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The Effectiveness of an Educational Intervention Using AI-Based Automated Question Generation Tools on Students' Academic Engagement and Autonomous Motivation

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ABSTRACT

This study aimed to determine the effectiveness of an AI-based Automated Question Generation (AQG) tool (using the Gemini 2.5 Pro model) in teaching research methodology concepts on the academic engagement and autonomous motivation of male students at Zahedan University of Medical Sciences.

The research design was quasi-experimental, utilizing a pre-test/post-test format with a control group. The final statistical sample consisted of 47 students (22 in the experimental group and 25 in the control group) selected through multi-stage cluster random sampling. The experimental group participated in an educational intervention using the AI tool for eight 90-minute sessions. Data collection instruments included the Vallerand Academic Motivation Scale (1992) and the Reeve Academic Engagement Scale (2013).

Data analysis was performed using multivariate analysis of covariance (MANCOVA). The results indicated that after controlling for the pre-test effect, a significant difference existed between the two groups regarding the dependent variables ($p<0.001$). The use of the AI tool led to a significant increase in academic engagement and autonomous motivation within the experimental group. Based on the partial eta-squared index, the intervention accounted for 19% of the variance in academic engagement and 24% of the variance in autonomous motivation, demonstrating the strong impact of this technology.

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Introduction

The dawn of the 21st century has witnessed a paradigm shift in the educational landscape that has fundamentally altered the ways in which knowledge is disseminated, consumed, and constructed. The expansion of Information and Communication Technologies (ICT) has transformed from a supplementary luxury into an infrastructural necessity and has accelerated the migration from traditional (didactic) teaching methods to dynamic e-learning environments. This digital evolution is not merely about digitizing content; rather, it represents an innovative approach to transferring skills and knowledge through interactive, scalable, and flexible frameworks that are accessible at any time and place (Georgieva, Todorov, & Smrikarov, 2003). For such learning environments to be truly effective, they must incorporate two-way interaction, scalability, and innovation, moving beyond the static repositories of the past (Smith et al., 2020). In this context, universities, as platforms for socio-economic and cultural development, are faced with the imperative to align their pedagogical strategies with these technological advancements. Higher education institutions are tasked with training a specialized workforce capable of navigating modern complexities. Consequently, maintaining the status quo is no longer a viable option (Abdi et al., 2020). Sattary (2013) argues that to improve educational outcomes, institutions require a deep awareness of teaching quality and the effectiveness of their delivery systems. This necessity became vividly apparent during the post-COVID-19 era, where the rapid shift toward virtual learning revealed significant vulnerabilities in student focus and engagement, necessitating more robust digital solutions (Ebadi & Heidaranlu, 2020).

Nowhere is this educational imperative more critical than in medical education. The medical curriculum is notoriously rigorous and is characterized by high information density, rapid pace, and significant cognitive load. This high-pressure environment often leads to "academic burnout," which results in a crisis of student disengagement (discontinuity) (Dyrbye et al., 2016). Academic engagement, a multifaceted construct, serves as the primary antidote to these challenges. Engagement, which was initially defined to understand dropout and academic failure, has evolved into a comprehensive measure of student success. Fredricks et al. (2004), in their seminal work, conceptualize engagement not as a monolithic trait but as a combination of three distinct dimensions:

Behavioral Engagement: It is based on the idea of participation; it includes involvement in academic and social or extracurricular activities and is vital for preventing dropout and ensuring consistent attendance.

Emotional Engagement: It involves positive and negative reactions to teachers, classmates, academic issues, and the university. It acts as the affective bond that connects students to the institution and influences their willingness to perform tasks.

Cognitive Engagement: It is based on the idea of investment; it includes thoughtfulness and a willingness to exert the effort necessary to comprehend complex ideas and master difficult skills (Fredricks et al., 2004).

In the field of medical education, fostering deep levels of engagement particularly cognitive engagement is of paramount importance. Archambault et al. (2009) note that engagement emphasizes dimensions such as connection with the learning environment and commitment. Disengaged (disconnected) students are not only prone to dropping out but are also less likely to develop the critical clinical reasoning skills required for patient care. Klem and Connell (2004) further conceptualize engagement as a psychological process involving attention, interest, investment, and effort directed toward learning.

Motivation is a theoretical concept used to clarify human behavior and provide a basis for need satisfaction (Maslow, 1943; Cook & Artino, 2016). Building on Self-Determination Theory (SDT), contemporary educational psychology distinguishes between autonomous motivation (doing something for its inherent satisfaction or personal value) and controlled motivation (doing something due to external pressure or rewards) (Ryan & Deci, 2000). Ryan and Deci (2000) hypothesize that autonomous motivation remains sustainable when three basic psychological needs are met: autonomy (the need to feel volition), competence (the need to feel efficacy), and relatedness (the need to feel connected to others).

Faculty members play a pivotal role in this dynamic. As highlighted by Darvish Ghadimi and Roudbari (2012), the teaching style of professors is a determining factor in fostering or suppressing this internal drive. Similarly, Hanifi et al. (2012) argue that educators play a decisive role in motivating the learning process. However, traditional lecture-based formats in medical schools, which are often driven by standardized assessments, frequently fail to support these needs, leading to a reliance on external regulation, which is a weaker predictor of deep learning. The interaction between professor and student lies at the heart of the learning process (Zolfagharian et al., 2018).

Entering this complex pedagogical matrix is Artificial Intelligence (AI) and specifically the burgeoning field of Generative AI (GenAI). The integration of AI into medical sciences has garnered increasing attention due to its potential to revolutionize learning outcomes. Recent studies from 2024 and 2025 emphasize that proficiency in AI is no longer optional; rather, it is a core competency for future healthcare professionals who must navigate an increasingly technology-driven medical landscape (Moldt et al., 2024).

A specific application of this technology is Automated Question Generation (AQG). Historically, AQG relied on rigid formats with limited linguistic flexibility. However, the advent of Large Language Models (LLMs) has heralded a new era of "intelligent" AQG. These AI-based systems can significantly reduce instructor workloads while providing adaptive and immediate feedback a component often missing in traditional environments due to time constraints (Wang et al., 2007). Research indicates that AI-generated assessments, such as Multiple Choice Questions (MCQs), can improve student performance and engagement (Palm et al., 2024; Emekli & Karahan, 2025). Unlike static questions in textbooks, AI can generate infinite variations of clinical scenarios, allowing for "targeted practice". Furthermore, Durgungoz and Durgungoz (2025) found that AI-generated gamified quizzes significantly increased student engagement in online modules.

Despite the growing literature on Artificial Intelligence in education, significant gaps remain. Empirical studies that utilize quasi-experimental designs to measure the causal impact of specific LLMs, such as Gemini 2.5 Pro, on academic engagement and autonomous motivation particularly in the contexts of medical education in developing countries are scarce. On the other hand, while the potential of AI is praised, there is a lack of rigorous data on how these tools perform when integrated into teaching "research methodology" concepts concepts that are often perceived as dry and difficult by medical students. Accordingly, the main question of the present study is: Is an AI-based automated question generation tool effective in teaching research methodology concepts on the academic engagement and autonomous motivation of students?

Method

Sample and Sampling Method

The purpose of the present study was to determine the effectiveness of an AI-based automated question generation tool in teaching research methodology concepts on the academic engagement and autonomous motivation of male students at Zahedan University of Medical Sciences. The research design was quasi-experimental, utilizing a pretest-posttest format with a control group. The statistical population of the present study consisted of all male undergraduate students at Zahedan University of Medical Sciences during the academic year 2024-2025 . This research was conducted exclusively on male students with the aim of controlling the gender variable. The initial statistical sample of the present study included 60 undergraduate male students who were selected using a multi-stage cluster random sampling method. In the first stage, 4 faculties were randomly selected from among the faculties of Zahedan University of Medical Sciences; in the second stage, one class was randomly selected from each faculty; and in the third stage, from among the students of these classes, 30 participants were assigned to the experimental group and 30 participants to the control group. However, during the implementation of the present study, the final statistical sample was reduced to 47 individuals, including 22 in the experimental group and 25 in the control group. The reasons for the reduction in the initial sample size were a lack of inclination to participate in the study, failure to complete the questionnaires, and failure to submit learning assignments.

Tools Used

Academic Motivation Scale (AMS)

This scale was first designed in 1992 by Vallerand et al. The test consists of 28 items and seven subscales, including three subscales for the intrinsic motivation dimension (motivation to know, toward accomplishment, and to experience stimulation) with items 2, 9, 16, 23, 6, 13, 20, 27, 4, 11, 18, and 25; three subscales related to extrinsic motivation (identified regulation, introjected regulation, and external regulation) with items 3, 10, 17, 24, 7, 14, 21, 28, 1, 8, 15, and 22; and one subscale for amotivation with items 5, 12, 19, and 26. This questionnaire is scored on a seven-point Likert scale ranging from "does not correspond at all" (1) to "corresponds exactly" (7). The minimum and maximum scores for the questionnaire items are 28 and 196, respectively (Vallerand, 1992). Vallerand reported the Cronbach's alpha for the subscales of the test between 0.83 and 0.86. The reliability coefficient obtained from the test-retest of the subscales over a one-month interval was also reported between 0.71 and 0.83. Confirmatory factor analysis also confirmed the seven-factor structure of the construct, indicating the desirable construct validity of this scale. In Iran, in the study by Yousefi et al. (2019), the Cronbach's alpha for this scale across all components was estimated between 0.67 and 0.90.

Reeve's Academic Engagement Scale

This scale was designed by Reeve in 2013. The test consists of 17 items and four subscales, which are scored on a 7-point Likert scale from "strongly disagree" (1) to "strongly agree" (7). The lowest and highest scores on this scale are 17 and 119, respectively. In an exploratory factor analysis based on principal components, Reeve obtained four factors. He also estimated the reliability of the questionnaire in the agency, behavioral, emotional, and cognitive subscales as 0.86, 0.86, 0.90, and 0.84, respectively, which indicates desirable internal consistency (Reeve, 2013). In Iran, Nokhostin Goldoust et al. (2024) estimated the reliability of this scale using the Cronbach's alpha method at 0.73.

To develop the intervention protocol, assumptions such as learning objectives, content, methods and instructions, and assessment and evaluation were considered. Therefore, based on the aforementioned frameworks, the headings of research methodology concepts for teaching were first determined. Then, the intervention-based learning objectives were specified using the AI tool. In the next step, the time required for performing and submitting learning activities, and the selection of the media environment and necessary educational materials were identified. Finally, to assess the students' learning, the "assessment for learning" method was used through the provision of feedback by the instructor. A summary of the intervention sessions for the AI-based question generation tool is presented in Table 1.

Table 1. Summary of intervention sessions for the AI-based question generation tool

Session	Description of Session
First	Holding an in person class and introducing class members to each other; explaining educational goals aligned with the course headings, including an introduction to the scientific method, its nature, and the stages of implementing a research design. After the class, educational and learning objectives proportional to the session's topic were shared with students in a virtual group so that they could subsequently use the AI tool to generate questions and answers, as well as complete and submit assignments by the specified deadline.
Second	Selecting a research topic; identifying and stating the research problem, problem statements, and how to articulate them; the theoretical and conceptual framework of the research and their characteristics; research questions and hypotheses. After the class, educational and learning objectives proportional to the session's topic were shared with students in a virtual group so they could use the AI tool to generate questions and answers and complete assignments.
Third	Explaining types of research methods, including experimental and non-experimental methods, and introducing single-subject designs; emphasizing the recognition of characteristics and applications of each method according to research goals. After the in-person class, students' learning activities continued through generating and answering questions using the AI question generation tool and completing assignments in the virtual group.
Fourth	Teaching sampling and its methods, including random and non-random sampling; methods for determining sample size; the concept of sampling bias and stating the limitations of sampling methods. After the class, students used the AI tool to design and answer questions related to the session's topics.
Fifth	Data collection and explaining types of information gathering methods including questionnaires, interviews, and observations; reviewing the characteristics, applications, and limitations of each method. After the in-person class, students' learning activities were followed by generating questions and answering based on the AI tool and performing assignments in the virtual group.
Sixth	Explaining the characteristics of data collection tools and reviewing concepts of scientific reliability and validity of tools; focusing on the importance of validity and reliability in scientific research. After the in-person class, students engaged in educational activities and submitted assignments in the virtual group with the help of the AI question generation tool.
Seventh	Quantitative data analysis in experimental designs, including introducing multivariate statistical methods; reviewing statistical assumptions and familiarity with parametric and non-parametric tests. After the in-person class, sharing educational and learning goals proportional to the session's heading, analytical exercises were followed through generating and answering questions using the AI tool and completing assignments in the virtual group.

Eighth	Quantitative data analysis in non-experimental designs, including correlation analyses and relationship measurement indices; teaching the reporting of results for parametric and non-parametric analyses; drafting the research report and presenting research suggestions. At the end, students used the AI question generation tool to summarize the topics and complete final activities in the virtual group.

Procedure

After reviewing the content of the protocol provided by the instructor using AI tools, and considering criteria such as support for the Persian language, generation of valid content, being free of charge, and easy accessibility to control the negative impacts of using this technology, the Gemini 2.5 Pro AI tool was ultimately selected for use in the intervention. In the present study, after the two groups were determined, a pretest was conducted, and then an educational session was held to introduce this tool to the experimental group. The intervention for the experimental group was implemented for 8 sessions of 90 minutes each. After the completion of the intervention, a posttest was administered to both groups, and finally, the data of the present study were analyzed using the multivariate analysis of covariance (MANCOVA) method.

Results

Data analysis in the present study was conducted in two sections: descriptive and inferential. In the descriptive statistics section, the descriptive statistics of the research variables, including mean and standard deviation, were described. Subsequently, for the inferential analysis of the research data, the multivariate analysis of covariance (MANCOVA) test was utilized.
The mean and standard deviation scores for the pretest and posttest of students' academic engagement and autonomous motivation are as follows (Table 2).

Table 2. Results of descriptive statistics for pretest and posttest by group

Group	Variables	Pre test Mean	Pre test SD	Post test Mean	Posttest SD
Control	Academic Engagement	71.64	17.62	72.36	19.01
	Autonomous Motivation	15.24	3.7	16.09	3.45
Experimental	Academic Engagement	67.95	19.40	75.77	22.14
	Autonomous Motivation	13.73	3.82	16.32	3.95

Multivariate analysis of covariance (MANCOVA) was used to investigate the impact of the AI-based automated question generation tool on students' academic engagement and autonomous motivation. Before conducting this test, it is mandatory to examine several statistical assumptions. One of the assumptions of the MANCOVA test is the normality of the distribution of variables. To examine this assumption, the Shapiro-Wilk test was utilized, the results of which are reported in Table 3.

Table 3. Results of the Shapiro-Wilk test to examine the normality of the distribution of variables

Variables	Condition	Statistic	Significance Level (p-value)
Academic Engagement	Pretest	0.97	0.053
	Posttest	0.98	0.097
Autonomous Motivation	Pretest	0.99	0.089
	Posttest	0.98	0.071

According to the results in Table 3, the Shapiro-Wilk statistic for the academic engagement variable is 0.97 in the pretest and 0.98 in the posttest. Additionally, this statistic for the autonomous motivation variable is 0.99 in the pretest and 0.98 in the posttest, which is not significant. Given that the results of this test are not significant ($p > 0.05$), it can be concluded that the distribution of the research variables in both the pretest and posttest is normal.

One of the assumptions of the multivariate analysis of covariance (MANCOVA) is the homogeneity of covariance matrices, which was examined using Box's M test. The results of this test are presented in Table 4.

Table 4. Results of the test for homogeneity of covariance matrices

Box's M	F	df1	df2	Significance Level (p-value)
1.27	0.40	3	830653.85	0.75

As observed in Table 4, the Box's M value (1.27) is not significant at the 95% confidence level ($p>0.05$). Therefore, the homogeneity of the covariance matrices is confirmed.

Table 5. Results of Levene's test for examining the homogeneity of variances

Variable	F	df1	df2	Significance Level (p-value)
Academic Engagement	0.47	1	45	0.50
Autonomous Motivation	2.75	1	45	0.11

As shown in Table 5, the results of Levene's test for all variables are not significant at the 95% confidence level ($p>0.05$). Therefore, the homogeneity of variance for the variables which is another assumption of the multivariate analysis of covariance (MANCOVA) is confirmed.

Table 6: Multivariate Analysis of Covariance (MANCOVA) Results for the Effects of the Group Variable

Effect	Test	Value	F	Hypothesis df	Error df	Significance(p-value)	PartialEta Squared
Group	Pillai's Trace	0.32	10.14	2	42	0.001	0.33
	Wilks' Lambda	0.67	10.14	2	42	0.001	0.33
	Hotelling's Trace	0.48	10.14	2	42	0.001	0.33

	Roy's Largest Root	0.48	10.14	2	42	0.001	0.33

Based on the results of the multivariate analysis of covariance (MANCOVA), all four tests including Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root are significant at the 0.001 level (p<0.01). This indicates that there is a significant difference between the groups. The partial eta squared value (0.33) also indicates a high effect size of the independent variable on the dependent variables, which demonstrates the significant influence of the intervention or the factor under investigation.

Table 7. Results of the ANCOVA analysis within the MANCOVA framework on academic engagement and autonomous motivation scores

Variable	**Step**	**Sum of Squares**	**df**	**Mean Square**	**F**	**Significance (p-value)**	**Effect Size (Partial η2)**
Academic Engagement	Post test	416.84	1	416.84	9.97	0.003	0.19
	Error	1798.48	43	41.83			
	Total	280711.00	47				
Autonomous Motivation	Posttest	32.46	1	32.46	13.38	0.001	0.24
	Error	104.36	43	2.43			
	Total	12950.58	47				

The results in Table 7 indicated that after controlling for the pretest effect, a significant difference was observed between the groups in both dependent variables. Specifically, significant differences were found in the academic engagement variable (F=9.97, p<0.05, η2=0.19) and the autonomous motivation variable (F=13.38, p<0.001, η2=0.24). The effect sizes indicate that the intervention explained 19% and 24% of the variance in the dependent variables, respectively, demonstrating a strong and practical impact of the intervention on improving the studied variables.

Discussion and Conclusion

The primary objective of this study was to evaluate the effectiveness of AI-based Automated Question Generation (AQG) on medical students' academic engagement and autonomous motivation. The MANCOVA results revealed that the AI-integrated intervention significantly outperformed traditional instruction, explaining 19% of the variance in engagement and 24% of the variance in autonomous motivation. The first major finding of this study was a significant increase in academic engagement within the experimental group. This is consistent with recent findings by Palm et al. (2024) and Emekli and Karahan (2025), who reported that interactive AI tools generate higher participation rates compared to static learning materials.

However, our study extends these findings by elaborating on the nature of this engagement. By delegating the tasks of AI prompting and output critique to the students, the intervention transformed them from passive consumers into active architects of their own learning. This resonates with the assertion by Fredricks et al. (2004) that deep engagement requires a "psychological investment" in understanding complex ideas. The AI functioned not merely as a tool, but as a "More Knowledgeable Other" (in Vygotsky's terms), providing the necessary scaffolding for students to grapple with difficult research methodology concepts without the frustration that typically leads to disengagement.

The second key finding was a robust increase in autonomous motivation. This result supports the work of Yilmaz and Karaoglan Yilmaz (2023), who found that GenAI tools enhance self-efficacy and intrinsic drive. Through the lens of Self-Determination Theory (SDT) (Ryan & Deci, 2000), the success of Gemini 2.5 Pro can be attributed to the satisfaction of basic psychological needs:

Autonomy Support: Unlike rigid, standardized tests, Gemini 2.5 Pro allowed students to control their own assessment parameters (e.g., topic, difficulty level, clinical context). This shift from external control to internal volition is a hallmark of autonomous motivation.

Competence Enhancement: The immediate, accurate, and non-judgmental feedback provided by the AI enabled rapid error correction. Hattie and Timperley (2007) argue that feedback is most effective when it is timely and task-oriented. Traditional classrooms, with high student-to-faculty ratios, often lack this immediacy. The AI bridged this gap, reducing the "shame" associated with public failure and encouraging a mastery orientation.

Relatedness: Although the AI is a machine, its conversational content (utilizing Natural Language Processing) created a pseudo-social interaction. Mazzolini and Maddison (2003) noted that instructor intervention is vital for engagement; here, the AI simulated a private tutor, making the learning environment feel responsive and supportive.

This study was not without limitations. First, the sample was limited to male students to control for gender variables, which restricts the generalizability of the findings. Given the mixed evidence regarding gender differences in technological self-efficacy (Siami et al., 2014), future research should include diverse groups. Second, the study was cross-sectional in its post-test measurement. As Granström and Oppi (2025) suggest, the "novelty effect" of AI might diminish over time. Longitudinal studies are required to determine whether engagement remains high throughout an entire academic year. Finally, we focused specifically on Gemini 2.5 Pro; comparative studies pitting different LLMs against one another would be valuable for discerning the specific pedagogical advantages of each platform.

The integration of Gemini 2.5 Pro into the medical curriculum is more than a technological upgrade; it is a pedagogical evolution. This study provides empirical evidence that when AI is employed not as an answer engine but as an automated question generation partner, it significantly strengthens students' psychological investment in their learning. By decentralizing the assessment process and placing the power of inquiry in the hands of the learners, we cultivate a generation of medical professionals who are not only knowledgeable but also autonomous, engaged, and critical thinkers. In an era where medical knowledge expands exponentially, the ability to engage in AI-assisted learning may be the most vital skill we can impart.

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References

Abdi, H., Mirshah Jafari, S. I., Nili, M. R & ,.Rajajpour, S. (2020). A study of the visions and missions of Iran's higher education in 2025 plan: An analysis of priorities and opportunities. Higher Education Curriculum Studies, 13 (49), 223–250.https://www.jsfc.ir/article_109871.html

Archambault, I., Janosz, M., Fallu, J. S & ,.Pagani, L. S. (2009). Student engagement and its relationship with early high school dropout. Journal of Adolescence, 32 (4), 651–670.https://pubmed.ncbi.nlm.nih.gov/18708246/

Palm, E., Manikantan, A., Pepin, M., Mahal, H & ,.Belwadi, S. (2024). Assessing the Quality of AI-Generated Clinical Notes: A Validated Evaluation of a Large Language Model Scribe. arXiv preprint arXiv:2505.17047. https://arxiv.org/abs/2505.17047

Cook, D. A & ,.Artino, A. R. (2016). Motivation to learn: An overview of contemporary theories. Medical Education, 50 (10), 997–1014.https://pubmed.ncbi.nlm.nih.gov/27628718/

Darvish Ghadimi, F & ,.Roudbari, M. (2012). Teaching styles of faculty members in schools affiliated with Iran University of Medical Sciences. Iranian Journal of Medical Education, 11 (8), 917–925.https://ijme.mui.ac.ir/browse.php?a_id=1408&slc_lang=en&sid=1&printcase=1&hbnr=1&hmb=1

Durgungoz, A & ,.Durgungoz, F. C. (2025). Exploring effortless AI-generated gamified quizzes in an online special education module: Evaluating question quality, student engagement, and its potential to identify at-risk students. Education and Information Technologies .https://link.springer.com/article/10.1007/s10639-025-13765-5

Dyrbye, L. N., Thomas, M. R., & Shanafelt, T. D. (2016). *Medical student distress and burnout: a narrative review*. (PDF/resource).https://www.semanticscholar.org/paper/A-narrative-review-on-burnout-experienced-by-and-Dyrbye-Shanafelt/3eadc8cf89e597fdda636ce9442fdf1b2e152022

Ebadi, A & ,.Heidaranlu, E. (2020). Virtual learning: A new experience in the shadow of coronavirus disease. Shiraz E-Medical Journal, 21 (12), e103163.https://brieflands.com/journals/semj/articles/106712

Emekli, E & ,.Karahan, B. N. (2025). Artificial intelligence in radiology examinations: A psychometric comparison of question generation methods. Diagnostic and Interventional Radiology. https://www.dirjournal.org/pdf/beb8919b-f013-4ea1-b1c8-40332e840fe1/articles/dir.2025.253407/DIR-2025.253407.pdf

Fredricks, J. A., Blumenfeld, P. C & ,.Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. Review of Educational Research, 74 (1), 59–109.https://journals.sagepub.com/doi/10.3102/00346543074001059

Georgieva, G., Todorov, G & ,.Smrikarov, A. (2003, June). A model of virtual university-some problems during its development. In CompSysTech (pp. 709-715).https://dl.acm.org/doi/10.1145/973620.973739

Granström, M & ,.Oppi, P. (2025). Student engagement with AI tools in learning: Evidence from a large-scale Estonian survey. Frontiers in Education, 10 , 1688092.https://www.frontiersin.org/journals/education/articles/10.3389/feduc.2025.1688092/full

Hanifi, N., Parvizi, S & ,.Joolaee, S. (2012). Nurses as motivators or suppressors of nursing students' learning in clinical learning. Journal of Nursing Education, 1 (1), 14–24.https://jne.ir/browse.php?a_id=49&sid=1&slc_lang=en

Hattie, J & ,.Timperley, H. (2007). The power of feedback. Review of Educational Research, 77 (1), 112.https://journals.sagepub.com/doi/abs/10.3102/003465430298487

Klem ,A. M & ,.Connell, J. P. (2004). Relationships matter: Linking teacher support to student engagement and achievement. Journal of School Health, 74 , 262–273.https://pubmed.ncbi.nlm.nih.gov/15493703/

Maslow, A. H. (1943). A theory of human motivation. Psychological Review, 50 (4), 370–396.https://psycnet.apa.org/record/1943-03751-001

Mazzolini, M & ,.Maddison, S. (2003). Sage, guide or ghost? The effect of instructor intervention on student participation in online discussion forums. Computers & Education, 40 (3), 237–253.https://dl.acm.org/doi/10.1016/S0360-1315(02)00129-X

Moldt, J. A., Festl-Wietek, T., Fuhl, W., Zabel, S., Claassen, M., Wagner, S., Nieselt, K & ,.Herrmann-Werner, A. (2024). Assessing AI Awareness and Identifying Essential Competencies: Insights From Key Stakeholders in Integrating AI Into Medical Education. JMIR Medical Education, 10 , e58355.https://www.researchgate.net/publication/381585034_Assessing_AI_Awareness_and_Identifying_Essential_Competencies_Insights_From_Key_Stakeholders_in_Integrating_AI_Into_Medical_Education

Nokhostin Goldoust, A., Fatahi Sineh Sar, S. M., & Taklavi, S. (2024). *The effectiveness of teaching the brainstorming instructional method on students' academic engagement, academic vitality, and perception of the learning environment*. *Journal of Educational Psychology Studies*, 21(55), 1–29. [In Persian]https://jeps.usb.ac.ir/article_8590.html?lang=en

Reeve, J. (2013). How students create motivationally supportive learning environments for themselves: The concept of agentic engagement. Journal of Educational Psychology, 105, 579–595. DOI:10.1037/a0032690 https://www.researchgate.net/publication/263924266_How_Students_Create_Motivationally_Supportive_Learning_Environments_for_Themselves_The_Concept_of_Agentic_Engagement

Ryan, R. M & ,.Deci, E. L. (2000). Intrinsic and extrinsic motivations: Classic definitions and new directions. Contemporary Educational Psychology, 25 (1), 54–67.https://www.sciencedirect.com/science/article/pii/S0361476X99910202

Sattary, S. (2013). Assessment of effective teaching, components based on the students viewpoints. Research in Curriculum Planning, 10 (39), 134–146.https://www.magiran.com/paper/1210201/assessment-of-effective-teaching-components-based-on-the-students-viewpoints?lang=en

Smith, S., Maund, K., Hilaire, T., Gajendran, T., Lyneham, J & ,.Geale, S. (2020). Enhancing Discipline Specific Skills Using a Virtual Environment Built with Gaming Technology. International Journal of Work-Integrated Learning, 21 (3), 193–209.https://files.eric.ed.gov/fulltext/EJ1254848.pdf

Vallerand, R. J., Pelletier, L. G., Blais, M. R., Briere, N. M., Senecal, C & ,.Vallieres, E. F. (1992). The Academic Motivation Scale: A measure of intrinsic, extrinsic, and amotivation in education. Educational and Psychological Measurement, 52 (4), 1003-1017.https://psycnet.apa.org/record/1993-24226-001

Wang, W., Hao, T & ,.Liu, W. (2007). Automatic Question Generation for Learning Evaluation in Medicine. Springer Lecture Notes in Computer Science, 4823 , 242-251.https://link.springer.com/chapter/10.1007/978-3-540-78139-4_22

Yilmaz, R & ,.Karaoglan Yilmaz, F. G. (2023). The effect of generative artificial intelligence (AI)-based tool use on students' computational thinking skills, programming self-efficacy and motivation. Computers and Education: Artificial Intelligence, 4 , 100147. https://www.sciencedirect.com/science/article/pii/S2666920X23000267

Yousefi, N., Sharifi, H. P., & Sharifi, N. (2019). *A structural model of academic burnout based on perceived social support, educational justice, and students' academic motivation*. **Journal of Applied Psychology**, 12(3), 418–438. [In Persian]https://apsy.sbu.ac.ir/article_96701.html?lang=en

Zolfagharian, M., Aminbeidokhti, A & ,.Jafari, S. (2018). Structural relationship of faculty-student interaction and faculty's active teaching method. Journal of Research in Educational Science, 12 (40), 181–204.https://www.jiera.ir/article_65182_en.html