BMC Medical Education

RESEARCH

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The effect of artificial intelligence–based scenarios on the clinical education of rehabilitation students: an anatomy-based randomized controlled study

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Abstract

Background This study aims to investigate the effects of using patient scenarios generated by artificial intelligence in rehabilitation education through different training models (artificial intelligence-based, internet-supported + traditional, and traditional only) on students' digital competence, clinical self-efficacy, and attitudes towards artificial intelligence.

Methods Ninety volunteer students were included in the study and divided into three groups using block randomisation: (1) artificial intelligence-supported (2), internet-supported + traditional method, and (3) traditional method only. An 8-week training programme was conducted for each scenario, consisting of weekly 90-minute sessions that alternated between assessment and treatment applications. The Digital Competence Self-Assessment Scale, Clinical Self-Efficacy Scale, and Artificial Intelligence Attitude Scale were administered before and after the intervention. One-way ANOVA or Kruskal–Wallis tests were used for between-group comparisons, and paired t-tests were used for within-group changes ($\alpha = 0.05$).

Results In the intra-group analyses, a significant increase was observed in clinical self-efficacy and artificial intelligence attitude scores in all groups ($p < .05$). Digital competence increased in the AI-supported and internet-supported + traditional groups ($p < .05$). Intergroup comparisons revealed significant differences in digital competence and AI attitude scores ($p < .05$). The increase in clinical self-efficacy scores was not significant at the intergroup level ($p > .05$).

Conclusion Artificial intelligence-based scenario training increases the level of digital competence in rehabilitation students and develops positive attitudes towards artificial intelligence. The findings indicate that this method can be integrated into educational programmes to strengthen clinical training processes. Further studies with larger samples, longer-term interventions, and objective performance measures are recommended to understand the effects on clinical skills.

Keywords Artificial ıntelligence, Clinical competence, Educational technology, Rehabilitation

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Introduction

Artificial intelligence (AI) refers to computer systems that mimic certain characteristics of human intelligence to perform cognitive functions such as problem solving, learning, and prediction. Advances in machine learning and big data analytics, together with rapidly developing technologies, have enabled AI to be applied across a wide range of disciplines, positioning it as a transformative element in many fields [1].

Among these fields, education and healthcare have emerged as two of the most prominent areas of AI application. In healthcare, AI is widely used for early disease detection, clinical decision support, medical imaging, and treatment planning [2, 3]. In parallel, in educational settings, AI technologies are increasingly utilized to provide personalised learning experiences, monitor student performance, and deliver rapid, data-driven feedback [4, 5].

These developments are particularly relevant for health sciences education, where students are required to integrate theoretical knowledge with clinical practice. The ability to transfer theoretical knowledge into clinical decision-making processes is essential for developing professional competence. In rehabilitation education, this competence is reflected in students' ability to analyse patient cases and design appropriate treatment programmes based on their clinical knowledge [6].

Although traditional teaching methods and case-based learning approaches contribute to the development of these competencies, the rapid advancement of digital technologies has highlighted the need for integrating AI into educational environments. AI-based educational tools have the potential to support students' learning processes and may positively influence academic performance, clinical reasoning skills, and self-efficacy [7].

However, the effectiveness of AI-supported learning environments depends not only on technological capabilities but also on students' foundational knowledge. In many traditional educational contexts, basic science courses may remain abstract, making it difficult for students to relate theoretical knowledge to clinical applications. In this regard, AI-supported tools and simulations may facilitate the visualisation of complex structures and strengthen the connection between theoretical knowledge and clinical practice [8, 9].

In addition to these cognitive factors, students' attitudes toward AI and their level of digital literacy may further influence the effectiveness of AI-based learning environments. Previous studies have demonstrated that positive attitudes toward AI and higher levels of digital competence are associated with more effective learning processes, whereas negative attitudes may reduce learning efficiency and lead to cognitive resistance [10, 11].

Despite the growing integration of AI into health sciences education, existing research has primarily focused on knowledge acquisition, general learning processes, or attitudes toward technology. Evidence regarding the effectiveness of AI-supported clinical case scenarios, particularly in terms of anatomy-based reasoning, treatment programme development, and clinical decision-making processes, remains limited [3, 7].

Therefore, the present study aims to investigate the comparative effectiveness of AI-supported clinical case analysis in rehabilitation education by comparing AI-based learning with internet-supported and traditional learning methods. It is hypothesised that AI-based scenario training will lead to significant differences in digital competence, clinical self-efficacy, and attitudes toward AI.

Materials and methods

Study design

This study was designed as a three-group randomized controlled educational intervention study and conducted among second-year physiotherapy associate degree students.

After providing informed consent, participants were randomly allocated into three groups using a computer-generated simple block randomisation method (block size = 3): Group 1 (artificial intelligence), Group 2 (internet + traditional methods), and Group 3 (traditional methods only). The randomisation process was performed by an independent researcher who was not involved in the study.

Following randomisation, participants completed a personal information form including age, gender, daily computer/tablet usage time, and prior experience with educational simulations. Subsequently, baseline assessments were conducted using the Artificial Intelligence Attitude Scale (to assess attitudes toward AI), the Digital Competence Self-Assessment Scale (to evaluate digital competence), and the Clinical Self-Efficacy Scale (to measure clinical decision-making processes).

Participants were then presented with patient scenarios generated using an artificial intelligence programme (ChatGPT) and reviewed by two academics specialising in physiotherapy and rehabilitation. The scenarios focused on common musculoskeletal conditions frequently encountered in clinical practice and were designed to require assessment, clinical reasoning, and treatment planning based on anatomical and rehabilitation principles.

These AI-generated scenarios were not intended to replace clinical practice but were used as an educational support tool to facilitate the transfer of theoretical knowledge into clinical application and to enhance clinical reasoning skills.

Table 1 Summary characteristics of the case scenarios used in the study

Case	Age/Gender	Primary Complaint	Examination Findings
Cervical Disc Herniation	45 / Female	Neck pain for 1 month, numbness radiating to the left arm; prolonged computer use, poor posture	C5–C6 involvement, muscle weakness in the corresponding dermatomes
Patellofemoral Pain Syndrome	25 / Male	Pain in front of the right knee; worsening with squatting and climbing stairs; began after playing football	Weakness of the vastus medialis, lateral mobility of the patella
Carpal Tunnel Syndrome	50 / Female	Increased hand pain at night, numbness, weakness in the thumb; computer work	Tinel and Phalen tests positive
Total hip replacement	70 / Female	Postoperative (15 days) mobilisation and balance issues, muscle weakness	Trendelenburg positive, weakness in hip abductor muscles

Table 2 Timeline of clinical case scenarios and learning activities during the eight-week intervention

Week	Clinical Scenario	Learning Activity
Week 1	Cervical Disc Herniation	Case evaluation
Week 2	Cervical Disc Herniation	Treatment planning
Week 3	Patellofemoral Pain Syndrome	Case evaluation
Week 4	Patellofemoral Pain Syndrome	Treatment planning
Week 5	Carpal Tunnel Syndrome	Case evaluation
Week 6	Carpal Tunnel Syndrome	Treatment planning
Week 7	Total hip replacement	Case evaluation
Week 8	Total hip replacement	Treatment planning

In the artificial intelligence group, students used ChatGPT as an informational support tool to search for case-related information. However, clinical reasoning and treatment programme development were performed independently by the participants based on their own knowledge. Artificial intelligence was not used to generate treatment plans automatically, and the developed treatment programmes were not applied to real patients.

The intervention lasted eight weeks, with one session per week (approximately 90 min per session). During this period, participants analysed patient scenarios in one week and developed treatment programmes for the same case in the following week.

Group-specific learning approaches were defined as follows: participants in Group 1 used only artificial intelligence tools (ChatGPT); participants in Group 2 used a combination of academic resources (e.g., Google Scholar, PubMed) and traditional materials (e.g., books, lecture notes); and participants in Group 3 used only traditional learning methods.

At the end of the intervention, all baseline scales were re-administered in the same order. The main characteristics of the patient case scenarios are presented in Table 1, and the timeline of the intervention is shown in Table 2.

During the eight-week intervention, students analysed clinical case scenarios and developed treatment programmes based on the provided case information. Each scenario included patient history, symptoms, functional limitations, and relevant anatomical structures. Students were required to identify the affected anatomical structures and propose appropriate rehabilitation treatment plans based on clinical reasoning.

Students prepared written treatment plans and submitted them to the instructor for evaluation. The scenarios were used exclusively for educational purposes, and the treatment plans were not implemented on real patients.

Ethical considerations

In order to carry out this study, an application was submitted to the Scientific Research and Publication Ethics Committee of a local university, and ethical approval was obtained on 12 June 2025 (Reference No: E-18457941-050.99-181729). All stages of the study were conducted in accordance with the Declaration of Helsinki. This study was not registered in a clinical trial registry.

Sample characteristics

The study was conducted with second-year students enrolled in the Therapy and Rehabilitation Department (physiotherapy associate degree programme) at a local university health services vocational school.

Inclusion criteria

Participants were included in the study if they:

- Volunteered to participate,
- Provided written informed consent,
- Had sufficient competence to use digital applications.

Exclusion criteria

Participants were excluded if they:

- Did not provide written informed consent,
- Had previously received training in artificial intelligence–based simulation,
- Did not attend the training sessions or failed to complete the study process after randomisation.

Sample size calculation

The sample size calculation was performed using G*Power software (version 3.1.9.4). Based on Cohen's recommendations for behavioural sciences, a medium

effect size (f = 0.25), an alpha level of 0.05, and a statistical power (1 – β) of 0.80 were assumed. According to these parameters, the minimum required sample size for three groups was calculated as 66 participants (22 per group). Considering a potential dropout rate of approximately 15%, the target sample size was increased to 78 participants (26 per group). However, due to the higher number of volunteer students available during the study period, the final sample consisted of 90 participants (30 per group) [12].

Data collection tools

Personal information form

The personal information form, which is a form used to assess participants' demographic information, was created by the researchers. Within the framework of the personal information form, participants were asked about their gender, age, daily computer/tablet usage times, and whether they had experienced simulation for educational purposes.

Artificial Intelligence Attitude Scale

Is used to evaluate individuals' thoughts, feelings, and attitudes toward artificial intelligence. The scale consists of 13 items covering three sub-dimensions and is rated on a 5-point Likert scale, with higher scores indicating a more positive attitude [13].

Clinical Self-Efficacy Scale

Was developed to assess self-efficacy perceptions of health sciences students during patient evaluation and treatment stages. The scale consists of 10 items and is rated on a 5-point Likert scale, with higher scores indicating greater self-confidence [14].

Digital Competence Self-Assessment Scale (DYÖ)

Was developed to assess individuals' professional and academic use of digital technologies. The scale consists of 21 items covering five sub-dimensions and is rated on a 5-point Likert scale, with higher scores indicating higher levels of digital competence [15].

Statistical analysis

The data were analysed using IBM SPSS Statistics version 28.0. Prior to the analyses, the distribution of variables was assessed using both statistical tests and graphical methods. Since the sample size in our study exceeded 50 and the data did not deviate markedly from symmetry, the Kolmogorov–Smirnov test was applied, in conjunction with visual assessments such as histograms and outlier checks, to evaluate normality.

Continuous variables with a normal distribution were presented as mean ± standard deviation (SD), whereas non-normally distributed data were expressed as median (Q1–Q3). For group comparisons, one-way analysis of variance (ANOVA) was used for normally distributed continuous variables, while the Kruskal–Wallis H test was applied for skewed distributions. Categorical variables were analysed using the chi-square test or Fisher's exact test when expected frequencies were low.

Where multiple comparisons were significant, Tukey's test was applied for normally distributed variables, whereas Dunn–Bonferroni tests were conducted for non-parametric post-hoc analyses. All statistical tests were conducted in a two-tailed fashion, with a significance level of $p < .05$. In addition, effect sizes were reported: partial eta² for ANOVA results and Cohen's d (based on pooled standard deviations) for pairwise comparisons.

Results

The results of the study are summarised in Tables 2, 3, 4 and 5. Table 2 presents the demographic characteristics of the participants. Table 3 shows the baseline comparisons of outcome measures between the groups, while Tables 4 and 5 present the within-group and between-group analyses of the study variables.

Table 3 Demographic characteristics of the participants

Variables	*Artificial Intelligence-Based Training*	*Internet Supported+ Traditional Training*	*Traditional Training*	*p* value
Age	20(20–21)	20(19–21)	20(19–21)	$p = .930^{*1}$
Daily computer/tablet usage	2(2–2)	2(2–2)	2(2–2)	$p = .980^{*1}$
Sex, n (%)				
Female	20 (66.6)	19 (63.3)	20 (66.6)	$p = .935^{*2}$
Male	10 (33.4)	11 (36.7)	10 (33.4)	
Prior Simulation Training, n (%)				
Yes	0 (0.0)	0 (0.0)	0 (0.0)	$p = 1.00^{*2}$
No	30 (100.0)	30 (100.0)	30(100.0)	

Abbreviations:Q1 First quartile, *Q3* Third quartile

*1 Kruskal–Wallis test statistic

*2 Fisher's Exact test statistic

$p < .05$ was considered significant

Table 4 Pre-test scores of outcome measures

Outcome measure	Artificial Intelligence-Based Training (*n* = 30)	Internet *Supported*+ Traditional *Training* (*n* = 30)	Traditional *Training* (*n* = 30)	Test Statistic
Digital Competence	33.00 (32–34)	33.00 (31–34)	32.00 (29–33)	H(2) = 5.54, *p* = .063
Clinical Self-Efficacy	30.57 ± 4.17	29.73 ± 3.24	31.67 ± 0.96	F(2, 87) = 2.94, *p* = .058
AI Attitude	56.00 (54.25–58.75)	53.50 (51.0–59.75)	54.50 (52.00–56.75)	H(2) = 4.49, *p* = .106

Abbreviations: *Q1* First quartile, *Q3* Third quartile, *(M ± SD)* Mean ± Standard Deviation

H: Kruskal-Wallis test statistic; F: One-way ANOVA test statistic

$p < .05$

Table 5 Pre-test and post-test scores of digital competence, clinical self-efficacy, and AI attitude

Outcome measure	Pre-test (M ± SD)	Post-test (M ± SD)	Test Statistic
Digital Competence			
Artificial Intelligence-*Based Training*	30.57 ± 4.17	36.50 ± 3.69	t(29) = -6.00, $p < .001$
Internet *Supported*+ Traditional *Training*	29.73 ± 3.24	34.56 ± 3.32	t(29) = -8.49, $p < .001$
Traditional *Training*	31.67 ± 0.96	35.91 ± 1.76	t(29) = -0.12, $p = .906$
Clinical Self-Efficacy			
Artificial Intelligence-*Based Training*	30.57 ± 4.17	36.50 ± 3.69	t(29) = -7.95, $p < .001$
Internet *Supported*+ Traditional *Training*	29.73 ± 3.24	34.56 ± 3.32	t(29) = -5.98, $p < .001$
Traditional *Training*	31.67 ± 0.96	35.91 ± 1.76	t(29) = -9.78, $p < .001$
AI Attitude			
Artificial Intelligence-*Based Training*	56.57 ± 3.76	62.20 ± 3.11	t(29) = -5.79, $p < .001$
Internet *Supported*+ Traditional *Training*	55.37 ± 6.44	61.10 ± 3.14	t(29) = -3.94, $p < .001$
Traditional *Training*	54.23 ± 3.42	59.90 ± 4.87	t(29) = -4.91, $p < .001$

Abbreviations: *(M ± SD)* Mean ± Standard Deviation

t: Paired samples t-test statistic

Statistically significant results ($p < .05$). $p < .05$

Table 6 Between-group comparisons of change scores

Outcome measure	Artificial Intelligence-Based Training (*n* = 30)	Internet Supported+ Traditional Training (*n* = 30)	Traditional Training (*n* = 30)	Test Statistic
Digital Competence	3.67 ± 3.35	4.27 ± 2.75	0.10 ± 4.57	F(2,87) = 11.50, $p^* < .001$
Clinical Self-Efficacy	6.70 ± 4.62	4.90 ± 4.49	4.33 ± 2.43	F(2,87) = 2.90, $p = .060$
AI Attitude	5.63 ± 5.33	5.73 ± 7.97	5.67 ± 6.32	F(2,87) = 0.00, $p = .998$

Abbreviations:*(M ± SD)* Mean ± Standard Deviation

F: One-way ANOVA test statistic

($^*p < .05$); $p < .05$

No statistically significant differences were found for any of the participants' demographic variables ($p > .05$) (Table 3).

The analysis conducted for the pre-test evaluation of the variables revealed no significant difference between the groups ($p > .05$) (Table 4).

When examining participants' initial and final tests, a significant change was observed in the digital competence-self-assessment variable for groups 1 and 2 ($p < .05$), while no significant change was observed for group 3 ($p > .05$). In the clinical self-efficacy and attitude towards AI assessments, significant changes were observed in all three groups ($p < .05$) (Table 5).

Between-group analyses showed a significant difference only for digital competence change scores ($p<.001$), with Group 3 showing lower improvements compared to Groups 1 and 2. No significant between-group differences were observed for clinical self-efficacy ($p=.060$) or attitude towards AI ($p=.998$) (Table 6).

Discussion

Principal findings

This study was conducted to evaluate the effectiveness of artificial intelligence–based scenario training on learning outcomes, including digital literacy, clinical self-efficacy, and attitudes toward artificial intelligence among students undergoing rehabilitation training.

The findings indicate that AI-based training contributed to significant improvements in digital literacy and attitudes toward artificial intelligence. However, although clinical self-efficacy improved within groups, no statistically significant differences were observed between groups.

Interpretation of findings and comparison with previous studies

A key finding of this study is that AI-based scenario training resulted in significant improvements in digital literacy. This finding is consistent with previous studies demonstrating that various educational interventions—such as face-to-face learning, simulation-based training, distance education, and blended learning—are effective in enhancing digital competence among health sciences students and professionals [16]. Similarly, educational programmes have been reported to play a critical role in improving digital competence at both individual and institutional levels [16, 17].

In line with the literature, both AI-supported and internet-supported learning approaches in our study were associated with increased digital literacy levels. These findings suggest that AI-supported scenario-based education may contribute to the development of digital skills alongside cognitive learning processes.

Previous research has consistently demonstrated a positive relationship between digital competence and attitudes toward artificial intelligence. Studies conducted among educators and healthcare professionals have shown that individuals with higher digital literacy levels tend to exhibit more positive attitudes toward AI [18–21]. Our findings support this relationship and further suggest a potentially reciprocal interaction: while digital competence may influence attitudes toward AI, AI-based training itself may also contribute to improvements in digital literacy.

The literature also indicates that attitudes toward artificial intelligence are generally positive among health sciences students. Previous studies have reported high levels of acceptance and trust in AI systems, as well as significant associations between AI literacy and attitudes toward AI [22–25]. Consistent with these findings, our study showed that positive attitudes toward AI increased following AI-based scenario training.

However, improvements in attitudes were also observed in the internet-supported and traditional groups. This may be explained by increased exposure to AI-related concepts, the motivational effect of participating in the study, and greater familiarity with digital learning materials. The relatively smaller increase observed in the traditional group supports this interpretation and suggests that AI-supported learning environments may provide an additional advantage in shaping positive attitudes and motivation.

With regard to clinical self-efficacy, our findings are consistent with previous studies reporting limited evidence for the effectiveness of AI-based interventions in improving clinical performance outcomes [25–27]. Although improvements were observed within groups, these changes did not reach statistical significance in intergroup comparisons.

Several factors may explain this finding. First, the relatively short duration of the intervention may have limited the development of observable differences in clinical skills. Second, the use of self-reported measures may not fully capture objective clinical performance. Third, shared educational components across groups and the motivational effect of voluntary participation may have contributed to improvements in all groups, thereby reducing between-group differences.

Overall, these findings suggest that while AI-based education may support improvements in digital competence and attitudes toward AI, its impact on clinical self-efficacy may require longer-term interventions and more objective assessment methods.

Conclusion

The findings of this study suggest that AI-based scenario training may contribute to improvements in digital competence and attitudes toward artificial intelligence among rehabilitation students. Although improvements in clinical self-efficacy were observed within groups, no significant differences were identified between groups. These results indicate that AI-supported learning environments may enrich rehabilitation education by supporting students' cognitive and digital development. Future studies including larger samples, longer intervention periods, and objective performance-based assessments are needed to better evaluate the potential impact of AI-based education on clinical skills.

Limitations and recommendations

This study has several limitations that should be considered when interpreting the findings. First, the participants were recruited from a single institution using a convenience sampling approach, which may limit the generalisability of the results. In addition, the outcomes were assessed using self-report scales, which may reflect participants' perceived competencies rather than objective performance. Clinical performance was not directly evaluated using objective performance-based assessments, and blinding was not

applied. Furthermore, the relatively short intervention period may have limited the ability to detect stronger effects on clinical skills. Future research should include more diverse samples, longer intervention and follow-up periods, and objective performance-based measures to provide stronger evidence regarding the effectiveness of the method.

Abbreviations

AI	Artificial Intelligence
ANOVA	Analysis of Variance
CSE	Clinical Self-Efficacy
DC	Digital Competence
SD	Standard Deviation
SPSS	Statistical Package for the Social Sciences

Acknowledgements
The authors would like to thank all the physiotherapy students who voluntarily participated in this study. We also extend our appreciation to the academic staff who supported the coordination of the training sessions and provided logistical assistance throughout the study. The authors express their gratitude to the Dicle University Scientific Research Projects Coordination Unit (DÜBAP) for its institutional support.

Authors' contributions
RY contributed to study design, data collection, data analysis, and manuscript writing. OSN contributed to scenario validation, methodological supervision, and critical manuscript revision. Both authors read and approved the final manuscript.

Funding
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Data availability
The datasets generated and/or analysed during the current study are not publicly available due to ethical restrictions related to the protection of personal participant information; however, they are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate
This study was conducted in accordance with the Declaration of Helsinki. Ethical approval was obtained from the Artvin Çoruh University Scientific Research and Publication Ethics Committee (Approval No: E-18457941-050.99-181729, Date: 12 June 2025). Written informed consent was obtained from all participants prior to their participation in the study.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Received: 30 December 2025 / Accepted: 9 April 2026
Published online: 14 April 2026

References

1. Malik P, Pathania M, Rathaur VK. Overview of artificial intelligence in medicine. J Fam Med Prim Care. 2019;8(7):2328–31.
2. Al Kuwaiti A, Nazer K, Al-Reedy A, Al-Shehri S, Al-Muhanna A, Subbarayalu AV, et al. A review of the role of artificial intelligence in healthcare. J Pers Med. 2023;13(6):951.
3. Chan KS, Zary N. Applications and challenges of implementing artificial intelligence in medical education: integrative review. JMIR Med Educ. 2019;5(1):e13930.
4. Holmes W. Artificial intelligence in education. Encyclopedia of education and information technologies. Cham: Springer; 2020. pp. 88–103.
5. Zawacki-Richter O, Marín VI, Bond M, Gouverneur F. Systematic review of research on artificial intelligence applications in higher education–where are the educators? Int J Educ Technol High Educ. 2019;16(1):1–27.
6. Young ME, Thomas A, Lubarsky S, Gordon D, Gruppen LD, Rencic J, et al. Mapping clinical reasoning literature across the health professions: a scoping review. BMC Med Educ. 2020;20(1):107.
7. Bozkurt SA, Aydoğan S, Dursun Ergezen F, Türkoğlu A. Artificial intelligence in healthcare education: a systematic review and sequential explanatory synthesis. Int Nurs Rev. 2025;72(2):e70018.
8. Nicholson DT, Chalk C, Funnell WRJ, Daniel SJ. Can virtual reality improve anatomy education? A randomized controlled study of a computer-generated three-dimensional anatomical ear model. Med Educ. 2006;40(11):1081–7.
9. Yammine K, Violato C. A meta-analysis of the educational effectiveness of three-dimensional visualization technologies in teaching anatomy. Anat Sci Educ. 2015;8(6):525–38.
10. Spante M, Hashemi SS, Lundin M, Algers A. Digital competence and digital literacy in higher education research: systematic review of concept use. Cogent Educ. 2018;5(1):1519143.
11. Van der Spoel I, Noroozi O, Schuurink E, Van Ginkel S. Teachers' online teaching expectations and experiences during the COVID-19 pandemic in the Netherlands. Eur J Teach Educ. 2020;43(4):623–38.
12. Faul F, Erdfelder E, Buchner A, Lang AG. Statistical power analyses using G*Power 3.1: tests for correlation and regression analyses. Behav Res Methods. 2009;41(4):1149–60.
13. İlhan AG, Önal N. Adaptation of the Artificial Intelligence Attitude Scale into Turkish: A validity and reliability study. Temel Eğit. 2019;7(25):71–86.
14. Zengin N, Pınar R, Akinci AC, Yildiz H. Psychometric properties of the self-efficacy for clinical evaluation scale in Turkish nursing students. J Clin Nurs. 2014;23(7–8):976–84.
15. Tutar H, Erdem AT, Şahin N. Digital Competence Scale (DCS): A validity and reliability study. Selçuk Üniv Sos Bilim MYO Derg. 2024;27(1):31–47.
16. Alotaibi N, Wilson CB, Traynor M. Enhancing digital readiness and capability in healthcare: a systematic review. BMC Health Serv Res. 2025;25(1):500.
17. Tischendorf T, Hasseler M, Schaal T, Ruppert SN, Marchwacka M, Heitmann-Möller A, et al. Developing digital competencies of nursing professionals: a scoping review. Front Med (Lausanne). 2024;11:1358398.
18. Abou Hashish EA, Alnajjar H. Digital proficiency among university nursing students. BMC Med Educ. 2024;24(1):508.
19. Asal MGR, Alsenany SA, Elzohairy NW, El-Sayed AAI. The impact of digital competence on pedagogical innovation among nurse educators. Nurse Educ Pract. 2025;85:104367.
20. Galindo-Domínguez H, Delgado N, Campo L, Losada D. Relationship between teachers' digital competence and attitudes toward AI. Int J Educ Res. 2024;126:102381.
21. Sergeeva OV, Masalimova AR, Zheltukhina MR, Chikileva LS, Lutskovskai LY, Luzin A. Impact of digital media literacy on attitude toward generative AI acceptance in higher education. Front Educ (Lausanne). 2025;10:1563148. https://doi.org/10.3389/feduc.2025.1563148.
22. Fitzek S, Choi KEA. Medical and dental students' perceptions of AI. BMC Med Educ. 2024;24(1):844.
23. Laupichler MC, Aster A, Meyerheim M, Raupach T, Mergen M. Medical students' AI literacy and attitudes. BMC Med Educ. 2024;24(1):401.
24. Sami A, Tanveer F, Sajwani K, Kiran N, Javed MA, Ozsahin DU, et al. Medical students' attitudes toward AI in education. BMC Med Educ. 2025;25(1):82.
25. Zheng L, Xiao Y. Assessing the impact of AI curricula on medical students. BMC Med Educ. 2025;25(1):1115.
26. Amiri H, Peiravi S, Rezazadeh Shojaee S, Rouhparvarzamin M, Nateghi MN, Etemadi MH, et al. Students' attitudes and knowledge toward AI: systematic review and meta-analysis. BMC Med Educ. 2024;24(1):412.
27. Atalla ADG, El-Gawad Mousa MA, Hashish EAA, Elseesy NAM. Abd El Kader Mohamed AI, Sobhi Mohamed SM. AI in nursing: attitudes and clinical reasoning. BMC Nurs. 2025;24(1):661.

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