BRAIN. Broad Research in Artificial Intelligence and Neuroscience
e-ISSN: 2067-3957 | p-ISSN: 2068-0473
Covered in: Web of Science (ESCI); EBSCO; JERIH PLUS (hkdir.no); IndexCopernicus; Google Scholar; SHERPA/RoMEO; ArticleReach Direct; WorldCat; CrossRef; Peeref; Bridge of Knowledge (mostwiedzy.pl); abcdindex.com; Editage; Ingenta Connect Publication; OALib; scite.ai; Scholar9; Scientific and Technical Information Portal; FID Move; ADVANCED SCIENCES INDEX (European Science Evaluation Centre, neredataltics.org); ivySCI; exaly.com; Journal Selector Tool (letpub.com); Citefactor.org; fatcat!; ZDB catalogue; Catalogue SUDOC (abes.fr); OpenAlex; Wikidata; The ISSN Portal; Socolar; KVK-Volltitel (kit.edu)
2025, Volume 16, Issue 3, pages: 258-270
Submitted: April 4th, 2025 | *Accepted for publication:* August 16th, 2025

Adaptive Learning based on Biometric Assessment of Cognitive Load in an Educational and Scientific Cluster

Halyna Kolomoiets
Candidate of Pedagogical Sciences, Senior Researcher, deputy director State Scientific Institution, Institute of Education Content Modernisation, Kyiv, Ukraine.
g0978423267@gmail.com
https://orcid.org/0000-0002-4315-3977

Iryna Holiiad
PhD in Pedagogical Sciences, Associate Professor, Senior Researcher, State Scientific Institution, Institute of Education Content Modernisation, Kyiv, Ukraine.
goliyad-ktnk@ukr.net
https://orcid.org/0000-0003-4979-828X

Vasyl Tutashynskyi
PhD in Pedagogical Sciences, Institute of Pedagogy NAPS in Ukraine, Kyiv, Ukraine.
tutashi@ukr.net
https://orcid.org/0000-0002-1842-0914

Larysa Hrytsenko
PhD in Pedagogical Sciences, Associate Professor of the Department of Theory and Methodology of Technological Education, Poltava V. G. Korolenko National Pedagogical University, Poltava, Ukraine.
grycenko_l@ukr.net
https://orcid.org/0000-0003-4754-4593

Ruslan Holiiad
Lecturer of the Department of Ecology, Computer Systems, and Automation.
Separate Structural Subdivision Kyiv Vocational College of Urban Economy of V. I. Vernadsky Tavria National University, Kyiv, Ukraine.
ballone.revoltad@gmail.com
https://orcid.org/0009-0004-8815-158X

Maryna Rebryna
Postgraduate Student at the Department of Technological Education,
Mykhailo Drahomanov Ukrainian State University, Kyiv, Ukraine
380991012381m@gmail.com
https://orcid.org/0009-0003-4461-6923

Abstract: *The article presents the results of an experimental study on the effectiveness of adaptive learning based on biometric assessment of students' cognitive load within an educational and scientific cluster. The main aim of the study was to examine the impact of physiological indicators, particularly heart rate, on the adaptation of the learning process to enhance its effectiveness. During the study, students' heart rates were monitored to determine their level of cognitive load. In cases of detected elevated load, the teaching pace was slowed down or breaks were introduced. The results of the final assessment demonstrated a statistically significant advantage of the experimental group over the control group. Correlation analysis revealed a strong relationship between heart rate levels and the quality of material assimilation, confirming the effectiveness of using biometric data to adapt the learning process. In addition, the article discusses biometric indicators such as skin conductivity and eye movements as objective markers of cognitive state during learning. The experience of integrating biometric feedback into educational platforms is analyzed, including studies in the field of augmented reality and the use of artificial intelligence for adaptive learning. A concept of AI system architecture for automated monitoring and adaptation of the learning process in real time is proposed. Special attention is given to educational and scientific clusters as environments for the development and implementation of innovative adaptive learning technologies based on biometric monitoring. The advantages of the cluster approach for the personalization of learning and the provision of interdisciplinary collaboration among educational institutions, research organizations, and the IT sector are outlined. Within the study, the effectiveness of adaptive learning based on biometric data for enhancing motivation, reducing stress, and improving students' academic performance during the educational process is substantiated.*

Keywords: *cognitive load; educational and scientific cluster; adaptive learning; biometrics; artificial intelligence; technical drawing; heart rate.*

How to cite: Kolomoiets, H., Holiiad, I., Tutashynskyi, V., Hrytsenko, L., Holiiad, R., & Rebryna, M. (2025). Adaptive learning based on biometric assessment of cognitive load in an educational and scientific cluster. BRAIN. *Broad Research in Artificial Intelligence and Neuroscience, 16*(3), 258-270. https://doi.org/10.70594/brain/16.3/18

1. Introduction and Related Works

In today’s educational landscape, there is an increasing focus on utilising biometric data to monitor students' cognitive load, intending to adapt the learning experience. Biometric indicators, such as heart rate, heart rate variability, skin conductance, and eye movements, provide objective measures of cognitive load during the learning process. Research indicates that incorporating biometric feedback into learning platforms can enhance reading comprehension, boost motivation, and alleviate anxiety among students. For example, a study conducted using an AI-enhanced platform showed significant improvements in reading, motivation, and cognitive load management in the experimental group as compared to the control group (Yuan, 2025). Furthermore, the use of physiological methods to measure cognitive load in augmented reality demonstrates the potential for creating adaptive learning environments that respond to users' physiological signals, providing more effective learning (Anshu, 2025). The authors (Hamdani & Chihi, 2025) studied SMARTe-VR platforms for online education that collect facial biometric data and learning metadata for adaptive learning. They presented a dataset of TOEIC VR sessions with facial features and comprehension scores. Preliminary experiments showed the potential of using facial features to detect comprehension through machine learning models. In our work, we focused more on the analysis of pulse metrics as a biometric indicator of cognitive load for the correction of the learning process during adaptive learning.

The implementation of biometric data into the learning process is already demonstrating positive results. Research in the field of virtual reality has shown that adapting learning content based on biometric indicators improves material assimilation and reduces students' stress. Moreover, the use of such technologies in special education allows for better consideration of individual students' needs and increases their motivation for learning (Khasawneh & Khasawneh, 2024).

Another important aspect of the study is the place and form of conducting the learning process (Malykhin, Aristova, & Aleksieieva, 2023). This research was conducted within the framework of an educational and scientific cluster. Such clusters serve as integrated platforms that unite educational institutions, scientific organisations, and technological companies for the joint development of innovative educational technologies. In the context of adaptive learning, educational and scientific clusters create a favourable environment for the implementation and testing of systems that use biometric data to assess students' cognitive load (Slipchyshyn et al., 2024).

The study by Fadieieva (2023) highlights the importance of the cluster approach in the study of adaptive learning, emphasising the role of artificial intelligence, eye-tracking technologies, and physiological measurements in personalising the learning process. This indicates the potential of the educational and scientific cluster in the development and implementation of such technologies.

The research dedicated to the analysis of cognitive load in adaptive learning technologies for special education highlights the need to consider the individual characteristics of students when designing and implementing such systems (Chervinska, 2021; Liubchenko, 2023). This underscores the importance of the interdisciplinary approach, which is characteristic of educational and scientific clusters, in creating effective adaptive learning environments (Holiiad & Tropina, 2024; Zelenska & Sivachenko, 2020).

Educational and scientific clusters act as key platforms for researching, developing, and implementing adaptive learning systems based on biometric assessment of cognitive load. They ensure interdisciplinary collaboration and the integration of innovative technologies into the educational process (Slipchyshyn & Dorokhin, 2024). Our study was precisely based on an educational and scientific cluster.

Adaptive learning, based on the principles of personalisation, is increasingly seen as a key tool for enhancing the effectiveness of the educational process amid the dynamic development of digital technologies. An educational and scientific cluster creates a unique environment for the large-scale implementation of adaptive learning models (Yakymovych, 2023). Educational and scientific clusters possess a number of advantages that promote the active application of adaptive approaches:

- access to high-tech infrastructure: digital platforms, cloud computing, systems for collecting and processing biometric data;
- constant interaction with a research base: the opportunity for rapid testing of new pedagogical strategies (Holiiad & Rebryna, 2024);
- partnerships with business and IT: facilitating the development and improvement of algorithms for adapting learning content.

Within educational and scientific clusters, adaptive learning is implemented through: systems of intelligent analysis of student performance data (performance tracking); biometric monitoring platforms that analyse physiological indicators (pulse, ECG, skin-galvanic response) to assess cognitive state; real-time recommendations for instructors that allow adjusting the pace, style, or depth of material delivery depending on the individual student's condition (Bondarchuk et al., 2024).

Importantly, in an educational and scientific cluster, adaptive learning is not limited to students alone. It also includes postgraduate students and young researchers who study and conduct research simultaneously. This opens up additional opportunities for adapting the learning process in a scientific context. For example, flexible scheduling of scientific seminars, individualised research training paths, and the integration of biometric analysis results into the design of learning trajectories (Krynytska & Dubnytska, 2022).

We consider educational and scientific clusters as an environment where adaptive learning can realise its full potential by leveraging cutting-edge advances in bioinformatics, artificial intelligence, and cognitive pedagogy. This forms the basis for creating a truly individualised educational experience based on objective data and scientific approaches.

Within an educational and scientific cluster, it is possible to implement a wide range of solutions that ensure the adaptation of the learning process based on students' biometric data. Thanks to the interdisciplinary interaction of educators, scientists, engineers, and AI system developers, it has become significantly easier to implement innovative learning models in such an environment. Details are presented in Table 1.

Table 1. Examples of adaptive learning solutions in the educational and scientific cluster

№	Area of Implementation	Example / Description	Technologies / Tools
1	Biometric monitoring of students	Monitoring heart rate (HR), heart rate variability (HRV), galvanic skin response (GSR) during lectures	Wearables, cardiac sensors, smartwatches
2	Adaptive pacing of content delivery	Slowing down the teaching pace when signs of fatigue or overload are detected	AI module + instructor recommendation interface
3	Personalised assignments	Automatically adjusting task difficulty based on cognitive load and previous performance	AI-based content adaptation system
4	Automated break triggers	When ≥60% of students show critical cognitive load, a break is automatically initiated	Biometric data input + event-based trigger system
5	Analysis of topic effectiveness	Identifying “difficult” topics that consistently cause high cognitive load	Analytics dashboards + heatmaps
6	Scientific training for PhD students	Adapting research reading/study pace using biometric feedback	Data-driven learning paths for early-career researchers
7	Gamification with biofeedback	Game elements change based on the real-time psychophysiological condition of the student	Biofeedback + adaptive UI/UX systems

2. Previously Unstudied Areas (Problem)

Despite the availability of theoretical and experimental developments, a significant portion of research remains generalised and does not focus on the specifics of individual fields of knowledge. This is particularly true for disciplines that are highly demanding in terms of cognitive load, such as technical drawing, engineering, materials science, mathematics, physics, and chemistry, which require a high level of abstract thinking, spatial imagination, and understanding of complex theoretical models.

Moreover, the issue of implementing biometric-adaptive learning models has not been explored in the context of educational and scientific clusters.

Thus, the novelty of the presented study lies in the experimental testing of adaptive learning based on biometric monitoring during the study of technical disciplines, implemented within an educational and scientific cluster. The focus is on assessing the effectiveness of such a model, comparing it with the traditional form of teaching, and forming the prerequisites for the further development of intelligent educational systems with elements of AI and personalised analytics.

3. Methods

In the course of the study, the following scientific methods were used: theoretical methods (analysis, synthesis, generalisation, systematisation), and empirical methods: pedagogical observation, surveys (questionnaires, interviews) of participants in the educational process; pedagogical experiment within the educational and scientific cluster; statistical data processing methods, for quantitative analysis of the results of the experimental stage of the study and for verifying the effectiveness of the adaptive learning assessment approach.

4. Experimental Part

The aim of the experiment was to investigate its effectiveness in adaptive learning based on biometric assessment of cognitive load among students within an educational and scientific cluster. The main hypothesis was the assumption that dynamic regulation of the learning pace according to physiological indicators of fatigue would contribute to better assimilation of the learning material. A total of 30 students participated in the study and were randomly divided into two equal groups of 15 individuals each:

• Control Group (CG) — studied using a standard methodology without adaptation of the lesson pace.

• Experimental Group (EG) — studied with consideration of biometric indicators (real-time heart rate monitoring).

The experiment lasted 5 weeks (two lessons per week), totalling 10 lessons. The lesson topics covered various sections of the "Technical drawing" course. Details are presented in Table 2.

Table 2. Topics covered during the "Technical drawing" course

№ Lesson	Topic of the Lesson
1	Fundamentals of graphic representations
2	Design
3	Principal views
4	Sections
5	Cutaways
6	Working drawings of parts
7	Assembly of parts
8	Technical drawing interpretation
9	Assembly drawings
10	Schematics

In the experimental group, fitness trackers with an accuracy of ±2 beats per minute (bpm) were used. The overload threshold was determined individually before the experiment (the average threshold was 100 bpm). If ≥50% of students exceeded the threshold for 3 minutes, the instructor would:

• reduce the pace of material delivery;
• in the case of prolonged overload, announce a 5-minute break.

After completing the course, all students took a final test, with a maximum score of 100 points. Table 3 presents the individual results and the average score, providing a quantitative basis for evaluating the effectiveness of adaptive learning in both groups.

Table 3. Test results

№	CG (score)	EG (score)
1	67	83
2	72	86
3	75	91
4	65	82
5	70	85
6	68	88
7	74	87
8	73	90
9	69	89
10	66	85
11	71	92
12	70	86
13	68	88
14	72	90
15	69	87
Average score	**69,7**	**87,1**

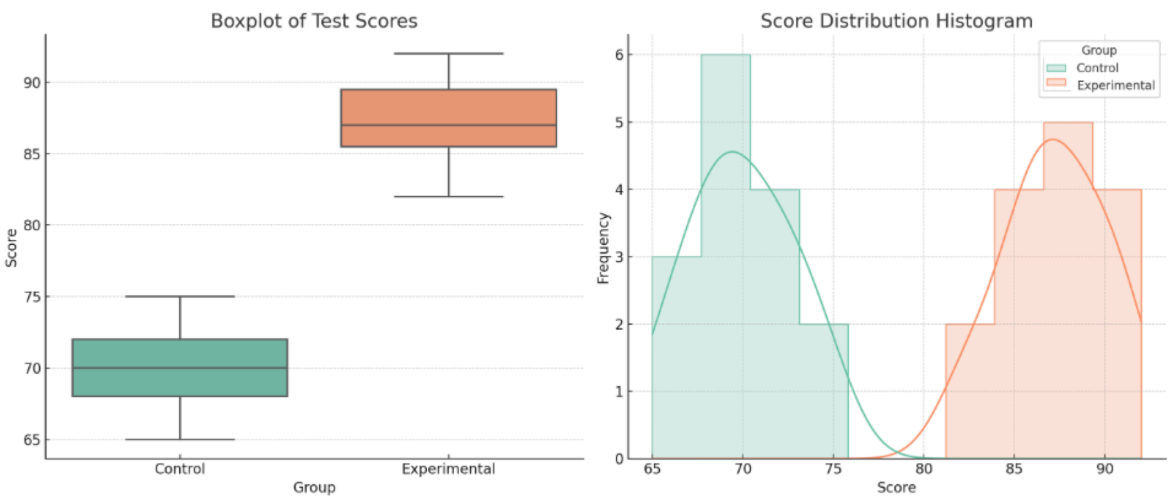

Figure 1. Comparison of the results of the control and experimental groups

The boxplot (on the left side of Figure 1) shows that in the experimental group:

- the median is significantly higher (approximately 88);
- the data are more tightly clustered (showing less variation);
- there are no outliers, indicating the stability of the results.

The histogram (on the right side of Figure 1) demonstrates a clear rightward shift in the distribution of the experimental group (toward higher scores), whereas the control group's scores are more widely spread and tend to cluster around 70.

After each session, students completed a short test (maximum 10 points), and we recorded the average score for each group. Details are presented in Table 4 as shown below.

Table 4. Average test scores by lesson

Lesson	CG (Average Score)	EG (Average Score)
1	7.2	8.8
2	6.5	8.1
3	6.9	8.6
4	7.0	8.7
5	7.4	9.0
6	6.2	7.8
7	6.6	8.5
8	6.7	8.4
9	6.4	8.3
10	7.3	8.9

Observations:

- The EG consistently demonstrates higher average results at all stages in comparison with the CG;
- The increase in results in the CG is slower progress, and the fluctuations are greater;
- Adaptive learning allows students to consistently demonstrate high and stable performance.

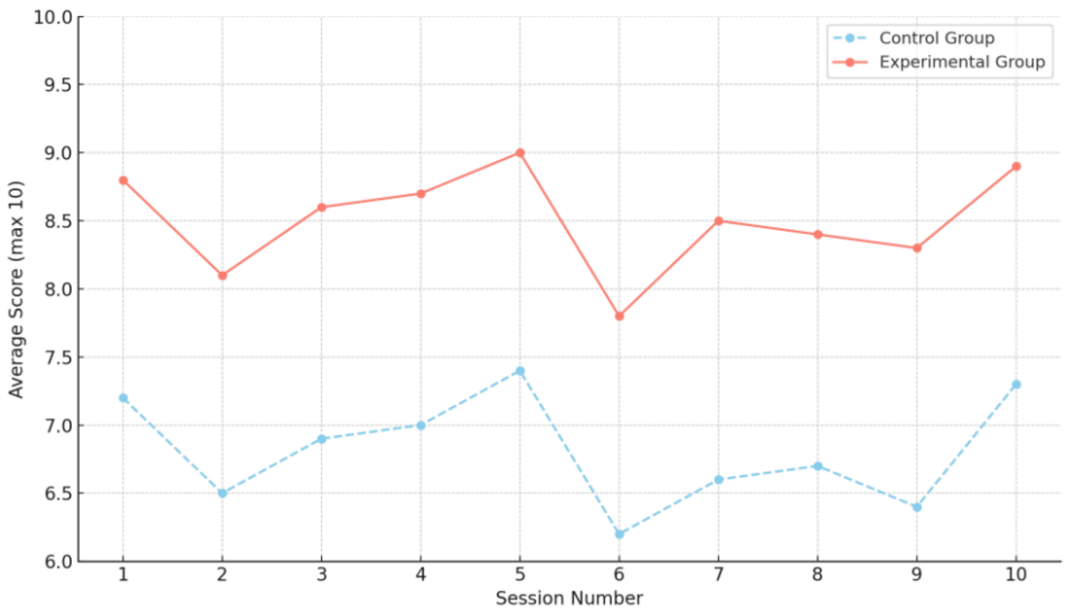

Figure 2. Average score per session

Figure 2 visually illustrates the variations in average scores among students following each session for both groups. The experimental group, which benefited from instruction tailored to biometric feedback, consistently outperformed the control group from the beginning sessions onward. This indicates that adaptive strategies informed by real-time cognitive load monitoring enhance effective knowledge acquisition and promote sustained learning outcomes.

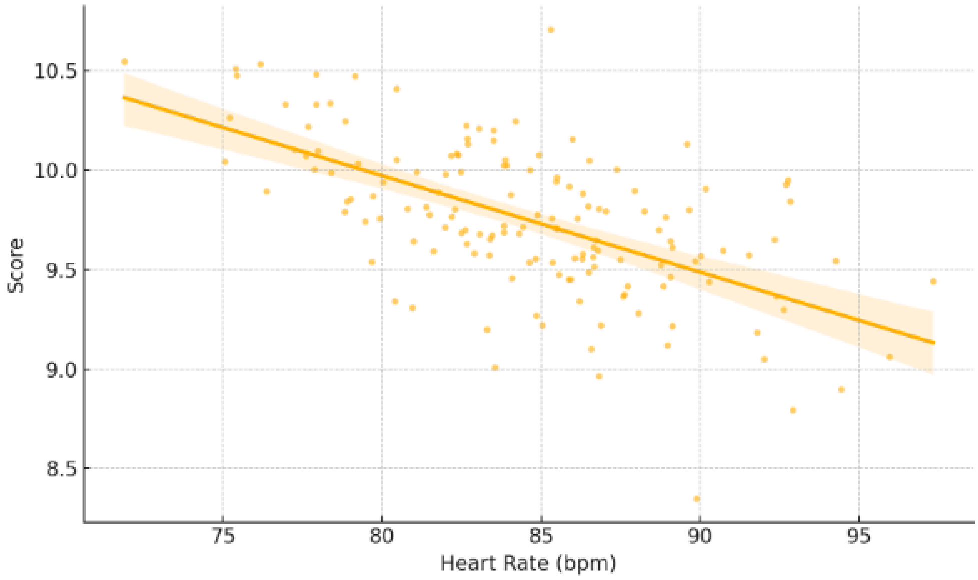

Figure 3. Correlation between heart rate and score.

Figure 3 shows a negative correlation between heart rate and test scores:

- The higher the pulse rate, the lower the student's score on the session;
- Correlation coefficient: r = -0.60, which indicates a moderate inverse relationship.

This confirms that overload (specifically, physiological, measured by heart rate) negatively affects the effectiveness of material assimilation.

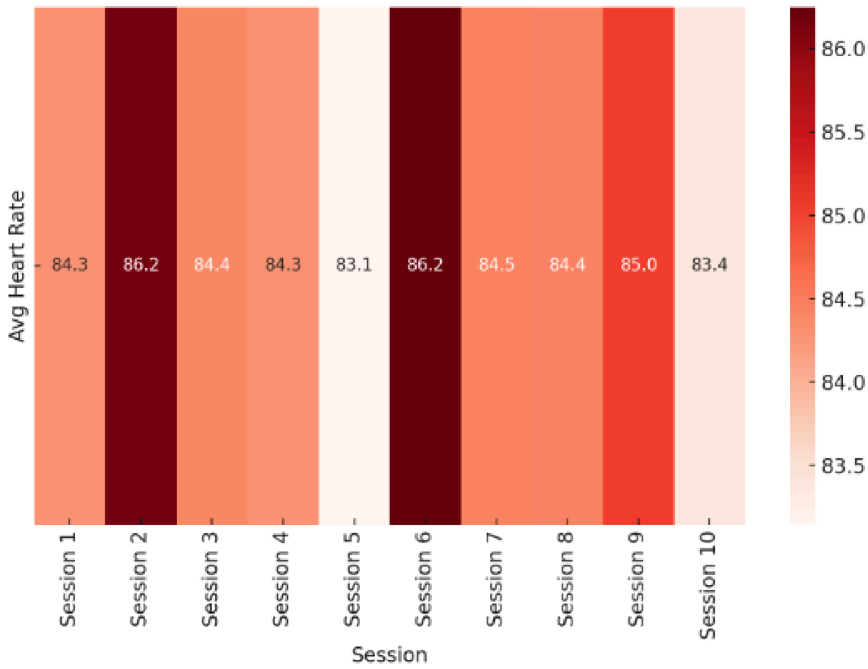

Figure 4. Average heart rate per session

The cognitive load heatmap, depicted in Figure 4, shows the average heart rate for each session for the experimental group:

- Sessions with a higher average heart rate (shades of red) indicate greater cognitive load;
- During these sessions, breaks were taken, and the pace of information delivery was slowed down.

5. Statistical Analysis

To evaluate the effectiveness of the adaptive learning approach, an independent samples t-test (Student's t-test) was applied, which allows for the comparison of the means of two groups under the conditions of normal distribution and approximately equal variance. Details are presented in Table 5.

Table 5. Initial statistical indicators

Indicator	Control Group (CG)	Experimental Group (EG)
Number of participants (n)	15	15
Mean Score	69.70	87.10
Standard Deviation (SD)	3.13	2.88
Standard Error (SE)	0.81	0.74

Calculation of the t-statistic (formula 1).

$$t = \frac{X_1 - X_2}{\sqrt{\frac{SD_1^2}{n_1} + \frac{SD_2^2}{n_2}}}$$

$$t = \frac{69.7-87.1}{\sqrt{\frac{3.13^2}{15}+\frac{2.88^2}{15}}} = \frac{-17.4}{\sqrt{\frac{9.8}{15}+\frac{8.29}{15}}} = \frac{-17.4}{\sqrt{1.36}} = \frac{-17.4}{1.17} \approx -14.87 \qquad (1)$$

For $n_1+n_2-2=28$ degrees of freedom and a significance level of $\alpha=0.01$, the critical t-value is approximately ±2.76. Since $|t|=14.87>2.76$, the null hypothesis of no difference between the means is rejected with a high level of confidence ($p<0.001$).

Therefore, the results demonstrate a statistically significant advantage of the experimental methodology over the traditional one. Adaptive learning, adjusted according to physiological indicators, indeed improves the assimilation of learning material.

6. Conclusions

The obtained results demonstrate the advantages of implementing an adaptive learning approach based on monitoring students' biometric indicators. The experimental group, in which the intensity of material presentation was adjusted according to heart rate, as an indicator of cognitive load, showed a higher level of material assimilation compared to the control group. The average scores at the end of each of the 10 sessions were consistently higher in the experimental group. Applying statistical analysis using the independent samples t-test (Student's t-test), we obtained confirmation of a statistically significant difference between the groups ($p<0.01$), which indicates the effectiveness of the adaptive strategy. In particular, the maximum increase in results compared to the control group was observed in the 7th and 9th sessions, when the cognitive load was likely highest, and adaptation played a key role in maintaining productivity.

The correlation analysis between heart rate and scores revealed a moderate negative relationship (r = −0.60), supporting the hypothesis that excessive cognitive load leads to a decrease in material assimilation effectiveness. To enhance our adaptive approach, we developed a heatmap illustrating the average heart rate per session, which helped us pinpoint sessions with elevated cognitive demands. This data will facilitate more precise planning of breaks and adjustments to pacing in the future.

However, the coefficient of determination (R^2), calculated for both groups, was low (0.021 for the CG and 0.0006 for the EG), indicating a weak linear trend in the change of scores depending on the session number. This suggests that other influential factors could be present: the content of the topics, prior knowledge, motivation, etc.

Overall, the results confirm the effectiveness of using biometric indicators to adapt the learning process in real-time. Further studies could examine optimising response algorithms, studying other physiological parameters (e.g., skin conductance or brain activity), as well as the long-term effects of such strategies in the educational environment.

7. Limitations

Despite the promising outcomes of this study, certain limitations must be acknowledged. Firstly, the sample size was relatively small, consisting of 30 students, all drawn from a single educational-scientific cluster. While this setting provides a relevant context for the application of adaptive learning in technical drawing education, the restricted scope may diminish the generalizability of the findings. Future research should aim to include a larger and more diverse sample, encompassing students from various academic disciplines, educational levels, and institutional settings.

Secondly, the study focused specifically on the teaching of technical drawing, which inherently demands a high cognitive load. While this choice allowed us to observe pronounced effects of adaptive pacing based on biometric monitoring, it also limits the applicability of the results to other subject areas. Further investigations are needed to determine whether similar adaptive approaches are equally effective in fields with different cognitive demands, such as the humanities or social sciences.

Thirdly, the intervention was conducted over the course of only ten lessons. Although the short-term effects were significant, longer-term studies are required to assess the sustained impact of biometric-driven adaptation on learning outcomes, knowledge retention, and cognitive fatigue. Longitudinal research could also explore how students adapt to and internalise such adaptive strategies over time.

Moreover, the adaptive intervention was limited to heart rate monitoring as the primary biometric indicator. While heart rate is a useful proxy for cognitive load and fatigue, it may not fully capture the complexity of students' mental states. Incorporating additional biometric signals, such as eye-tracking, electrodermal activity (EDA), or EEG, could provide a more comprehensive view of cognitive engagement and stress levels.

The technical infrastructure required to implement real-time biometric feedback and data-driven adaptation presents another challenge. Although the system was successfully piloted within a university cluster equipped with relevant tools, many educational environments, particularly in under-resourced regions, may lack the necessary hardware, software, and trained personnel. Future research should consider cost-effective and scalable solutions to support the broader adoption of such adaptive technologies, especially in under-resourced regions.

8. Prospects for Further Research and Implementation of AI Technologies

The results of the conducted experiment open up broad prospects for further research in the field of adaptive learning using biometric data. The application of heart rate as a marker of cognitive load has demonstrated high efficiency in improving the quality of material assimilation. This confirms the feasibility of creating comprehensive systems that would automate the process of monitoring the student's state and adapting the learning environment in real-time.

The development of AI-powered systems is a particularly promising, capable of:

- Collecting and analysing biometric data (pulse, temperature, skin conductance, concentration indicators, etc.);
- Implementing algorithms for recognising the student's state (overload, decreased attention, optimal level of engagement);
- Generating personalised recommendations for the teacher, displayed as an intuitive interface (e.g., notifications about the need for a break, a change in teaching style, or a transition to a practical block).

Possible vectors of development:

- Integration with Learning Management Systems (LMS) — to create adaptive content based on the student's cognitive state.
- Multimodal approach — using cameras to track facial microexpressions, eye movements (eye-tracking), and body posture, which, combined with biometrics, will allow for a more accurate determination of the level of engagement.
- Mobile solutions — developing applications or smart gadgets that can be used both in educational institutions and in individual learning.
- Adaptive visualisations and audio — creating an environment that changes the colour scheme, interface, or pace of presentation depending on the student's cognitive state.

In the future, such systems could become part of educational and scientific clusters, where intelligent platforms will not only support the learning process but also collect large datasets for analytics, educational forecasting, and the formation of personalised learning paths.

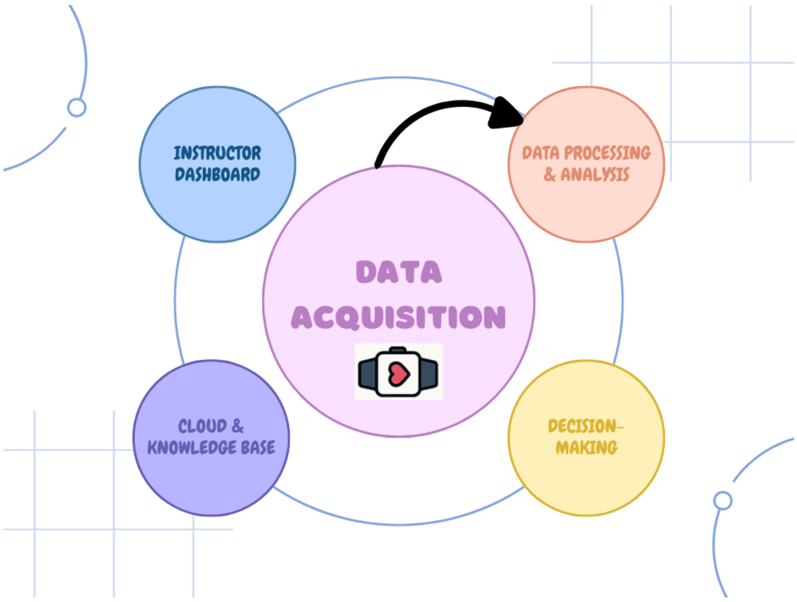

Figure 5. Hypothetical Architecture of an AI System for Adaptive Learning

The hypothetical architecture of an AI system for adaptive learning (Figure 5) includes:

1. Data acquisition layer
   - Biosensors: wearable devices (smartwatches, bracelets, sensor belts) that measure:
     - Heart rate
     - Heart rate variability (HRV)
     - Body temperature
     - Stress level (GSR - galvanic skin response)

   - Cameras / Microphones: additionally track facial expressions, posture, voice (emotional state, focus of attention)
2. Data processing & analysis layer
   - Pre-processing: noise filtering, data normalisation, stream synchronisation
   - Biometrics interpretation:
     - Machine learning models classify student states (e.g., optimal attention, overload, decreased motivation)
     - Use of rules or neural networks to detect critical moments
3. Decision-making layer
   - Analysis of lesson context (topic, activity type, time of day)
   - AI-based recommendation generator:
     - Slow down the pace
     - Add a break or reflective task
     - Switch to interactive content / practice
     - Provide personalised hints to the student
4. Instructor dashboard
   - Intuitive panel with visualisation of each student's / group's state
   - Real-time recommendations (colour-coding, notifications, advice)
   - Post-session analytics (load heatmap, peak performance moments)
5. Cloud & knowledge base
   - Historical data for each student
   - Training of AI models based on accumulated patterns
   - Integration with the institution's LMS / CRM systems

Accordingly, the development of comprehensive solutions using artificial intelligence will significantly expand the prospects and improve the quality of education for educational institutions that integrate these technologies into their learning process.

Acknowledgement

Halyna Kolomoiets developed the research design and outlined the significance of integrating biometric feedback into adaptive learning systems. Larysa Hrytsenko established the theoretical framework of the study, including a literature review on adaptive learning, cognitive load theory, and the role of artificial intelligence in education. Iryna Holiiad organised and conducted experimental sessions with students within the context of an educational and scientific cluster. Vasyl Tutashynskyi and Maryna Rebryna carried out statistical analysis and interpreted the quantitative results. Ruslan Holiiad developed the conceptual architecture of an AI system for real-time monitoring and generating recommendations based on biometric data. Maryna Rebryna and Ruslan Holiiad analysed current trends in the development of educational and scientific clusters and contributed to the discussion on the prospects of integrating AI into scalable learning environments of the future.

References

Anshu, R. (2025). AI agents bolstering security for biometric authentication. *Biometric Update*. https://www.biometricupdate.com/202503/ai-agents-bolstering-security-for-biometric-authentication

Bondarchuk, O., Briukhovetska, O., Karamushka, L., & Pinchuk, N. (2024). Psychological and pedagogical support of professional training and advanced training of specialists under martial law. *XIII International Scientific and Practical Conference, May 22, 2024. Bulletin of* *the National Academy of Educational Sciences of Ukraine.*, *6*(1), 1-6. https://doi.org/10.37472/v.naes.2024.6134

Chervinska, I., (2021). Cluster approach to the development of innovative educational institutions. *Pedagogical education: theory and practice: Collection of scientific papers. Kamianets-Podilskyi National Ivan Ohienko University; Institute of Pedagogy of the National Academy of Educational Sciences of Ukraine.* (31(2). Kyiv: *Milenium*. 94-104. https://doi.org/10.32626/2309-9763.2021-31

Fadieieva, L. (2023). Adaptive learning: A cluster-based literature review (2011–2022). *Educational Technology Quarterly* [Online], *2023*(3), 319–366. https://doi.org/10.55056/etq.613

Hamdani, R., & Chihi, I. (2025). Adaptive human-computer interaction for industry 5.0: A novel concept, with comprehensive review and empirical validation. *Computers in Industry, 168*, 104268. https://doi.org/10.1016/j.compind.2025.104268

Holiiad, I., & Rebryna, M. (2024). Psychological and pedagogical support for future technology teachers in the educational-scientific-production cluster. *Problems of Education*, *2*(101), 128–146. https://doi.org/10.52256/2710-3986.2-101.2024.09

Holiiad, I., & Tropina, M. (2024). Training specialists of the new generation: The role of the maker space in the innovation and educational cluster. In *Collection of scientific papers on the occasion of the 30th anniversary of the establishment of the Lviv Educational and Scientific Center of Vocational Education "Modern Challenges of Vocational Education: Theory and Practice"* (pp. 22–28). Retrieved from https://enpuir.npu.edu.ua/handle/123456789/47657?show=full&locale-attribute=en

Khasawneh, Y., & Khasawneh, M. (2024). Cognitive load analysis of adaptive learning technologies in special education classrooms: A quantitative approach. *International Journal of Advanced and Applied Sciences, 11*(12), 34–41. https://doi.org/10.21833/ijaas.2024.12.004

Krynytska, L., & Dubnytska, O. (2022). Personal-oriented and cluster approaches to the organization of professional training of the unemployed population. *Modern trends in the development of education and science: problems and prospects.* 43-52. Retrieved from:https://new.meduniv.lviv.ua/uploads/repository/kaf/kaf_armymed/05.%D0%92%D0%B8%D0%B4%D0%B0%D0%B2%D0%BD%D0%B8%D1%87%D0%B0_%D0%B4%D1%96%D1%8F%D0%BB%D1%8C%D0%BD%D1%96%D1%81%D1%82%D1%8C/LNNCPO-Zbirnyk-10.pdf#page=44

Liubchenko, N. V. (2023). Cluster approach in the management of professional development of the head of a general secondary education institution: a special course. *National Academy of Educational Sciences of Ukraine, SHEE "University of Educational Management"*. Kyiv, 1-52. Retrieved from: https://uvu.org.ua/download/klasternyi-pidhid-lubchenko.pdf

Malykhin, O. V., Aristova, N. O., & Alekseeva, S. V. (2023). *Індивідуалізація навчання як засіб компенсації освітніх втрат учнів закладів загальної середньої освіти в умовах воєнного стану та повоєнний час: методичні рекомендації* [Individualiszation of learning as a means of compensating for educational losses of general secondary education students under martial law and in the post-war period: Methodical recommendations] [Electronic edition]. Institute of Pedagogy of the National Academy of Educational Sciences of Ukraine. https://doi.org/10.32405/978-966-644-720-6-2023-59

Slipchyshyn, L., & Dorokhin, A. (2024). Clustering as an innovative mechanism for training modern competitive specialists. *Development of professional culture of future specialists: challenges, experience, strategies: collection of materials of the VI All-Ukrainian scientific-practical conference*. 88–92. Retrieved from: https://enpuir.npu.edu.ua/bitstream/handle/123456789/45403/2024-clasteryzacija%20prof%20pidgotovky.pdf?sequence=1

Slipchyshyn, L., Holiiad, I., Yakymovych, T., Dubovyk, O., & Tropina, M. (2024). *Повоєнна модернізація освіти: Цифрове освітнє середовище як ключовий елемент* *інноваційно-освітнього кластеру* [Post-war modernization of education: The digital educational environment as a key element of the innovative-educational cluster]. *Psykhologo-pedahohichni problemy suchasnoi shkoly* [Psychological and Pedagogical Problems of the Modern School], (2(12), 56–67. https://doi.org/10.31499/2706-6258.2(12).2024.315010

Yakymovych, T. (2023). Modeling a multilevel system for training future teachers in the conditions of an educational-scientific-production cluster. In *IX International Scientific and Practical Conference "Topical Issues of Graphic Training: Theory, Practice and Development Paths," dedicated to the memory of Corresponding Member of the National Academy of Educational Sciences of Ukraine Viktor Sydorenko* (pp. 214–220). Retrieved from https://enpuir.npu.edu.ua/bitstream/handle/123456789/43780/Yakymovych.pdf?sequence=1

Yuan, H., (2025), Artificial intelligence in language learning: biometric feedback and adaptive reading for improved comprehension and reduced anxiety. *Humanit Soc Sci Commun.* 12. 556. https://doi.org/10.1057/s41599-025-04878-w

Zelenska, L., & Sivachenko, I. (2020). Innovative educational clusters: Global experience and prospects for its adaptation in Ukraine. *Current Issues of Humanities: Interuniversity Collection of Scientific Papers of Young Scientists*, *27*(6), 76–79. Drohobych Ivan Franko State Pedagogical University. Retrieved from https://dspace.hnpu.edu.ua/handle/123456789/10060