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Artificial intelligence in creating virtual laboratories for engineering education

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ABSTRACT

The purpose of this proposed study is to analyze the possibilities of applying artificial intelligence (AI) technologies in creating virtual laboratories for engineering education, identify key technological and pedagogical components of such systems and assess their potential impact on the quality of education. The methodological framework was based on a quasi-experimental design. For this purpose, 124 students were selected and divided into experimental and control groups. Data were collected using the Engineering Skills Assessment, Social Engagement Scale (SES) and AI log files. The analysis was conducted using t-tests. The results noted that students who worked in an AI-supported virtual laboratory demonstrated significantly higher final scores ($M = 76.84$) compared to the control group ($M = 65.37$), and the increase in competencies was +18.13 points versus +7.47, respectively. The analysis confirmed the high significance of these differences ($t(122) = 4.87$, $p < 0.001$). The conclusions confirm that virtual laboratories, enhanced with adaptive AI algorithms, are an effective tool in engineering education, capable of improving the results of students' practical training.

Keywords: AI, Virtual laboratories, Engineering education, Learning outcomes, Digital simulation.

1. Introduction

1.1. Problem statement

The rapid development of artificial intelligence (AI) technologies has significantly influenced approaches to engineering education. Among other things, it has opened opportunities for the creation of new forms of learning, virtual laboratories. Although the traditional model of engineering training, laboratory classes were key components of the formation of professional competencies, they have always required significant material resources, special equipment, consumables and compliance with strict safety conditions. This significantly limited the scalability of laboratory classes, made it difficult for students to access practical experience outside the classroom and reduced the flexibility of the educational process. Under such circumstances, virtual laboratories have become an alternative, more innovative environment for further ensuring a high level of interactivity, repeatability of experiments and personalization of learning. The integration of AI into virtual laboratories has made it possible to create adaptive simulations that recreate complex engineering processes, respond to the actions of the student in real time and automatically adjust the learning trajectory in accordance with the level of training of the student. Such systems were able to analyze errors, predict optimal learning scenarios, and provide recommendations for the formation of individualized learning. AI capabilities contributed to the development of critical thinking, technical literacy, and experimentation skills. A number of studies have demonstrated that AI-oriented learning environments had a significant positive impact on the acquisition of complex engineering concepts, reduced cognitive load, and at the same time increased the involvement of students [1], [2]. However, the effectiveness of such laboratories as a pedagogical tool in conditions of mass use was and is an open question [3].

Despite significant progress in the field of digital simulations, a coherent approach to the creation and evaluation of AI-based virtual laboratories has not yet been formed. Most of the existing solutions focus on graphical modeling of processes (partly on the process of computing automation) [4]. Less attention has been paid to the complex integration of adaptive learning mechanisms, diagnostic modules and competency assessment systems [5]. At the same time, there has been much less empirical research. Accordingly, there has been a lack of comparison of educational outcomes of students in traditional and virtual laboratories and scientific works with descriptions of pedagogical principles for creating such environments in the context of engineering training.

Modern engineering education has been transformed by the impact of digitalization, so the need for flexible, scalable and safe forms of practical training has increased significantly. In the traditional model of education, laboratory classes were a central tool for the formation of professional competencies [6]. Among the negative aspects of their use were identified high financial costs, limited access to equipment and risks in the field of student safety [7], [8]. As a result, interest in using the capabilities of virtual laboratories has significantly increased, which made it possible to model individual technical processes with the implementation of experiments and the reproduction of complex engineering phenomena in a digital equivalent. The conclusions of modern research have shown that the main element of the development of this direction has become AI [9]. The use of such systems has increased adaptability, individualization and a high level of automated support during training. Researchers have noted the most common areas of use of AI in virtual laboratories:

1. Intelligent simulation models, which made it possible to reproduce physical and technical processes with high accuracy [10].

2. Automatic error diagnosis systems [2], [11].

3. Adaptive learning modules that are adjusted to determine the complexity of tasks according to the level of training of education seekers [9, 12].

4. Intelligent agents that performed the functions of virtual mentors during training [13].

Research in the field of engineering pedagogy has shown that the use of AI in virtual laboratories has contributed to an increase in the understanding of technical concepts, the development of modeling and analysis skills [14]. Scientists have also noted the formation of independence and motivation of students [15], [16]. Comparative experiments have shown that students who worked with AI elements more often demonstrated higher accuracy rates of task completion [17]. However, there are also some problems in scientific literature. First, there was a lack of comprehensive models that describe the integration of AI into the full cycle of laboratory training [18], [19]. Another problem is the limited number of scientific works comparing the effectiveness of such laboratories with traditional training formats [20]. The problems of the long-term impact of AI on the development of practical engineering competencies have also been insufficiently studied. Therefore, this promising topic will require further study.

1.2. Aim and research questions

The purpose of this proposed study is to analyze the possibilities of applying AI technologies in creating virtual laboratories for engineering education, identify key technological and pedagogical components of such systems, and assess their potential impact on the quality of education. The study is aimed at forming a conceptual model that can serve as the basis for further development and implementation of intelligent laboratory environments in higher technical educational institutions.

2. Research method

2.1. Research design

The study was conducted in a quasi-experimental design with repeated measurements, which made it possible to assess the impact of using a virtual laboratory on the formation of engineering competencies of education seekers (based on the use of AI). The chosen design involved comparing the learning outcomes of two groups - experimental (use of AI) and control (work in a traditional laboratory) – according to the indicators of learning outcomes before and after completing the laboratory module. This approach provided an opportunity to determine not only the level of competence formation, but also the increase due to work in different educational conditions. The study was interventional, since both groups were subjected to a certain educational influence. At the same time, the use of AI was an independent variable, while learning outcomes, errors, speed of execution and involvement of education seekers became dependent variables.

2.2. Participants

The proposed study involved 124 second and third-year engineering students. The study involved students in the following majors: electrical engineering, mechanical engineering, and computer engineering. The age of the participants ranged from 18 to 20 years, which is quite typical for a bachelor's degree in Ukraine. All participants had previously worked in laboratories, performing traditional tasks. Regarding the tasks in virtual laboratories, previous experience was minimal. This ensured sample homogeneity, largely minimizing potential biases associated with previous digital skills. All participants participated in the quasi-experiment voluntarily.

2.3. Sample

The students were divided into two equal groups randomly, using a pseudorandom number generator. The experimental group consisted of 62 people ($n = 62$). They worked in a virtual laboratory that was created using AI algorithms. Their specialization was as follows: 34 belonged to the specialty “computer engineering”, 18 - to the specialty “electrical engineering”, 10 - to the specialty “mechanical engineering”. The control group also had a similar number ($n = 62$), performed similar laboratory tasks in a traditional educational laboratory. Students in the control group also worked with other traditional equipment - physical equipment and printed methodological materials. The composition of this group was similarly balanced: 32 students majoring in “computer engineering”, 16 in “electrical engineering”, and 14 in “mechanical engineering”. The average age of the participants was 19.4 years ($SD = 0.9$). There were no statistical differences between the groups in terms of age or average grade point average for the previous semester ($t = 0.84$, $p = 0.401$). The sample size was determined using the following parameters: statistical significance level $\alpha = 0.05$, desired test power = 0.80, expected average effect Cohen's $d = 0.50$. It is worth noting that this was quite consistent with typical effects in studies comparing traditional and digital educational interventions. The results of this analysis demonstrated that the minimum required sample size for the two independent groups was 51 participants in each group ($N = 102$ in total). Therefore, the actual sample size – 124 students (62 in each group) – exceeded the minimum by 21.5%. This result increased the accuracy of the effect estimation and reduced the likelihood of type II errors (see Table 1).

Table 1. Characteristics of the Study Sample

Indicator	Experimental group (AI Virtual Lab) (n = 62)	Control group (Traditional Lab) (n = 62)	In general (N = 124)
Mean age (M ± SD)	19.3 ± 0.9	19.5 ± 0.8	19.4 ± 0.9
Gender			
– Male	38 (61.3%)	40 (64.5%)	78 (62.9%)
– Female	24 (38.7%)	22 (35.5%)	46 (37.1%)
Major			
– Computer Engineering	34 (54.8%)	32 (51.6%)	66 (53.2%)
– Electrical Engineering	18 (29.0%)	16 (25.8%)	34 (27.4%)
– Mechanical Engineering	10 (16.1%)	14 (22.6%)	24 (19.4%)
Previous academic performance (GPA, 100-point scale)	83.4 ± 6.2	82.7 ± 6.8	83.0 ± 6.5
Difference between groups by GPA (t, p)	$t = 0.84$, $p = .401$	—	—
Required minimum sample size (power analysis)	≥ 51	≥ 51	≥ 102
Actual sample size	62	62	124

In addition, the proposed sample size provided sufficient conditions for the application of the ANOVA method with repeated measures, since statistical models of this type required at least 30–40 participants per group to ensure the stability of assessments. Therefore, the actual distribution of participants guaranteed an appropriate level of statistical reliability, allowing for the subsequent correct interpretation of the results of educational achievements in two types of laboratory environments.

2.4. Data collection

Data collection was carried out in several stages - over four weeks. During the first stage, both groups underwent preliminary testing using the Engineering Skills Assessment, which made it possible to determine the basic level of engineering competencies. At the second stage, students completed four laboratory tasks. The experimental group worked in a virtual laboratory using intelligent modules for automatic action analysis. The control group completed identical tasks in the laboratory using traditional equipment. At the third stage, both groups re-passed the test to record the increase in competencies. After that, the participants completed the Student Engagement Scale, which assessed the level of cognitive, behavioral and emotional engagement. For the experimental group, the AI-system logs were additionally analyzed, which recorded the number of errors made, the speed of completing tasks and the number of requests for hints.

The quality of the data was also checked in several stages. First of all, the analysis of omissions and anomalous values made it possible to identify individual unrepresentative results or technical errors in the tests. Information containing deviations from the expected norms was checked again, with adjustments and even deletions. Also, the reliability of the questionnaire "Student Engagement Scale" was confirmed by internal consistency (Cronbach's $\alpha = 0.87$). This indicated a high level of reliability.

2.5. Data analysis

The data analysis was carried out using SPSS 28 software. To determine the impact of the virtual laboratory on learning outcomes, paired t-tests (posttest and pretest) were used. The interaction between the factor "group" (experimental/control) and the factor "time" (before/after) was formed using analysis of variance with repeated measures. To assess the strength of statistical effects, Cohen's d and the η^2 indicator were calculated. Pearson correlation analysis allowed us to assess the relationship between the level of engagement of education seekers and their learning outcomes. A p-value < 0.05 can be considered significant.

2.6. Ethical considerations

All procedures related to data collection and processing were approved by the Ethics Committee. This document confirmed that the study met the requirements for the protection of rights, safety of participants and protection of confidential information. The participation of the students was completely voluntary. Before the start of the study, all participants were informed about the purpose, content, possible risks and confidentiality conditions. After that, the students from the experimental and control groups provided written informed consent. Students were able to refuse to participate in the study at any stage without any academic consequences.

3. Results and discussion

The results of statistical analysis demonstrated the existence of significant differences between the experimental and control groups in the increase in engineering competencies and in the accuracy of laboratory tasks. Additional analysis of normality of distribution indicated the correctness of the use of parametric tests. The Shapiro-Wilk test showed that the distribution of indicators in all four main variables (pre-test, post-test, number of errors, SES) was within normal limits ($p > .05$).

Therefore, the statistical prerequisites for the use of t-tests and ANOVA were met. A positive effect was also noted on the level of student engagement. At the pre-test stage, no statistically significant differences were found between the groups ($t(122) = 0.74$, $p = .460$). This result demonstrated their equivalence at the start of the study. After completing the laboratory module, the experimental group had significantly higher results ($t(122) = 4.87$, $p < .001$, $d = 0.87$) (See Table 2).

Table 2. Pre-test and Post-test Results for Experimental and Control Groups

Score	Group	n	Pre-test M (SD)	Post-test M (SD)	Growth M	t	p	Cohen’s d
Engineering Skills Score	Experimental	62	58.71 (6.42)	76.84 (7.11)	+18.13	15.22	< .001	1.93
	Control	62	57.90 (6.88)	65.37 (7.44)	+7.47	8.01	< .001	1.02

The results obtained showed a significant impact of using a virtual laboratory with AI elements on the formation of engineering competencies in students. The increase in results in the experimental group was on average 18.13 points, while in the control group - only 7.47 points. In fact, this means that students who worked with AI tools showed approximately 2.4 times more progress than those who performed tasks in a classic laboratory (See Figure 1).

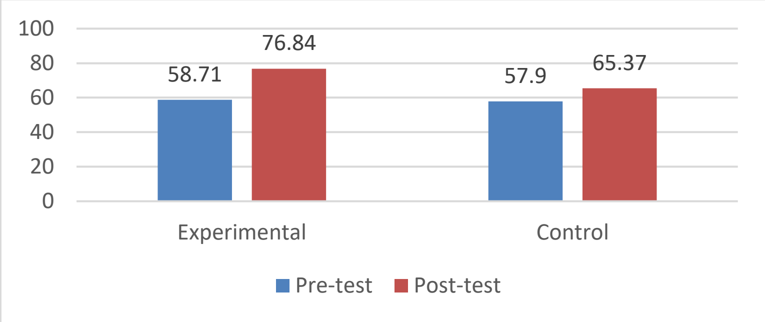

Figure 1. Table 1. Pre/Post Engineering Skills Scores

This result indicated a significantly better efficiency of the digital laboratory environment, which provided adaptability, personalized support and automatic error correction. The virtual laboratory algorithms allowed the number of errors during the task performance. The experimental group had an average of 4.21 errors, which was much lower than the control group's average of 9.47 errors; this difference was statistically significant, $t(122) = 7.94$, $p < .001$ (see Table 3).

Table 3. Comparison of Error Rates Between Groups

Indicator	Experimental (n = 62)	Control (n = 62)	t	p	Cohen's d
Average number of errors	4.21 (2.18)	9.47 (3.05)	7.94	< .001	1.42
Execution time (min)	28.4 (6.2)	36.9 (7.1)	6.59	< .001	1.18
Number of AI prompts accessed	3.87 (1.33)	–	–	–	–

Comparative analysis showed that students from the experimental group made fewer errors. With the support of AI, they also completed the tasks faster than their colleagues from the traditional laboratory. The average number of errors in the experimental group was 4.21, in the control group - 9.47. Accordingly, the percentage of reduction was a high 55.5%. Such a significant reduction in errors demonstrated the qualitative advantage of the educational process, which was based on the use of adaptive AI algorithms (See Figure 2).

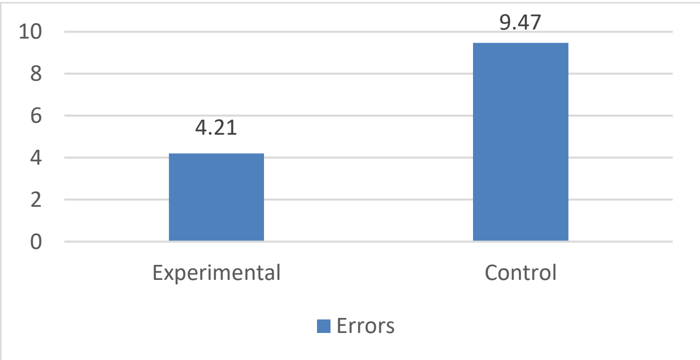

Figure 2. Errors and Execution Time

In particular, an important element was instant feedback, which immediately identified incorrect actions and directed students to the correct methodology. While completing tasks in the traditional laboratory, students did not immediately notice errors. Therefore, AI ensured timely correction of experiments, avoidance of repetition of errors, and effective understanding of the mechanism of task completion. The correlation matrix showed that the level of cognitive engagement was negatively correlated with the number of errors made ($r = –0.41$, $p < .001$) and with the time to complete the tasks ($r = –0.36$, $p < .01$). This showed that students who worked more actively with AI tools better learned the material, worked faster and more accurately. In addition, the number of appeals to AI prompts had a positive relationship with improved results ($r = .47$, $p < .001$). This indicated the effectiveness of the adaptive learning algorithm.

The level of involvement (SES) was significantly higher in the experimental group ($t(122) = 5.02$, $p < .001$). with the largest differences observed in the cognitive component (See Table 4).

Table 4. Student Engagement Scores

Engagement Component	Experimental M (SD)	Control M (SD)	t	p	d
Cognitive Engagement	4.42 (0.51)	3.71 (0.64)	6.03	< .001	1.09
Behavioral Engagement	4.18 (0.57)	3.84 (0.59)	3.11	.002	0.56
Emotional Engagement	4.09 (0.62)	3.52 (0.68)	4.41	< .001	0.80
Total SES Score	4.23 (0.44)	3.68 (0.51)	5.02	< .001	0.90

So, students in the experimental group were significantly more engaged in the learning process. The overall level of engagement was 15% higher, and the effect size ($d = 0.90$) demonstrated a significant pedagogical impact of the AI-enabled virtual environment.

The obtained values $F(1,122) = 39.74$, $p < .001$, $\eta^2 = .25$ indicated the existence of a strong interaction effect between the factor “group” (experimental vs. control) and the factor “time” (before/after). That is, both groups showed some increase in competence after completing the laboratory module, but the rates of this increase were significantly different. The experimental group demonstrated much higher progress, while the control group demonstrated only moderate. The effect size $\eta^2 = .25$ made it possible to establish that 25% of the total variance in changes in results was formed under the influence of the intervention, which is considered a significant indicator in educational research. This result demonstrated the systemic nature of the impact. The correlation between the levels of student engagement in the virtual laboratory ($r = 0.54$, $p < 0.001$) showed a moderate positive relationship. This meant that students who actively interacted with AI prompts performed more operations in general, viewed simulations more often, independently reproduced experiments, and achieved significantly higher learning outcomes. In fact, adaptive AI mechanisms (personalized feedback, automatic analysis of actions, and variable task complexity) created opportunities for further increasing student interest in learning.

The results confirmed the hypothesis of other researchers that the use of virtual laboratories created using AI algorithms contributed to an increase in the level of engineering competence, accuracy in performing experimental tasks, and the involvement of students in the educational process [21], [22]. Therefore, according to the proposed results, students in the experimental group demonstrated an almost 2.4-fold increase in the integral indicator of competencies. Thus, the effect size $d \approx 1.9$ indicated a significant impact of the educational intervention. Such results fully confirmed the conclusions of other scientists who emphasized the potential of virtual laboratories for the development of practical skills [6], [23], [24]. Studies in the field of engineering education have shown that the combination of simulations, interactive visualization, and step-by-step instructions contributed to significantly better learning of the material, especially compared to the use of only traditional laboratory methods [25], [26].

The proposed results indicate a decrease in the number of technical and procedural errors among students in the experimental group. In particular, the total number of errors decreased by 55.5% compared to the results of students in the control group. This confirmed the findings of other researchers who showed that automated action analysis and immediate feedback had an impact on the detection and correction of errors in the student environment [27], [28]. Previous work on intelligent learning systems in STEM disciplines indicated that the most effective interfaces are those that combine real-time formative assessment with local prompts [29], [30]. The proposed results confirmed the following conclusions: constant monitoring of students’ actions in the virtual laboratory improved the process of “learning by error” and suggested alternative solutions. Among the proposed results is a significant increase in the level of engagement of students in the experimental group. The greatest differences were noted in cognitive engagement, which indicated deeper intellectual activity, readiness to independently search for solutions, and more intensive processing of educational material. Higher indicators of emotional engagement were consistent with the results of scientific work by other researchers, who noted the tools of interactivity [31], gamification [32], personalization as ways to increase students’ interest in tasks [33], [34]. Several works on the use of AI in engineering education emphasized that it was the feeling of control over the educational process [35], the ability to experiment without the risk of damaging expensive equipment [36], [37], and the presence of a visual experimental environment that most contributed to the increase in engagement [38]. The proposed results complemented such conclusions, since the addition of the AI module additionally strengthened the motivational effect [39], [40].

At the same time, the methodology proposed in the study has some limitations. First, the use of a quasi-experimental design limited the possibility of complete randomization of participants. Although students were randomly assigned to groups, factors related to their previous academic performance, digital literacy, or learning motivation could partially affect the results of the intervention. The second limitation was the specificity of the context of the study, which was conducted at a single technical university.

4. Conclusions

The proposed results demonstrate that the use of virtual laboratories with AI tools had a significant positive impact on the formation of students' engineering competencies. Compared to traditional laboratory classes, students who used AI demonstrated significantly better learning outcomes. They made fewer mistakes and completed the tasks set before them faster. The increase in the level of cognitive, behavioral, and emotional engagement of students confirmed the effectiveness of adaptive AI mechanisms, feedback, and personalized support.

The proposed results confirmed that elements of intellectual adaptation, rather than simply digitalizing the laboratory process, can become an important factor in further increasing efficiency in education. The study showed that virtual laboratories with AI can become a full-fledged and pedagogically productive alternative to physical laboratories, especially in terms of mass training of engineers. At the same time, the results obtained opened prospects for further expanded research aimed at assessing the long-term prospects for integrating AI laboratories into wider use.

Declaration of competing interest

The authors declare that they have no any known financial or non-financial competing interests in any material discussed in this paper.

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Author contribution

Nataliia Volianiuk: study conception and design, draft preparation. Heorhii Lozhkin: data collection, and draft preparation. Olga Moskalenko: draft preparation, analysis and interpretation of results. Iryna Blokhina: analysis and interpretation of results. Vladyslav Papusha: analysis and interpretation of results. All authors approved the final version of the manuscript.

References

[1] A. Stănescu, "The impact of AI on education: Exploring the role of ChatGPT," in *Int. Conf. Virtual Learn. - Virtual learn. - Virtual reality (19th Ed.)*. Nat. Inst. Res. Develop. Inform. - ICI Bucharest (ICI Publishing House), 2024, pp. 193–202. https://doi.org/10.58503/icvl-v19y202416

[2] R. A. Abumalloh *et al.*, "The impact of coronavirus pandemic (COVID-19) on education: The role of virtual and remote laboratories in education," *Technol. Soc.*, vol. 67, p. 101728, Nov. 2021. https://doi.org/10.1016/j.techsoc.2021.101728

[3] O. Tuyboyov, N. Sharipova, L. Ergasheva, and S. Nasirdinova, "The role and impact of AI-enhanced virtual laboratories in mechanical engineering education," in *Proc. Iv Int. Conf. Advances Sci., Eng., Digit. Educ.: Asedu-Iv 2024*, Navoi, Uzbekistan. AIP Publ., 2025, p. 070019. https://doi.org/10.1063/5.0257378

[4] A. Pérez-García and J. F. L. Feliciano, "Impact of COVID-19 on education: Evolution of virtual laboratories," in *2023 IEEE World Eng. Educ. Conf. (EDUNINE)*, Bogota, Colombia, Mar. 12–15, 2023. IEEE, 2023. https://doi.org/10.1109/edunine57531.2023.10102907

[5] H. Akolekar *et al.*, "The role of generative AI tools in shaping mechanical engineering education from an undergraduate perspective," *Scientific Rep.*, vol. 15, no. 1, Mar. 2025. https://doi.org/10.1038/s41598-025-93871-z

[6] D. Psillos, "The Role and Impact of Virtual Laboratories in Physics Teaching and Learning: A Synthesis of Literature," in *The International Handbook of Physics Education Research: Teaching Physics*. AIP Publ., 2023, pp. 1–28. https://doi.org/10.1063/9780735425712_002

[7] D. May, C. Terkowsky, V. Varney, and D. Boehringer, "Online laboratories in higher engineering education – solutions, challenges, and future directions from a pedagogical perspective," *Eur. J. Eng. Educ.*, vol. 48, no. 5, pp. 779–782, Sep. 2023. https://doi.org/10.1080/03043797.2023.2248820

[8] D. May, I. Jahnke, and S. Moore, "Online laboratories and virtual experimentation in higher education from a sociotechnical-pedagogical design perspective," *J. Comput. Higher Educ.*, Aug. 2023. https://doi.org/10.1007/s12528-023-09380-3

[9] S. M. C. Atchia and A. Rumjaun, "The Real and Virtual Science Laboratories," in *Contemporary Issues in Science and Technology Education*. Cham: Springer Nat. Switz., 2023, pp. 113–127. https://doi.org/10.1007/978-3-031-24259-5_9

[10] M. N. A. Wahyudi, C. W. Budiyanto, I. Widiastuti, P. Hatta, and M. S. B. Bakar, "Understanding Virtual Laboratories in Engineering Education: A Systematic Literature Review," *Int. J. Pedagogy Teacher Educ.*, vol. 7, no. 2, p. 102, Jul. 2024. https://doi.org/10.20961/ijpte.v7i2.85271

[11] H. Hanine, N. Farajy, M. Boutaib, H. Boutracheh, and A. Moumen, "The Virtual Laboratories in Education System : A Bibliometric Review," in *2025 5th Int. Conf. Innovative Res. Appl. Sci., Eng. Technol. (IRASET)*, Fez, Morocco, May 15–16, 2025. IEEE, 2025, pp. 1–8. https://doi.org/10.1109/iraset64571.2025.11008229

[12] Y. Zhang, M. A. Feijoo-Garcia, Y. Gu, V. Popescu, B. Benes, and A. J. Magana, "Virtual and Augmented Reality in Science, Technology, Engineering, and Mathematics (STEM) Education: An Umbrella Review," *Information*, vol. 15, no. 9, p. 515, Aug. 2024. https://doi.org/10.3390/info15090515

[13] B. Shambare and C. Simuja, "Exploring the Integration of Virtual Laboratories in Science Education," *Int. J. Virtual Pers. Learn. Environ.*, vol. 14, no. 1, pp. 1–19, Jul. 2024. https://doi.org/10.4018/ijvple.348957

[14] P. Gupta, B. Toksha, T. Kulkarni, B. Rajaguru, and A. Mishra, "Virtual Experimentation," in *Technology and Tools in Engineering Education*. Boca Raton: CRC Press, 2021, pp. 1–27. https://doi.org/10.1201/9781003102298-1

[15] J. D. González, J. H. Escobar, J. R. Beltrán, L. García-Gómez, and J. D. La Hoz, "Virtual laboratories of electromagnetism for education in engineering: A perception," *J. Phys.: Conf. Ser.*, vol. 1391, p. 012157, Nov. 2019. https://doi.org/10.1088/1742-6596/1391/1/012157

[16] C. Sellberg, Z. Nazari, and M. Solberg, "Virtual Laboratories in STEM Higher Education: A Scoping Review," *Nordic J. Systematic Rev. Educ.*, vol. 2, Mar. 2024. https://doi.org/10.23865/njsre.v2.5766

[17] Samuel, F. Adenugba, A. Adesanya, A. Daudu, B. Owolabi, and D. Ogbe, "The Prospects of Virtual Laboratories in Engineering Education across Africa – A Case Study in Electrical Engineering," *J. Phys.: Conf. Ser.*, vol. 1299, p. 012055, Aug. 2019. https://doi.org/10.1088/1742-6596/1299/1/012055

[18] V. Bulgakov, S. Pascuzzi, S. Ivanovs, V. Nadykto, and J. Nowak, "Kinematic discrepancy between driving wheels evaluated for a modular traction device," *Biosyst. Eng.*, vol. 196, pp. 88–96, Aug. 2020. https://doi.org/10.1016/j.biosystemseng.2020.05.017

[19] D. Wahyono, H. Putranto, D. Saryono, K. Asfani, and Sunarti, "Development of a Personalized Virtual Laboratory Using Artificial Intelligent," in *Int. Conf. Learn. Innov. 2019 (ICLI 2019)*, Malang, Indonesia, Oct. 9–10, 2019. Paris, France: Atlantis Press, 2020. https://doi.org/10.2991/assehr.k.200711.018

[20] A. Craifaleanu and I. Craifaleanu, "A co-creation experiment for virtual laboratories of mechanics in engineering education," *Comput. Appl. Eng. Educ.*, Feb. 2022. https://doi.org/10.1002/cae.22498

[21] Frady, "Use of virtual labs to support demand-oriented engineering pedagogy in engineering technology and vocational education training programmes: a systematic review of the literature," *Eur. J. Eng. Educ.*, pp. 1–20, Nov. 2022. https://doi.org/10.1080/03043797.2022.2141610

[22] Klami, T. Damoulas, O. Engkvist, P. Rinke, and S. Kaski, "Virtual laboratories: transforming research with AI," *Data-Centric Eng.*, vol. 5, 2024. https://doi.org/10.1017/dce.2024.15

[23] J. Williamson, "New digital laboratories of experimental knowledge production: Artificial intelligence and education research," *London Rev. Educ.*, vol. 18, no. 2, Jul. 2020. https://doi.org/10.14324/lre.18.2.05

[24] S. Behr *et al.*, "Uniting Knowledge and Application in a Hybrid Laboratory Experiment in Virtual Reality – A Cross-Reality Laboratory with Applications of Artificial Intelligence for Industry 4.0," in *Open Science in Engineering*. Cham: Springer Nat. Switz., 2023, pp. 287–298. https://doi.org/10.1007/978-3-031-42467-0_26

[25] Z. Dosbayev, A. Tuleshov, A. Osmanov, B. Sadykova, N. Smailov, and A. Sabibolda, "Development of a literacy enhancement system based on IoT and web technologies: integration of ESP8266 and Laravel," *Eastern-Eur. J. Enterprise Technol.*, vol. 4, no. 9 (136), pp. 51–60, Aug. 2025. https://doi.org/10.15587/1729-4061.2025.337999

[26] M. Kurtz, A. Benabbou, C. Pons, and J. Broisin, "Collaboration in virtual and remote laboratories for education: A systematic literature review," *Int. J. Computer-Supported Collaborative Learn.*, Sep. 2025. https://doi.org/10.1007/s11412-025-09454-7

[27] M. Daun, A. M. Grubb, V. Stenkova, and B. Tenbergen, "A systematic literature review of requirements engineering education," *Requirements Eng.*, May 2022. https://doi.org/10.1007/s00766-022-00381-9

[28] D. Watters, A. Hill, M. Weinrich, C. Supalo, and F. Jiang, "An Artificial Intelligence Tool for Accessible Science Education," *J. Sci. Educ. Students with Disabilities*, vol. 24, no. 1, pp. 1–14, Sep. 2021. https://doi.org/10.14448/jsesd.13.0010

[29] Talbi, Z. A. Haddouchane, S. Bakkali, and S. Ajana, "Developing a Virtual Laboratory Framework Based on the Lean Approach in Engineering Education: A Response to Industry 4.0 Skills," in *SMILE 2025*. Basel Switzerland: MDPI, 2025, p. 13. https://doi.org/10.3390/engproc2025097013

[30] P. Press, "A Rationale to Form a Community to Develop Free Online Simulations that improve Access to Higher Education Science and Engineering Courses for Students in Low-Income Countries," in *Online-Labs in Education*. Nomos Verlagsgesellschaft mbH Co. KG, 2022, pp. 471–478. https://doi.org/10.5771/9783957104106-471

[31] C.-P. Poo, Y.-y. Lau, and Q. Chen, "Are Virtual Laboratories and Remote Laboratories Enhancing the Quality of Sustainability Education?," *Educ. Sci.*, vol. 13, no. 11, p. 1110, Nov. 2023. https://doi.org/10.3390/educsci13111110

[32] Keddi and S. Frerich, “Enhancing Engineering Education by Virtual Laboratories,” in *Cross Reality and Data Science in Engineering*. Cham: Springer Int. Publishing, 2020, pp. 359–365. https://doi.org/10.1007/978-3-030-52575-0_30

[33] T. Richard and R. Rajakumari, “Virtual Laboratories in Higher Education Enhancing Chemistry and Biology Learning Outcomes,” in *2023 Int. Conf. Innovative Comput., Intell. Communication Smart Elect. Syst. (ICSES)*, Chennai, India, Dec. 14–15, 2023. IEEE, 2023. https://doi.org/10.1109/icses60034.2023.10465586

[34] G. Tabunshchyk, T. Kapliienko, and P. Arras, “Sustainability of the Remote Laboratories Based on Systems with Limited Resources,” in *Smart Industry & Smart Education*. Cham: Springer Int. Publishing, 2018, pp. 197–206. https://doi.org/10.1007/978-3-319-95678-7_22

[35] L. Bosman, B. Kotla, A. Madamanchi, S. Bartholomew, and V. Byrd, “Preparing the future entrepreneurial engineering workforce using web-based AI-enabled tools,” *Eur. J. Eng. Educ.*, pp. 1–18, Sep. 2022. https://doi.org/10.1080/03043797.2022.2119122

[36] V. Plevris, “A Glimpse into the Future of Civil Engineering Education: The New Era of Artificial Intelligence, Machine Learning, and Large Language Models,” *J. Civil Eng. Educ.*, vol. 151, no. 2, Apr. 2025. https://doi.org/10.1061/jceecd.eieng-2193

[37] I. Simatupang, E. Sormin, L. S. L. Purba, N. Harfa, and A. Nugroho, “Development of Virtual Reality Laboratory Integrated with Artificial Intelligence for Acid-Base Titration Practicum,” *J. Penelit. Pendidik. IPA*, vol. 11, no. 7, pp. 1186–1192, Jul. 2025. https://doi.org/10.29303/jppipa.v11i7.11587

[38] H. Hanine, N. Farajy, M. Boutaib, H. Boutracheh, and A. Moumen, “The Virtual Laboratories in Education System: A Bibliometric Review,” in *2025 5th Int. Conf. Innovative Res. Appl. Sci., Eng. Technol. (IRASET)*, Fez, Morocco, May 15–16, 2025. IEEE, 2025, pp. 1–8. https://doi.org/10.1109/iraset64571.2025.11008229

[39] H. M. Hubal, “The einstein law for the system "brownian particle in thermostat" based on the presented probability approach,” *Int. J. Pure Apllied Math.*, vol. 93, no. 6, Jun. 2014. https://doi.org/10.12732/ijpam.v93i6.12

[40] Oktageri, Sukardi, Usmeldi, W. Wagino, and H. Effendi, “Emerging Trends of Virtual Laboratories in Vocational Education: A Bibliometric Analysis,” *J. Lesson Learn. Stud.*, vol. 8, no. 2, pp. 351–364, Jul. 2025. https://doi.org/10.23887/jlls.v8i2.96277