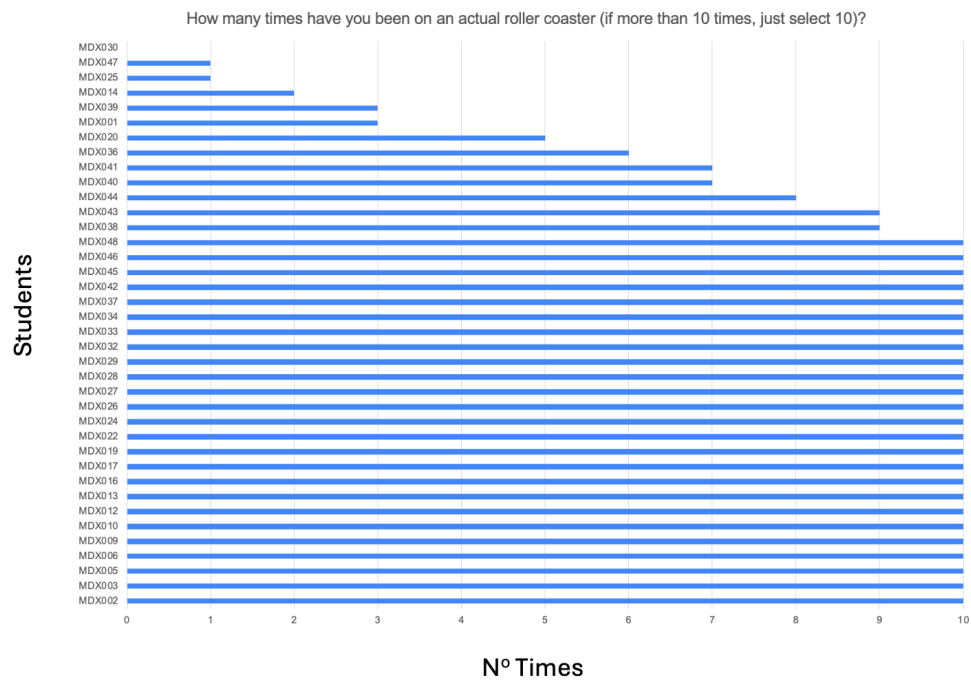


Fig. 7. Participants answers to the question about the experience on an actual roller coaster

In addition to this, a further analysis was carried out, which mainly focused on identifying the perceptions of the participants in each cluster, how enjoyable and scary the VR roller coaster was.

A 5-point Likert response scale was used to assess the perception: 1- Strongly Disagree (SD); 2- Disagree (D); 3- Neutral (N); 4- Agree (A); 5- Strongly Agree (SA).

Table 3. Answers to the question about the level of enjoyment grouped per Clusters

Clusters	SA	A	N	D	SD
Cluster 1 <i>Stress</i>	33.33 %	48.48 %	0 %	15.15 %	3.03 %
Cluster 2 <i>High stress</i>	75 %	8.33 %	16.67 %	0 %	0.00 %
Cluster 3 <i>Very high stress</i>	33.33 %	33.33 %	0 %	33.33 %	0.00 %

The results in Table 3 indicate a good level of enjoyment in all clusters by showing a general satisfaction (SA+A). Despite this, it is important to highlight how satisfaction decreases with increasing stress, specifically in cluster 3, identified as “very high stress” (SA+A equal to 66%), compared to cluster 1 and cluster 2 (“stress” and “high stress”) where the score is in the range of 81% - 83%.

Table 4. Answers to the question about the level of fear grouped per Clusters

Clusters	SA	A	N	D	SD
Cluster 1 <i>Stress</i>	3.57 %	10.71 %	42.86 %	17.86 %	25.00 %
Cluster 2 <i>High stress</i>	0 %	23.08 %	38.46 %	30.77 %	7.69 %
Cluster 3 <i>Very high stress</i>	0 %	0 %	33.33 %	33.33 %	33.33 %

On the other hand Table 4 shows that the level of fear is quite low in all clusters, with only 14% (SA+A) in cluster 1 (stress) , 23%(SA+A) in cluster 2 and 0 % (SA+A) in cluster 3. The fact that participants don’t perceive fear contrasts with the results obtained in Table 3. Indeed usually people find pleasure in fear inducing experiences such as roller coaster ride [36]. One possible reason why people don’t experience fear on a VR rollercoaster is that they know they are in a safe environment and can stop the simulation if they feel uncomfortable. The evidence presented suggest that VR technology can be a way to ensure that people can freely express their emotions and try experiences they normally don’t want to try, making VR simulation accessible and inclusive also to people with neurodiversity and disabilities.

5 Conclusion

In VR simulation, it's not always easy to detect changes in emotional states during immersive scenarios and usually the adoption of questionnaires is used for this purpose.

A possible solution for extracting the emotional changes during the VR simulation could be to find the stress level of the participants during the activity. The study investigated the potential effectiveness of an in-house developed physical VR roller coaster simulation and examined participants' reactions during the activity, by processing biometric data with AI techniques to determine their stress levels and by comparing this data with their self-perceptions to assess the realism of a virtual reality simulation.

In this paper, HR and GS values collected using an IoT wearable device were processed with unsupervised machine learning models to create three different clusters, each of them identifying a group of VR rollercoaster participants with different levels of stress (stress, high stress and very high stress). The results show that there are correspondences between the stress level detected by the processing of biometric values and the participants' perceptions in terms of immersion (average 7.57 out of 10) and enjoyment (cluster 1 with 81%, cluster 2 with 83% and cluster 3 with 66%), confirming that the simulation experienced in the VR roller coaster is comparable to a real roller coaster.

In conclusion, future developments of this study aim to further explore the potential contribution of wearable devices, including additional sensors such as body temperature, to increase the accuracy and precision of participants' stress levels.

Disclosure of Interests

The authors have no competing interests to declare that are relevant to the content of this article

References

1. Herur-Raman A., Almeida N.D., Greenleaf W., Williams D., Karshenas A. , Sherman J.H., Next-Generation Simulation—Integrating Extended Reality Technology Into Medical Education. *Frontiers in Virtual Real*, 2, (2021).
2. Pensieri C., Pennacchini M.: Overview: virtual reality in medicine. *Journal For Virtual Worlds Research*, 7(1) (2014).
3. Mathur A.S. : Low cost virtual reality for medical training. In *2015 IEEE Virtual Reality (VR)*, pp. 345-346 (2015).
4. Li L., Yu F., Shi D., Shi J., Tian Z., Yang J., Jiang Q.: Application of virtual reality technology in clinical medicine. *American journal of translational research* 9, pp. 3867 (2017)
5. Izard S. G., Juanes J. A., García Peñalvo F. J., Estella J.M., Ledesma M. J. S., Ruisoto P.: Virtual reality as an educational and training tool for medicine. *Journal of medical systems* 42, pp.1-5 (2018).

6. Nguyen T.T.M., Zheng Q., Yi E.J., Bellere A.D., Jin X., Kim H.Y., Yi T.H.: The Potential Teeth Bleaching and Halitosis Prevention Effects of *Pediococcus inopinatus* THK-30, a Kimchi-Derived Lactic Acid Bacterium: In Vitro Study. *Journal of Functional Biomaterials*, 15(3), pp.64 (2024).
7. Gallagher A.G., Cates C.U.: Approval of virtual reality training for carotid stenting: what this means for procedural-based medicine. *Jama* 292, pp. 3024-3026 (2004).
8. Falah J., Khan S., Alfalah T., Alfalah S.F., Chan W., Harrison D.K., Charissis V.: Virtual Reality medical training system for anatomy education. In 2014 Science and information conference IEEE, pp. 752-758 (2014).
9. Conrad M., Kablitz D., Schumann S.: Learning effectiveness of immersive virtual reality in education and training: A systematic review of findings. *Computers & Education: X Reality* 4, pp. 100053 (2024).
10. Concannon B.J., Esmail S., Roduta Roberts M.: Head-mounted display virtual reality in post-secondary education and skill training. *Frontiers in education* 4, pp. 80 (2019).
11. Hickman L., Akdere M.: Exploring virtual reality for developing soft-skills in STEM education. In 2017 7th World Engineering Education Forum (WEEF) IEEE pp. 461-465 (2017).
12. Venkat S., Varadharajulu K.: Effectiveness of virtual reality in soft skill development. In ICERI2024 Proceedings IATED, pp. 6015-6020 (2024).
13. Beimler R., Bruder G., Steinicke F.: Immersive guided tours for virtual tourism through 3D city models. In Proc. GI Workshop on Virtual and Augmented Reality (GI VR/AR), pp. 69-75 (2013).
14. Shen Y. S.: Technological innovations and sustainable urban tourism. In *Handbook on Sustainable Urban Tourism*, pp. 178-190 (2024).
15. Kalving M., Paananen S., Seppälä J., Colley A., Häkkinen J.: Comparing VR and desktop 360 video museum tours, In Proceedings of the 21st International Conference on Mobile and Ubiquitous Multimedia, pp. 282-284 (2022).
16. Shehade M., Stylianou-Lambert T.: Virtual reality in museums: Exploring the experiences of museum professionals. *Applied sciences* 10, pp. 4031 (2020).
17. Godovykh M., Baker C., Fyall A.: VR in Tourism: A New Call for Virtual Tourism Experience amid and after the COVID-19 Pandemic. *Tourism and Hospitality* 3(1), pp. 265-275 (2022).
18. Somarathna R., Bednarz T., Mohammadi G.: Virtual reality for emotion elicitation - a review. *IEEE Transactions Affect. Comput.* (2021).
19. Linares-Vargas B. G., Cieza-Mostacero S.E.: Interactive virtual reality environments and emotions: a systematic review. *Virtual Reality* 29 (2024).
20. Pizzolante M., Bartolotta S., Sarcinella E.D., Chirico A., Gaggioli A.: Virtual vs. real: exploring perceptual, cognitive and affective dimensions in design product experiences. *BMC psychology*, 12 (2024).
21. Boyd L.E., Day K., Stewart N., Abdo K., Lamkin K., Linstead E.: Leveling the playing field: Supporting neurodiversity via virtual realities. *Technology & Innovation* 20, pp. 105-116 (2018).
22. Magalhães M., Coelho A., Melo M.: Measuring users' emotional responses in multisensory virtual reality: a systematic literature review. *Multimed Tools Appl* 83, pp. 43377–43417 (2024).
23. Markowitz D.M., Bailenson J.N.: Virtual reality and emotion: A 5-year systematic review of empirical research (2015–2019). In R. L. Nabi & J. Gall Myrick (Eds.) *Emotions in the digital world: Exploring affective experience and expression in online interactions* Oxford University Press, pp. 134–152 (2023).

24. Purnomo F.A., Arifin F., Surjono H.D.: Utilizing virtual reality for real-time emotion recognition with artificial intelligence: a systematic literature review. *Electrical Engineering and Informatics*, 14, pp. 447-456 (2025).
25. Passmore P., Tennent P., Walker B., Philpot A., Markowski M., Karamanoglu M., "Archives of thrill: the V-Armchair experience", *ICAT-EGVE 2017*, pp.125-132 (2017).
26. Nalli G., Dafoulas G., Tsiakara A., Langari B., Mistry K., Aria F.T.: Hybrid Educational Environments–Using IoT to detect emotion changes during student interactions. *Interaction Design & Architecture (s)–IxD&A Journal* 58, pp. 39-52 (2023).
27. Nalli G., Culmone R., Perali A., Amendola D.: Online tutoring system for programming courses to improve exam pass rate. *Journal of e-Learning and Knowledge Society* 19, pp. 27–35 (2023).
28. Sisodia D., Singh L., Sisodia S., Saxena K.: Clustering techniques: a brief survey of different clustering algorithms. *International Journal of Latest Trends in Engineering and Technology (IJLTET)* 1, pp. 82-87 (2012).
29. Saxena A., Prasad M., Gupta A., Bharill N., Patel O.P., Tiwari A., Lin C.T.: A review of clustering techniques and developments. *Neurocomputing* 267, pp.664-681 (2017).
30. Rokach L., Maimon O.: Clustering methods. *Data mining and knowledge discovery handbook*, pp. 321-352 (2005).
31. De Amorim R.C., Hennig C.: Recovering the number of clusters in data sets with noise features using feature rescaling factors. *Information sciences* 324, pp. 126-145 (2015).
32. Shutaywi M., Kachouie N.N.: Silhouette analysis for performance evaluation in machine learning with applications to clustering. *Entropy* 23, pp. 759 (2021).
33. Hackeling G.: *Mastering Machine Learning with scikit-learn*. Packt Publishing Ltd (2017).
34. Bholowalia P., Kumar A.: EBK-means: A clustering technique based on elbow method and k-means in WSN. *International Journal of Computer Applications* 105 (2014).
35. Liu F., Deng Y.: Determine the number of unknown targets in open world based on elbow method. *IEEE Transactions on Fuzzy Systems* 29, pp. 986-995 (2020)
36. Kovács A. B.: The Pleasure of Fear: The Roller-Coaster Ride: Revisiting the “paradox of horror”. *Negative Emotions in the Reception of Fictional Narratives*, pp. 3-19 (2022).
37. Picard R.W., Vyzas E., Healey J.: Toward machine emotional intelligence: Analysis of affective physiological state. *IEEE transactions on pattern analysis and machine intelligence* 23(10), pp.1175-1191(2001)
38. Vijayanthi S., Arunnehu J. Human emotion recognition from body posture with machine learning techniques. In *International Conference on Advances in Computing and Data Sciences*, pp. 231-242 (2022)
39. Wang S., Qu J., Zhang Y., Zhang Y. Multimodal emotion recognition from EEG signals and facial expressions. *IEEE Access*, 11, pp. 33061-33068 (2023)
40. Lima R., Chirico A., Varandas R., Gamboa H., Gaggioli A., Badia, S.B. Multimodal emotion classification using machine learning in immersive and non-immersive virtual reality. *Virtual Reality*, 28(2) (2024)
41. Bidargaddi N., Sarela A., Korhonen I. Physiological state characterization by clustering heart rate, heart rate variability and movement activity information. In *2008 30th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*, pp. 1749-1752 (2008)
42. Iqbal T., Elahi A., Wijns W., Shahzad, A. Exploring unsupervised machine learning classification methods for physiological stress detection. *Frontiers in Medical Technology*, 4, pp.782756 (2022)
43. Rescioa G., Leonea A., Sicilianoa P. Unsupervised-based framework for aged worker's stress detection. *Work Artif Intell an Ageing Soc*, 2804, pp.81-7 (2020)

44. Bigiotti A., Bottoni M.P.F., Nalli, G. Blockchain in e-learning platform to enhance trustworthiness and sharing of micro-credentials. International Conference on Advanced Information Systems Engineering, Springer, pp. 5-17 (2024)