OPEN PRAXIS

Exploring the Impact of Artificial Intelligence in Advancing Smart Learning in Education: A Meta-Analysis with Statistical Evidence

RESEARCH ARTICLE

MUHAMMAD YOUNAS
ISKANDER ISMAYIL
DINA ABDEL SALAM EL-DAKHS
BEHZAD ANWAR

*Author affiliations can be found in the back matter of this article

INTERNATIONAL COUNCIL FOR OPEN AND DISTANCE EDUCATION

ABSTRACT

This meta-analysis examines the diverse effects of artificial intelligence (AI), notably ChatGPT, on intelligent learning in the education industry over the last four years. Despite the rapid integration into education of AI tools such as ChatGPT, which have the potential to enhance personalized learning and administrative efficiency, there remains a dearth of comprehensive, evidence-based research evaluating their long-term educational impacts. This study sought to address this gap by examining the subtle impacts of AI on different educational levels, geographical regions, and functionality. This project employed a meta-analysis methodology to thoroughly examine peer-reviewed articles published between 2020 and 2023. Its objective was to measure the efficacy of AI applications in enhancing critical thinking and personalized learning. The key findings suggest that AI technologies, such as intelligent tutoring systems and adaptive learning platforms, greatly improve the personalization and engagement of learning. However, we still need to address difficulties related to ethical considerations and potential biases. These findings emphasize the importance of implementing strict ethical norms and strong educational frameworks to guarantee the fair and efficient incorporation of AI into educational processes.

CORRESPONDING AUTHORS:

Iskander Ismayil

Xinjiang Teacher's College, Urumqi, P.R China

iskander_ismayil@hotmail.com

Muhammad Younas

Prince Sultan University, Saudi Arabia

myounas@psu.edu.sa

KEYWORDS:

Artificial Intelligence; GenAI; Smart Learning; Meta-Analysis; Personalized Learning; Ethical Considerations; Learning Innovation; AI in Education; Impact; Statistical evidence

TO CITE THIS ARTICLE:

Younas, M., Ismayil, I., El-Dakhs, D. A. S., & Anwar, B. (2025). Exploring the Impact of Artificial Intelligence in Advancing Smart Learning in Education: A Meta-Analysis with Statistical Evidence. *Open Praxis*, *17*(3), pp. 594–610. DOI: https://doi.org/10.55982/openpraxis.17.3.842

INTRODUCTION

Artificial intelligence (AI) has greatly influenced the field of education. ChatGPT, created by OpenAI, is a remarkable tool among the available AI applications. This cutting-edge application produces coherent, rational, and fluent responses, delivering an interactive experience that emulates human communication. Educators in the education sector use ChatGPT to enhance the learning experience by customizing course content and providing individualized feedback (Holmes et al., 2019; Lee & Kwan, 2024; Tlili et al., 2023). Additionally, Javaid et al. (2023) stated that ChatGPT assists in automating tasks such as grading assignments and administering tests, freeing up educators to concentrate on instructional activities. Mhlanga (2023) argued that ChatGPT enhances tailored education for younger learners, allowing them to prioritize critical thinking and fundamental academic content. In addition, Doughty et al. (2024) emphasized the exceptional precision of ChatGPT-4 in numerous languages, and its capacity to produce code in diverse programming languages. These features aid students in comprehending intricate ideas and concepts, hence enhancing their learning experience.

Although ChatGPT has many advantages, it has also sparked apprehension among the educational community. Educators have expressed concerns about the potential negative effects of ChatGPT on students' ability to express themselves and to think independently. As a result, numerous academic institutions have implemented prohibitions on its use (Lampropoulos, 2024). There are also concerns about AI-powered chatbots such as ChatGPT potentially enabling academic dishonesty (Morocco-Clarke et al., 2024). Roose (2022) explored the potential of ChatGPT to facilitate scholarly research and writing, but there is also the potential for students to misuse it as a means to avoid their academic duties, which could hinder their growth in competence (Shrivastava, 2023). Considering the diverse viewpoints on this subject, we sought to perform a thorough meta-analysis of publications from the last 7 years to investigate the impact of ChatGPT and other AI technologies on improving smart learning. The main goal was to understand the complex impact of AI and ChatGPT on education, promoting a comprehensive understanding of the increasing connection between technological progress and educational methods.

RESEARCH GAP AND OBJECTIVE

Although AI is said to have an effect on student learning, the lack of a meta-analysis on the topic makes an evidence-based conclusion difficult (Dimitriadou & Lanitis, 2023). The gaps in understanding of its effects can be filled by conducting a meta-analysis that can provide robust evidence-based findings on the influence of AI on smart learning advancements. Addressing these gaps was therefore the aim of this study, which had a prime focus on identifying how AI has been adopted at each level of education and in each geographical region, and what kinds of AI tools have been used. Based on the findings, this analysis aimed to contribute to the understanding of how AI tools such as ChatGPT may be implemented in suitable educational practices for the betterment of learning outcomes. To sum up, this study addressed the research lacunae through a comprehensive meta-analysis of the impact of AI on the progress of smart learning, focusing primarily on the overall influence of the use of AI tools on educational outcomes at different educational levels and in different geographic locations.

RESEARCH QUESTIONS

The major research questions the study aimed to answer are:

1. How can ChatGPT be used to provide personalized learning experiences and help students develop their critical thinking abilities?
2. What are the possible risks and ethical considerations while using ChatGPT in an educational environment?
3. How does the use of ChatGPT in administrative tasks impact instructional quality and efficiency in education?

LITERATURE REVIEW

AI has become a pivotal force in the transformation of education, bringing with it innovative ways to enhance the teaching and learning processes. AI technologies such as OpenAI's ChatGPT have garnered much attention since they can generate fluent, contextually appropriate responses, simulating human-like interactions. These technologies have been employed to personalize learning experiences, automate administrative tasks, and offer data-driven insights (Javaid et al., 2023; Tlili et al., 2023; Younas et al., 2025; Imran et al., 2025).

Personalized learning is a cornerstone of AI applications in education, tailoring educational content to meet the unique needs of each student. According to Kulik and Fletcher (2016), the existence of intelligent tutoring systems (ITS) that offer feedback features and adaptive learning materials increases the efficiency of student success. There is pacing for every student, so long as the tutor caters to their learning pace. Mhlanga (2023) emphasized that AI offers a personalized kind of learning that improves critical thinking and understanding of the matter.

Engagement is vital for effective learning, and AI technologies such as VR and AR are so created in a manner that engages the student's mind. Cukurova et al. (2020) further elaborated on how AI-powered VR and AR make abstract concepts tangible and memorable, hence enhancing students' understanding and retention. Haleem et al. (2022) and Hanshaw et al. (2024) stated that AI is going to change the nature of education itself through personalized learning, and that intelligent tutoring systems will become instrumental to a dynamic technology-infused learning environment.

Evidently, lifelong learning and the development of professionalism have become some of the most salient issues brought about by AI. AI-driven platforms offer personalized learning pathways, helping individuals acquire new skills throughout their careers. Bhatt and Muduli (2023) elaborated how learning becomes truly perpetual, following continuously adjusting labor market demands. This ensures that learners remain flexible in skills, keeping them competitive in the job market through emerging trends.

While there are tremendous potentials of AI in education, its implementation harbors many ethical issues. As Williamson and Eynon (2020) argued, transparency, fairness, and inclusivity in the formation of AI algorithms may prevent or lessen bias in its outputs. Ethical use of AI within an educational context is key to ensuring equal opportunities for all learners. Özer (2024) and Bashir et al. (2025) discussed both the advantages and risks of using AI in education and presents a way forward whereby education should be restructured urgently to fit into the interventions that AI is making against ethical concerns.

METHODOLOGY

The research outlines the influence of AI on smart learning advancement. The other aspect is the fact that the meta-analysis approach will be put into place due to the evidence-based findings. The use of a deductive approach in this meta-analysis helps in identifying the influence of AI on students' learning outcomes.

SEARCH OF THE LITERATURE AND SCREENING

Screening of all literature retrieved is carried out to ensure that the study is rigorous and accurate (Di & Zheng, 2022; Ma et al., 2022; Tang et al., 2021; Zhang & Ma, 2023) (Figure 1). The screening criteria for documents are as follows:

1. Literature conducted on AI analysis of the impact of teaching on the results of learning.
2. Type of document must be for experimental research literature.
3. Experiment in the literature must include an experimental group and a control group.
4. The literature must contain data for measuring learning effects (learning performance, learning efficiency, etc.), and the effect value can be calculated. The data include sample sizes (N), mean values (M), standard deviations (SD), or values of both the experimental and control groups that are mainly needed for effect value calculation.
5. Duplicate literature should be excluded.

CALCULATION FORMULA

The effect size is an indicator that reflects the strength of the experimental effect or the strength of the variable association. It is not affected by the sample size (or the effect is very small). The difference in effect size was mainly analyzed to explore the differences in the impact of AI technology on learning effects under different teaching conditions. Since the number of included studies was small and it was a small sample study, Hedges' g

DOI: 10.55982/openpraxis.17.3.842

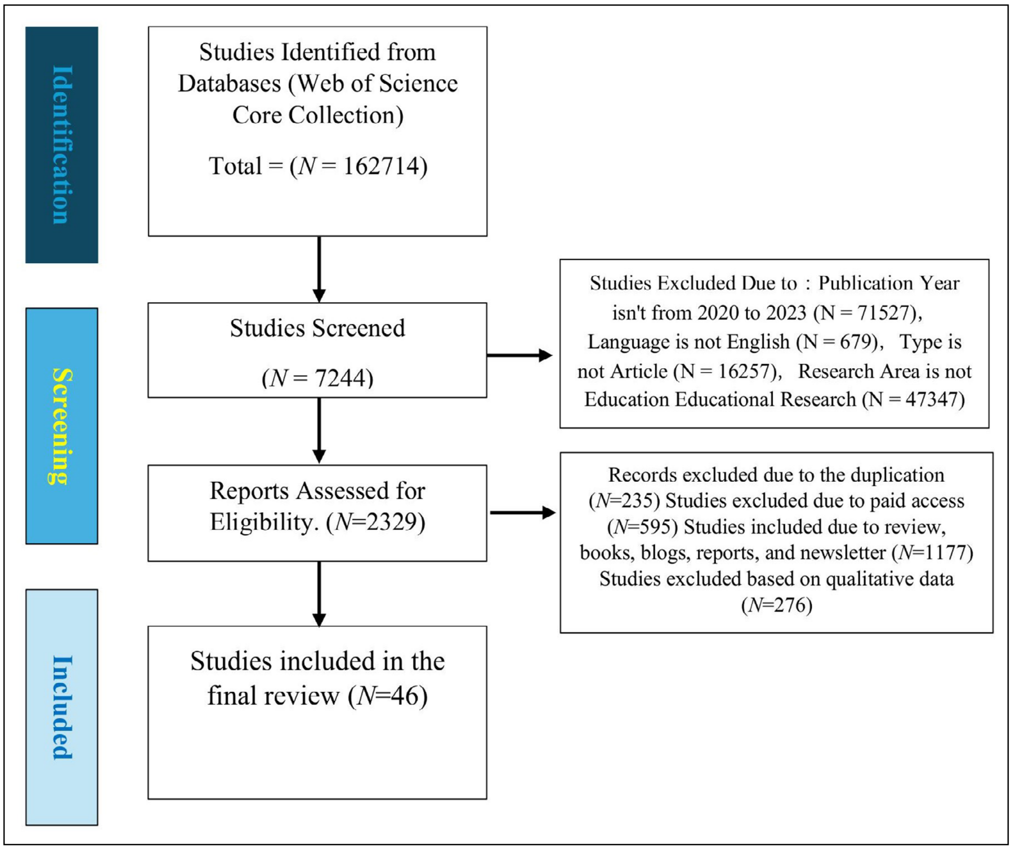


Figure 1 The Literature Search Process.

(hereinafter referred to as g value) was used as the effect value indicator. When calculating the effect size of each study, the selected data are mainly the mean, standard deviation (SD), and sample size (N) of the experimental group and the control group. According to scholars such as Lipsey and Wilson (2017), when a study contributes more than one effect size in the analysis, it will lead to statistical dependence, thereby causing a deviation in the overall effect. Therefore, when there were multiple independent and dependent variables in the literature to be included in the analysis, only one of them was used to calculate the effect value. For this reason, we selected learners' learning effect as the only dependent variable.

When the study sample size is small, Cohen's d will seriously overestimate the effect value. Hedges' g value can be corrected by multiplying the standardized mean difference (d) by the correction factor (*J*).

Effect size g (Hedges' g) calculation:

Suppose a study has two independent groups and we want to compare the means of the two groups, where μ_1 and σ_1 are the population mean and standard deviation of the first group, and μ_2 and σ_2 are the population mean and standard deviation of the second group; if we assume that the two population standard deviations are the same (as is the assumption of most parametric analysis methods), then $\sigma_{12} = \sigma_{22}$, and the standardized mean difference parameter and the population standardized mean difference are defined as:

$$\delta = \frac{\mu_1 - \mu_2}{\sigma}$$

In the following section, we will describe how to estimate the value of δ for independent group design studies. Assuming that the variances are equal, $\sigma_{12} = \sigma_{22}$, this allows for a simple estimate of the standard deviation without discussing the case of unequal variances. We can estimate the standardized mean difference in the group design study as

$$d = \frac{\overline{X}_1 - \overline{X}_2}{S_{within}}$$

where $\overline{X}_1$ and $\overline{X}_2$ are the sample means of the two groups, and the denominator *S* is the within-group standard deviation, which is obtained by combining the two groups:

$$S_{within} = \sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}}$$

where n_1 and n_2 are the sample sizes of the two groups, and S_1 and S_2 are the standard deviations in the two groups. The reason for combining the two sample standard deviation estimates is that we assume that the population standard deviations are equal ($\sigma_1 = \sigma_2 = \sigma$), but the sample standard deviations S_1 and S_2 cannot be exactly the same. Combining the estimates of the two standard deviations can obtain a more accurate estimate of the common standard deviation.

The sample estimate of the standardized mean difference is often referred to as the Cohen's (2013). Confusion about this terminology arises from the fact that δ, originally proposed by Cohen as a common parameter for describing effect size in statistical power analysis, is sometimes referred to as d. In this article, we use the symbol δ to refer to the effect size parameter and d to refer to the sample estimate of that parameter.

d^{th} variance and given by (a very good estimate):

$$V_d = \frac{n_1 + n_2}{n_1 n_2} + \frac{d^2}{2(n_1 + n_2)}$$

In the formula, the first term on the right side of the equal sign reflects the uncertainty of the mean difference estimate, while the second term reflects the uncertainty value of the *S* within the estimate.

d the standard error is the square root of V_d

$$SE_d = \sqrt{V_d}$$

It turns out that d has a small bias; that is, it overestimates δ when the sample size is small. This bias can be corrected by a simple method to obtain an unbiased estimate of δ. This unbiased estimate is called Hedges' *g* (Hedges, 1981).

To convert d to Hedges' g, we use a correction factor, called J. Hedges (1981) proposed an exact formula for J, but in common practice, researchers use an approximation:

$$J = 1 - \frac{3}{4df - 1}$$

In the above formula, df is the degree of freedom, which is used to estimate *S* within, which is $n_1 + n_2 - 2$ for two independent groups. This approximation usually has an error of less than 0.007. When $df > 10$ (Hedges, 1981), it is less than 0.035%. Then,

$$g = J \times d$$

Effect size is a measure that reflects the strength of the experimental effect or the strength of the association of variables (Borenstein et al., 2009; Hwang, 2016). Sample size has no effect on it (or the effect is too small). The difference in the effect size was mainly analyzed to examine the differences in the impact of AI technology on learning effects under different teaching conditions. Since the number of studies included is small and this is a small-sample study, we use Hedges' *g* as the effect value indicator hereafter (*g* value). The data selected when calculating the effect size of each study were primarily the mean, standard deviation (*SD*), and sample size (*N*) of the experimental group and the control group. As Lipsey and Wilson (2017) and Hedges and Olkin (2014) stated, when a study provides more than one effect size that is entered into the analysis, it will establish statistical dependence and create a divergence in the overall effect. This is the reason why, when there are several independent and dependent variables in the literature to be included in the analysis, only one is used to calculate the effect value. Accordingly, in this study, we selected only one dependent variable: learners' learning effect.

When the study sample size is small, Cohen's *d* will seriously overestimate the effect value. However, Hedges' *g* value can be corrected by multiplying the standardized mean difference (*d*) by the correction factor (J).

DOI: 10.55982/openpraxis.17.3.842

Effect size *g* (Hedges' *g*) calculation:

$$g = \left(1 - \frac{3}{4df - 1}\right) \times \left(\frac{\bar{X}_1 - \bar{X}_2}{S_{within}}\right)$$

In the above formula, *df* is the degree of freedom, which is used to estimate *S* within, which is $n_1 + n_2 - 2$ for two independent groups.

DATA ANALYSIS

Table 1 provides an overview of the main studies on AI applications in education from 2020 to 2023. It classifies the type of AI deployed, such as personal tutors, intelligent support for collaborative learning, or intelligent VR, by continent, subject, and educational level. Also, it lists the intervention period, user roles, and learning context in order to provide a complete picture of how AI technologies have been applied in global educational experiences. This great volume of information informs us of the different approaches and impacts of AI, which has great potential to personalize learning, streamline administrative tasks, and engage learners in all forms of settings.

Table 1 Characteristics of the selected studies (N = 46) for meta-analysis (2020–2023).

AUTHORS (YEAR)	TYPE OF AI (PERSONAL TUTORS/ INTELLIGENT SUPPORT FOR COLLABORATIVE LEARNING/ INTELLIGENT VIRTUAL REALITY)	REGION	SUBJECT (HUMANITIES AND SOCIAL SCIENCES/ NATURAL SCIENCES)	EDUCATIONAL LEVEL (HIGHER EDUCATION/ SECONDARY EDUCATION/ PRIMARY EDUCATION/PRE-SCHOOL EDUCATION/ SPECIAL EDUCATION)	INTERVENTION DURATION (SHORT-TERM/ LONG-TERM)	USER ROLE (JOINTLY LED BY STUDENTS & TEACHER/ STUDENT-LED/ TEACHER-LED)	LEARNING ENVIRON MENT (FORMAL/ INFORMAL/ MIXED)
(Escalante et al, 2023)	Personal Tutors	USA	Social Sciences	Higher Education	Long-term	Jointly led	Mixed
(Huang et al, 2022)	Intelligent Support for Collaborative Learning	Asia	Natural Sciences	Secondary Education	Long-term	Jointly led	Mixed
(Li et al, 2022)	Personal Tutors	Asia	Natural Sciences	Higher Education	Short-term	Student-led	Formal
(Liew et al, 2022)	Personal Tutors	Asia	Natural Sciences	Higher Education	Short-term	Student-led	Formal
(Bachiri et al, 2023)	Intelligent Support for Collaborative Learning	Africa	Social Sciences	Primary Education	Long-term	Student-led	Informal
(Chiu et al, 2022)	Intelligent Support for Collaborative Learning	Asia	Social Sciences	Higher Education	Short-term	Jointly led	Formal
(Liyanawatta et al, 2022)	Intelligent Support for Collaborative Learning	Asia	Social Sciences	Secondary Education	Short-term	Jointly led	Formal
(Taskiran & Goksel, 2022)	Personal Tutors	Europe	Social Sciences	Higher Education	Long-term	Student-led	Informal
(Yang et al, 2023)	Intelligent Support for Collaborative Learning	Asia	Social Sciences	Higher Education	Short-term	Jointly led	Informal
(Chen et al, 2022)	Intelligent Virtual Reality	Asia	Social Sciences	Primary Education	Long-term	Jointly led	Formal
(Lin et al, 2023)	Personal Tutors	Asia	Natural Sciences	Secondary Education	Short-term	Jointly led	Formal
(Al et al, 2022)	Personal Tutors	Asia	Social Sciences	Secondary Education	Long-term	Jointly led	Formal
(Lai et al, 2019)	Intelligent Virtual Reality	Asia	Natural Sciences	Higher Education	Long-term	Jointly led	Formal
(Lin et al, 2023)	Intelligent Virtual Reality	Asia	Natural Sciences	Primary Education	Long-term	Jointly led	Formal
(Azamatova et al, 2023)	Personal Tutors	Asia	Social Sciences	Higher Education	Long-term	Jointly led	Formal
(Sichterman et al, 2023)	Intelligent Support for Collaborative Learning	Europe	Natural Sciences	Higher Education	Short-term	Jointly led	Formal
(Hu et al, 2022)	Personal Tutors	Asia	Social Sciences	Primary Education	Long-term	Student-led	Formal
(Huang et al, 2023)	Personal Tutors	Asia	Natural Sciences	Higher Education	Long-term	Student-led	Formal
(Hsu et al, 2023)	Personal Tutors	Asia	Natural Sciences	Secondary Education	Short-term	Student-led	Formal
(Bäuerle et al, 2023)	Intelligent Support for Collaborative Learning	Europe	Natural Sciences	Higher Education	Short-term	Student-led	Informal
(Lo et al, 2021)	Intelligent Support for Collaborative Learning	Asia	Natural Sciences	Higher Education	Long-term	Jointly led	Mixed

(Contd.)

AUTHORS (YEAR)	TYPE OF AI (PERSONAL TUTORS/ INTELLIGENT SUPPORT FOR COLLABORATIVE LEARNING/ INTELLIGENT VIRTUAL REALITY)	REGION	SUBJECT (HUMANITIES AND SOCIAL SCIENCES/ NATURAL SCIENCES)	EDUCATIONAL LEVEL (HIGHER EDUCATION/ SECONDARY EDUCATION/ PRIMARY EDUCATION/PRE-SCHOOL EDUCATION/ SPECIAL EDUCATION)	INTERVENTION DURATION (SHORT-TERM/ LONG-TERM)	USER ROLE (JOINTLY LED BY STUDENTS & TEACHER/ STUDENT-LED/ TEACHER-LED)	LEARNING ENVIRON MENT (FORMAL/ INFORMAL/ MIXED)
(Ng et al, 2024)	Intelligent Support for Collaborative Learning	Asia	Natural Sciences	Secondary Education	Long-term	Jointly led	Formal
(Lee et al, 2022)	Personal Tutors	Asia	Natural Sciences	Higher Education	Long-term	Student-led	Formal
(Lin, 2023)	Intelligent Support for Collaborative Learning	Asia	Natural Sciences	Higher Education	Long-term	Student-led	Formal
(Herodotou et al, 2018)	Intelligent Virtual Reality	Europe	Natural Sciences	Higher Education	Short-term	Student-led	Formal
(Schmidgall et al, 2020)	Intelligent Support for Collaborative Learning	Europe	Natural Sciences	Higher Education	Short-term	Student-led	Formal
(Schoeb et al, 2020)	Intelligent Virtual Reality	Europe	Social Sciences	Higher Education	Short-term	Student-led	Informal
(van Alten et al, 2020)	Intelligent Support for Collaborative Learning	Europe	Natural Sciences	Secondary Education	Long-term	Student-led	Formal
(van der Mei et al, 2020)	Intelligent Support for Collaborative Learning	Europe	Natural Sciences	Secondary Education	Short-term	Student-led	Formal
(Liu et al, 2020)	Intelligent Support for Collaborative Learning	Asia	Natural Sciences	Higher Education	Long-term	Jointly led	Informal
(Nabulsi et al, 2021)	Personal Tutors	Europe	Natural Sciences	Higher Education	Long-term	Student-led	Formal
(Hodges et al, 2020)	Intelligent Virtual Reality	USA	Natural Sciences	Primary Education	Long-term	Teacher-led	Formal
(Chen et al, 2020)	Intelligent Support for Collaborative Learning	Asia	Social Sciences	Primary Education	Long-term	Student-led	Formal
(Chen, 2020)	Intelligent Virtual Reality	Asia	Social Sciences	Primary Education	Long-term	Student-led	Formal
(Yousef, 2020)	Intelligent Virtual Reality	Africa	Natural Sciences	Primary Education	Long-term	Teacher-led	Formal
(Bergeler et al, 2020)	Intelligent Support for Collaborative Learning	USA	Natural Sciences	Higher Education	Short-term	Teacher-led	Formal
(Yang et al, 2020)	Intelligent Support for Collaborative Learning	Asia	Social Sciences	Secondary Education	Long-term	Student-led	Formal
(Yang et al, 2023)	Intelligent Virtual Reality	Asia	Natural Sciences	Higher Education	Long-term	Student-led	Formal
(Wu & Chang, 2020)	Personal Tutors	Asia	Natural Sciences	Secondary Education	Long-term	Student-led	Formal
(Shih et al, 2020)	Intelligent Support for Collaborative Learning	Asia	Natural Sciences	Higher Education	Long-term	Jointly led	Mixed
(Zulnaidi et al, 2020)	Personal Tutors	Asia	Natural Sciences	Secondary Education	Long-term	Jointly led	Formal
(Liu et al, 2022)	Intelligent Virtual Reality	Asia	Natural Sciences	Higher Education	Short-term	Teacher-led	Formal
(Song et al, 2020)	Personal Tutors	USA	Social Sciences	Higher Education	Long-term	Student-led	Informal
(Chang et al, 2020)	Intelligent Virtual Reality	Asia	Natural Sciences	Secondary Education	Long-term	Student-led	Formal
(Drissi et al, 2024)	Personal Tutors	Africa	Natural Sciences	Higher Education	Long-term	Student-led	Informal

PUBLICATION BIAS TEST

We conducted bias detection, as the phenomenon of a deviation between the published result and actual result may exist in the analysis of related literature (Duval & Tweedie, 2000; Oh, 2002). Due to the small sample size of this article, publication bias was detected by qualitative funnel plots and quantitative Begg's tests. As Figure 2 depicts, the points on the funnel plot seemed to be more or less centrally focused to the combined effect value of 0.503 and showed a symmetrical distribution. It was preliminarily judged that publication bias was not obvious. The result of Begg's test was $Z = 1.941 < 1.96$, $p = 0.052 > 0.05$, further indicating that publication bias was not significant. Therefore, the combined value effect obtained in this paper is very accurate and highly robust.

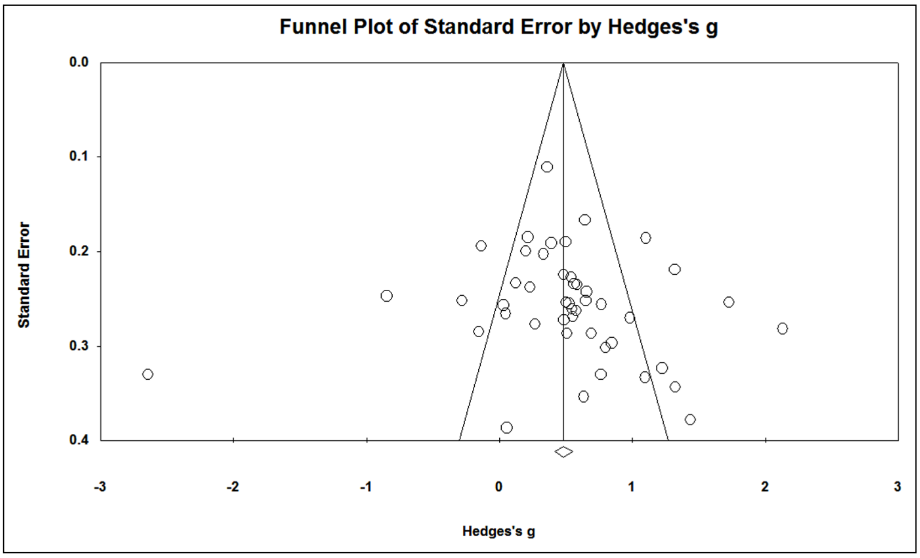
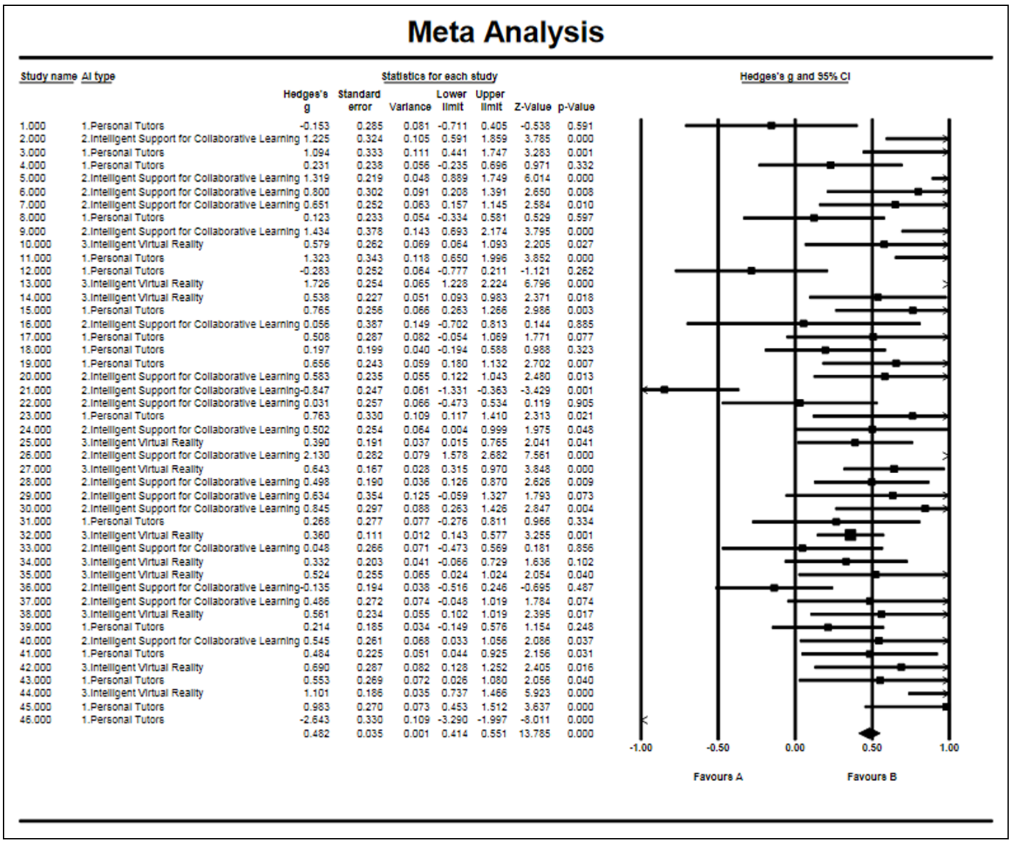


Figure 2 Funnel Plot of Sample Publication Bias Detection, Hedges' g.

FOREST PLOT

The collected data were analyzed using meta-essential software, facilitating quantitative analysis. The included studies were evaluated based on heterogeneity to assess variation in the data results. In Figure 3, the forest plot shows analysis of the distribution of the data as an overall estimate. Huang et al. (2020) emphasized that a forest plot is crucial for assessing the overall impact size of a study. Therefore, forest plots were included in the analysis.



Study name	AI type	Hedges's g	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value
1.000	1.Personal Tutors	-0.153	0.285	0.081	-0.711	0.405	-0.538	0.591
2.000	2.Intelligent Support for Collaborative Learning	1.225	0.324	0.105	0.591	1.859	3.785	0.000
3.000	1.Personal Tutors	1.094	0.333	0.111	0.441	1.747	3.283	0.001
4.000	1.Personal Tutors	0.231	0.238	0.056	-0.235	0.696	0.971	0.332
5.000	2.Intelligent Support for Collaborative Learning	1.319	0.219	0.048	0.889	1.749	6.014	0.000
6.000	2.Intelligent Support for Collaborative Learning	0.800	0.302	0.091	0.208	1.391	2.650	0.008
7.000	2.Intelligent Support for Collaborative Learning	0.651	0.252	0.063	0.157	1.145	2.584	0.010
8.000	1.Personal Tutors	0.123	0.233	0.054	-0.334	0.581	0.529	0.597
9.000	2.Intelligent Support for Collaborative Learning	1.434	0.378	0.143	0.693	2.174	3.795	0.000
10.000	3.Intelligent Virtual Reality	0.579	0.262	0.069	0.064	1.093	2.205	0.027
11.000	1.Personal Tutors	1.323	0.343	0.118	0.650	1.996	3.852	0.000
12.000	1.Personal Tutors	-0.283	0.252	0.064	-0.777	0.211	-1.121	0.262
13.000	3.Intelligent Virtual Reality	1.726	0.254	0.065	1.228	2.224	6.796	0.000
14.000	3.Intelligent Virtual Reality	0.538	0.227	0.051	0.093	0.983	2.371	0.018
15.000	1.Personal Tutors	0.765	0.256	0.066	0.263	1.266	2.986	0.003
16.000	2.Intelligent Support for Collaborative Learning	0.056	0.387	0.149	-0.702	0.813	0.144	0.885
17.000	1.Personal Tutors	0.508	0.287	0.082	-0.054	1.069	1.771	0.077
18.000	1.Personal Tutors	0.197	0.199	0.040	-0.194	0.588	0.988	0.323
19.000	1.Personal Tutors	0.656	0.243	0.059	0.180	1.132	2.702	0.007
20.000	2.Intelligent Support for Collaborative Learning	0.583	0.235	0.055	0.122	1.043	2.480	0.013
21.000	2.Intelligent Support for Collaborative Learning	-0.847	0.247	0.061	-1.331	-0.363	-3.429	0.001
22.000	2.Intelligent Support for Collaborative Learning	0.031	0.257	0.066	-0.473	0.534	0.119	0.905
23.000	1.Personal Tutors	0.763	0.330	0.109	0.117	1.410	2.313	0.021
24.000	2.Intelligent Support for Collaborative Learning	0.502	0.254	0.064	0.004	0.999	1.975	0.048
25.000	3.Intelligent Virtual Reality	0.390	0.191	0.037	0.015	0.765	2.041	0.041
26.000	2.Intelligent Support for Collaborative Learning	2.130	0.282	0.079	1.578	2.682	7.561	0.000
27.000	3.Intelligent Virtual Reality	0.643	0.167	0.028	0.315	0.970	3.848	0.000
28.000	2.Intelligent Support for Collaborative Learning	0.498	0.190	0.036	0.126	0.870	2.626	0.009
29.000	2.Intelligent Support for Collaborative Learning	0.634	0.354	0.125	-0.059	1.327	1.793	0.073
30.000	2.Intelligent Support for Collaborative Learning	0.845	0.297	0.088	0.263	1.426	2.847	0.004
31.000	1.Personal Tutors	0.268	0.277	0.077	-0.276	0.811	0.966	0.334
32.000	3.Intelligent Virtual Reality	0.360	0.111	0.012	0.143	0.577	3.255	0.001
33.000	2.Intelligent Support for Collaborative Learning	0.048	0.266	0.071	-0.473	0.569	0.181	0.856
34.000	3.Intelligent Virtual Reality	0.332	0.203	0.041	-0.066	0.729	1.636	0.102
35.000	3.Intelligent Virtual Reality	0.524	0.255	0.065	0.024	1.024	2.054	0.040
36.000	2.Intelligent Support for Collaborative Learning	-0.135	0.194	0.038	-0.516	0.246	-0.695	0.487
37.000	2.Intelligent Support for Collaborative Learning	0.486	0.272	0.074	-0.048	1.019	1.784	0.074
38.000	3.Intelligent Virtual Reality	0.561	0.234	0.055	0.102	1.019	2.395	0.017
39.000	1.Personal Tutors	0.214	0.185	0.034	-0.149	0.576	1.154	0.248
40.000	2.Intelligent Support for Collaborative Learning	0.545	0.261	0.068	0.033	1.056	2.086	0.037
41.000	1.Personal Tutors	0.484	0.225	0.051	0.044	0.925	2.156	0.031
42.000	3.Intelligent Virtual Reality	0.690	0.287	0.082	0.128	1.252	2.405	0.016
43.000	1.Personal Tutors	0.553	0.269	0.072	0.026	1.080	2.056	0.040
44.000	3.Intelligent Virtual Reality	1.101	0.186	0.035	0.737	1.466	5.923	0.000
45.000	1.Personal Tutors	0.983	0.270	0.073	0.453	1.512	3.637	0.000
46.000	1.Personal Tutors	-2.643	0.330	0.109	-3.290	-1.997	-8.011	0.000
		0.482	0.035	0.001	0.414	0.551	13.785	0.000

Figure 3 Forest Plot.

SUMMARY MEASURE AND FOREST PLOT FOR THE EFFECT SIZE OF SMART LEARNING ADVANCEMENT EDUCATION LEVEL

Meta-regression was used to analyze the possible variation, specifically in the effect size across different educational levels, including school, high school and university level (Cohen, 2013).

Surface 2 is the combined effect value of all studies. The sample heterogeneity test results showed Q = 276.208, $p = 0.000 < 0.10$, I2 = 83.708, which indicated that there was great heterogeneity among the samples, and hence a random effects model (Random model) had to be used. Data from Table 2 indicate that under the random effects model, the combined effect value of all studies was 0.503, which reached a statistically significant level of $p = 0.000 < 0.001$. This shows that AI technology-based teaching had a positive effect on students' overall learning outcomes. We used the effect size criteria defined by Cohen, namely an effect size of less than 0.2 is considered a small effect, 0.2 to 0.8 is a medium effect, and greater than 0.8 is a large effect.

MODEL	NUMBER OF STUDIES	POINT ESTIMATE	EFFECT SIZE AND 95% CONFIDENCE INTERVAL		TEST OF NULL (2-TAIL)		HETEROGENEITY			
			LOWER LIMIT	UPPER LIMIT	Z-VALUE	P-VALUE	Q-VALUE	DF (Q)	P-VALUE	I-SQUARED
Fixed	46	0.482	0.414	0.551	13.785	0.000	276.208	45	0.000	83.708
Random	46	0.503	0.330	0.677	5.691	0.000				

Table 2 Combined Effect Size of All Studies.

EFFECTS ON LEARNING OUTCOMES

Luckin & Holmes (2016) identified three types of AI software applications in education that are currently available: a) personal tutors; b) intelligent support for collaborative learning; c) cognitive virtual reality. As Table 3 shows: a) The combined effect value of personal tutors was 0.302, intelligent support for collaborative learning was 0.531, and the VR training system supported by AI was significant no matter combined impact was at level ($p = 0.000 < 0.001$), while inter-group effects were all significant (QBET = 13.002, $p = 0.002 < 0.01$), reaching statistical significance. It could therefore be inferred that the three types of AI technology-based teaching had a moderate statistically positive effect on students' learning outcomes. There were statistically significant differences in the level of effectiveness across the three types. Analysis of the data showed that the promoting effect of the three types based on AI teaching can significantly improve achievement for all, in achievement and correlative learning effectiveness aspect have guiding role to c) intelligent virtual reality promoting strongly follows b) intelligent support for collaborative learning. Furthermore, a) personal tutors weaker than the rest.

Table 3 Subgroup Analysis Results.

GROUPS		NUMBER STUDIES	POINT ESTIMATE	EFFECT SIZE AND 95% CONFIDENCE INTERVAL		TEST OF NULL (2-TAIL)		TOTAL BETWEEN
				LOWER LIMIT	UPPER LIMIT	Z-VALUE	P-VALUE	
AI Types	1. Personal Tutors	17	0.302	0.180	0.423	4.856	0.000	QBET = 13.002 (p = 0.002)
	2. Intelligent Support for Collaborative Learning	18	0.531	0.411	0.652	8.638	0.000	
	3. Intelligent Virtual Reality	11	0.598	0.483	0.712	10.238	0.000	
Region	Africa	3	0.982	0.704	1.259	6.931	0.000	QBET = 22.114 (p = 0.000)
	Asia	30	0.467	0.376	0.558	10.078	0.000	
	Europe	9	0.573	0.422	0.724	7.423	0.000	
	North America	4	0.235	0.066	0.404	2.726	0.006	
Subject	Humanities and Social Sciences	15	0.510	0.384	0.635	7.972	0.000	QBET = 0.264 (p = 0.608)
	Natural Sciences	31	0.471	0.389	0.553	11.257	0.000	
Educational Level	Higher Education	26	0.448	0.351	0.546	9.028	0.000	QBET = 1.254 (p = 0.534)
	Primary Education	8	0.488	0.350	0.625	6.936	0.000	
	Secondary Education	12	0.543	0.408	0.679	7.852	0.000	
Intervention Duration	Long-term	31	0.424	0.342	0.505	10.234	0.000	QBET = 7.046 (p = 0.008)
	Short-term	15	0.629	0.501	0.758	9.608	0.000	
User Role	Jointly led by student & teacher	17	0.512	0.382	0.642	7.742	0.000	QBET = 4.745 (p = 0.093)
	Student-led	25	0.518	0.426	0.611	11.029	0.000	
	Teacher-led	4	0.312	0.143	0.480	3.629	0.000	
Learning Environment	Formal	34	0.458	0.379	0.536	11.442	0.000	QBET = 19.049 (p = 0.000)
	Informal	8	0.748	0.582	0.915	8.824	0.000	
	Mixed	4	0.074	–0.195	0.343	0.539	0.590	

IMPACT OF AI-BASED TEACHING ON LEARNING OUTCOMES IN DIFFERENT REGIONS

The research from various countries was divided into six regions: Europe, Asia, Africa, North America, South America and Oceania. The combined effect value according to Table 3 data for Africa was found to be 0.982, that of Asia was 0.467, Europe was 0.573, and North America was 0.235. The combined effect values of the three most important regions (i.e., Asia, Europe and North America) were all statistically significant ($p = 0.000 < 0.001$), and North America's combined effect values were statistically significant ($p = 0.006 < 0.01$); b) The between-group adjustment chi-squared test (omnibus) showed it to be extraordinarily notable at QBET = 22.114, $p = 0.000 < 0.001$. These findings show that AI teaching of technology in Africa had a substantial effect on student learning outcomes. A positive impact was also noted for students from the Asian, European, and North American regions, indicating a medium positive impact. Differences in the impact on learning results were not negligible.

We also used data to analyze the performance based on AI teaching of technology in different regions, and concluded that both can significantly promote the realization of teaching objectives and learning effects. The promoting effect was significant in AI teaching of technology, and the order of the various regions from high to low is Africa, Europe, Asia, and North America.

THE IMPACT OF AI-BASED TEACHING ON THE LEARNING OUTCOMES OF DIFFERENT SUBJECT TYPES

This article divides all research into two types based on subject type: Humanities and Social Sciences, and Natural Sciences. As the Table 3 data show, the Humanities and Social Sciences combined effect value was 0.510, while that of the Natural Sciences was 0.471. The combined effect values for both types of disciplines were all significant at the 0.001 level ($p = 0.000 < 0.001$); however, the between-group effect was not significant, QBET = 0.264, $p = 0.608 > 0.05$.

We can conclude that based on AI, the technology-based teaching effect on the learning outcomes of students in different subject types had a medium positive impact. However, there was no significant difference in the learning effect of the two types of subjects. The results of data analysis show that AI technology had a higher positive impact on the learning outcomes of Humanities and Social Sciences compared to Natural Sciences.

THE IMPACT OF AI-BASED TEACHING ON LEARNING OUTCOMES AT DIFFERENT EDUCATIONAL LEVELS

This article divides all research into Higher Education, Secondary Education, Primary Education, Pre-school Education and Special Education according to the different levels at which the research was conducted.

As the data in Table 3 show, the combined effect value for Higher Education was 0.448, for Primary Education it was 0.488, and for Secondary Education it was 0.543. The effect values of the three types of education levels combined were all significant at the 0.001 level ($p = 0.000 < 0.001$), whereas the between-group effect was not significant: QBET = 1.254, $p = 0.534 > 0.05$.

THE IMPACT OF AI TEACHING WITH DIFFERENT INTERVENTION DURATIONS ON LEARNING OUTCOMES

This paper divides all the research into one-time and long-term interventions according to the development cycle of AI teaching experiments in each study.

As the Table 3 data show, the Long-term combined effect value was 0.424, while the Short-term was 0.629, and the two types of intervention combined effect values were all significant at the 0.001 level ($p = 0.000 < 0.001$). The inter-group effect was significant: QBET = 7.046, $p = 0.008 < 0.01$.

THE IMPACT OF AI-BASED TEACHING ON THE LEARNING OUTCOMES OF DIFFERENT USER ROLES

This paper divides all the research into the following categories according to the different user roles of each research discipline: Student-led, Teacher-led, Jointly led by student & teacher.

The Table 3 data show that the Jointly led by student and teacher combined effect value was 0.512, Student-led was 0.518, and Teacher-led was 0.312, while the combined effect values of the three types of user roles were all significant at the 0.001 level ($p = 0.000 < 0.001$). The between-group effect was not significant: QBET = 4.745, $p = 0.093 > 0.05$.

THE IMPACT OF AI TEACHING IN DIFFERENT ENVIRONMENTS ON LEARNING OUTCOMES

This paper divides all the studies into three categories based on the environment in which the AI teaching experiments were carried out in each study, namely Formal, Informal and Mixed environments.

As the Table 3 data show, the combined effect value for Formal was 0.458, for Informal it was 0.748, and for Mixed it was –0.195. The combined effect values of Formal and Informal were all significant at the 0.001 level ($p = 0.000 < 0.001$), but the merging effect in the Mixed environment was not significant. The between-group effect was extremely significant: QBET = 19.049, $p = 0.000 < 0.001$.

DISCUSSION

The integration of Artificial Intelligence (AI) into education represents a significant advancement in teaching and learning processes. This meta-analysis examined various facets of AI's influence on smart learning, revealing both benefits and challenges. This Discussion section consolidates these findings and examines the ramifications for educators, students, and policymakers.

AI in education greatly improves personalized learning, making it one of its most significant contributions. Research conducted by Wang et al. (2024) and Wu and Tu (2024) showed that AI-powered systems, such as intelligent tutoring systems (ITS) and adaptive learning platforms can customize instructional material according to the specific requirements of each student. This customization allows for the accommodation of various learning styles and speeds, resulting in improved overall learning outcomes. AI's capacity to offer immediate feedback and tailor learning materials enables students to actively immerse themselves in the information, promoting the development of critical thinking and problem-solving abilities (Chen et al., 2020; Noor et al., 2022; Younas et al., 2022). In addition, AI's ability to provide adaptable learning settings ensures that every student receives the required assistance and a suitable level of difficulty based on their comprehension, thereby increasing the efficiency and efficacy of learning (Hu, 2022; Hoke, 2024).

AI technologies, specifically virtual reality (VR) and augmented reality (AR), have revolutionized the learning process by enhancing interactivity and creating a more immersive experience (Yang et al., 2024; Wang et al., 2025; van den Berg, 2024). Luckin and Holmes (2016) explained that these technologies have the ability to transform abstract concepts into physical ones, resulting in increased student engagement and retention. The AI system emphasizes the creation of a dynamic learning environment that adjusts to the unique learning requirements of individuals and maintains their motivation (Ouyang et al., 2022). The use of AI-powered VR and AR can greatly improve comprehension and long-term memory of intricate topics, enhancing the enjoyment and efficacy of the learning process. These technologies facilitate an immersive learning environment in which students can actively engage with the subject, promoting profound understanding and comprehension (Dimitriadou & Lanitis, 2023; Timms, 2016; Zhou et al., 2022). The role of AI extends beyond conventional classroom settings to facilitate lifelong learning and enhance professional development. AI-powered platforms have the capability to provide tailored learning routes, assisting individuals in acquiring fresh expertise during the course of their professional lives.

Despite the extensive proof of the benefits of AI in education, certain areas still require attention. The majority of studies primarily examined the immediate advantages of AI, whereas there is a scarcity of studies investigating the long-term effects on educational achievements. Moreover, the insufficient exploration of the socio-cultural ramifications of AI in education, including its impact on teacher-student interactions and classroom dynamics, is evident. To effectively implement AI solutions in various educational environments, especially those with limited resources, further investigation is required. To address these gaps, it is necessary to conduct thorough longitudinal studies that take into account the wider effects of AI on education (Özer, 2024; Serpil & Kesim, 2024). Future studies should explore how AI fosters cooperative learning environments and how it impacts group dynamics and peer relationships (Zhan et al., 2024). It is critical to prioritize the development and implementation of AI technologies in a manner that promotes fairness and inclusiveness in order to effectively incorporate them into educational processes. Subsequent research should prioritize the creation of frameworks and norms to ensure the ethical use of AI in education. Additionally, it should explore the enduring impacts of AI on student learning and development. Also, it is important to test how well AI-powered personalized learning works at different grade levels and subjects so that the best strategies can be found, and areas that need improvement can be identified (Pham & Sampson, 2022).

CONCLUSION

Integrating AI into education has the potential to greatly improve personalized learning, student engagement, and lifetime learning. AI technologies such as ChatGPT have proven their potential to offer immediate feedback, personalized learning resources, and engaging learning experiences, thereby improving educational results. This meta-analysis has emphasized the diverse advantages of AI in education, such as its capacity to assist in tailoring learning paths to individual needs and enabling ongoing professional growth. It is essential to tackle issues of data privacy, ethical concerns, and potential biases in order to guarantee that AI-powered educational tools are equitable, inclusive, and advantageous for all students. In order to ensure ethical usage of AI in education, it is necessary to establish strong frameworks that prioritize openness, justice, and diversity. This involves guaranteeing that AI systems do not perpetuate preexisting disparities or add novel prejudices. This meta-analysis establishes a basis for future study and emphasizes the importance of continuously assessing and modifying AI technologies in education to ensure they align with the changing requirements of learners and educators.

DATA ACCESSIBILITY STATEMENT

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

SUSTAINABLE DEVELOPMENT GOALS (SDGs)

This study is linked to the following SDG(s): Quality education (SDG 4).

ETHICS AND CONSENT

No human participants were included in this study, it is a meta-analysis and there is no need for ethical approval.

FUNDING INFORMATION

The authors thank Prince Sultan University for funding this research project under the Applied Linguistics Research Lab grant [RL-CH-2019/9/1].

COMPETING INTERESTS

The authors have no competing interests to declare.

AUTHOR CONTRIBUTIONS (CRediT)

Muhammad Younas: Conceptualization, methodology, formal analysis, investigation, data curation, visualization, writing—original draft preparation, writing—review and editing; Dina Abdel Salam El-Dakhs & Behzad Anwar; supervision, project administration, funding acquisition, writing—original draft preparation, Iskander Ismayil; helped in methodology, writing—review and editing. All authors have read and agreed to the published version of the manuscript.

AUTHOR AFFILIATIONS

Muhammad Younas orcid.org/0000-0002-6397-326X
Prince Sultan University, Saudi Arabia

Iskander Ismayil orcid.org/0009-0001-9924-8924
Xinjiang Teacher's College, P.R. China

Dina Abdel Salam El-Dakhs orcid.org/0000-0003-2943-987X
Prince Sultan University, Saudi Arabia

Behzad Anwar orcid.org/0000-0002-4208-368X
University of Gujrat, Pakistan

REFERENCES

Al Hakim, V. G., Yang, S. H., Liyanawatta, M., Wang, J. H., & **Chen, G. D.** (2022). Robots in situated learning classrooms with immediate feedback mechanisms to improve students' learning performance. *Computers & Education*, *182*, 104483. https://doi.org/10.1016/j.compedu.2022.104483

Azamatova, A., Bekeyeva, N., Zhaxylikova, K., Sarbassova, A., & **Ilyassova, N.** (2023). The effect of using artificial intelligence and digital learning tools based on project-based learning approach in foreign language teaching on students' success and motivation. *International Journal of Education in Mathematics, Science, and Technology (IJEMST)*, *11*(6), 1458–1475. https://doi.org/10.46328/ijemst.3712

Bachiri, Y. A., Mouncif, H., & **Bouikhalene, B.** (2023). Artificial intelligence empowers gamification: Optimizing student engagement and learning outcomes in e-learning and moocs. *International Journal of Engineering Pedagogy*, *13*(8). https://doi.org/10.3991/ijep.v13i8.40853

Bashir, A., Aziz, A., Imran, M., & **Almusharraf, N.** (2025). Effect of CALL-based multimodal pedagogy on learner motivation and willingness to communicate in English: A study from university students' perspective. *Contemporary Educational Technology, 17*(2). https://doi.org/10.30935/cedtech/15961

Bäuerle, A., Albus, P., & **Störk, R., Seufert, T.,** & **Ropinski, T.** (2023). exploRNN: teaching recurrent neural networks through visual exploration. *Vis Comput*, *39*, 4323–4338. https://doi.org/10.1007/s00371-022-02593-0

Bergeler, E., & **Read, M. F.** (2021). Comparing Learning Outcomes and Satisfaction of an Online Algebra-Based Physics Course with a Face-to-Face Course. *J Sci Educ Technol*, *30*, 97–111. https://doi.org/10.1007/s10956-020-09878-w

Bhatt, P., & **Muduli, A.** (2023). Artificial intelligence in learning and development: A systematic literature review. *European Journal of Training and Development, 47*(7–8), 677–694. https://doi.org/10.1108/EJTD-09-2021-0143

Borenstein, M., Hedges, L. V., Higgins, J. P. T., & **Rothstein, H. R.** (2009). *Introduction to meta-analysis.* Wiley. https://doi.org/10.1002/9780470743386

Chen, C.-H. (2020), AR videos as scaffolding to foster students' learning achievements and motivation in EFL learning. *Br J Educ Technol*, *51*, 657–672. https://doi.org/10.1111/bjet.12902

Chen, C.-M., Li, M.-C., & **Chen, T.-C.** (2020). A web-based collaborative reading annotation system with gamification mechanisms to improve reading performance. *Computers & Education*, *144*, 103697. ISSN 0360–1315. https://doi.org/10.1016/j.compedu.2019.103697

Chen, L., Chen, P., & **Lin, Z.** (2020). Artificial intelligence in education: A review. *IEEE Access, 8*, 75264–75278. https://doi.org/10.1109/ACCESS.2020.2988510

Chen, Y.-T., Li, M., Huang, C.-Q., Han, Z.-M., Hwang, G.-J., & **Yang, G.** (2022). Promoting deep writing with immersive technologies: An SVVR-supported Chinese composition writing approach for primary schools. *British Journal of Educational Technology*, *53*, 2071–2091. https://doi.org/10.1111/bjet.13247

Chiu, M. C., Hwang, G. J., Hsia, L. H., & **Shyu, F. M.** (2022). Artificial intelligence-supported art education: a deep learning-based system for promoting university students' artwork appreciation and painting outcomes. *Interactive Learning Environments*, *32*(3), 824–842. https://doi.org/10.1080/10494820.2022.2100426

Cohen, J. (2013). *Statistical power analysis for the behavioral sciences*. Routledge. https://doi.org/10.4324/9780203771587

Cukurova, M., Luckin, R., & **Kent, C.** (2020). Impact of an artificial intelligence research frame on the perceived credibility of educational research evidence. *International Journal of Artificial Intelligence in Education*, *30*(2), 205–235. https://doi.org/10.1007/s40593-019-00188-w

Chang, Y. S., Chou, C. H., Chuang, M. J., Li, W. H., & **Tsai, I. F.** (2020). Effects of virtual reality on creative design performance and creative experiential learning. *Interactive Learning Environments*, *31*(2), 1142–1157. https://doi.org/10.1080/10494820.2020.1821717

Di, X., & **Zheng, X.** (2022). A meta-analysis of the impact of virtual technologies on students' spatial ability. *Educational Technology Research and Development, 70*(1), 73–98. https://doi.org/10.1007/s11423-022-10082-3

Dimitriadou, E., & **Lanitis, A.** (2023). A critical evaluation, challenges, and future perspectives of using artificial intelligence and emerging technologies in smart classrooms. *Smart Learning Environments, 10*(1), 12. https://doi.org/10.1186/s40561-023-00231-3

Doughty, J., Wan, Z., Bompelli, A., Qayum, J., Wang, T., Zhang, J., … & **Sakr, M.** (2024, January). A comparative study of AI-generated (GPT-4) and human-crafted MCQs in programming education. In *Proceedings of the 26th Australasian Computing Education Conference* (pp. 114–123). https://doi.org/10.1145/3636243.3636256

Drissi, S., Chefrour, A., Boussaha, K., & **Zarzour, H.** (2024). Exploring the effects of personalized recommendations on student's motivation and learning achievement in gamified mobile learning framework. *Educ Inf Technol*, *29*, 15463–15500. https://doi.org/10.1007/s10639-024-12477

Duval, S., & **Tweedie, R.** (2000). A nonparametric, "trim and fill" method of accounting for publication bias in meta-analysis. *Journal of the American Statistical Association, 95*(449), 89–98. https://doi.org/10.1080/01621459.2000.10473905

Escalante, J., Pack, A., & **Barrett, A.** (2023). AI-generated feedback on writing: Insights into efficacy and ENL student preference. *International Journal of Educational Technology in Higher Education*, *20*(1), 57. https://doi.org/10.1186/s41239-023-00425-2

Haleem, A., Javaid, M., Qadri, M. A., & **Suman, R.** (2022). Understanding the role of digital technologies in education: A review. *Sustainable Operations and Computers, 3*, 275–285. https://doi.org/10.1016/j.susoc.2022.05.004

Hanshaw, G., Vance, J., & **Brewer, C.** (2024). Exploring the effectiveness of AI course assistants on the student learning experience. *Open Praxis, 16*(4), 627–644. https://doi.org/10.55982/openpraxis.16.4.719

Hedges, L. V. (1981). Distribution theory for Glass's estimator of effect size and related estimators. *journal of Educational Statistics, 6*(2), 107–128. https://doi.org/10.3102/10769986006002107

Hedges, L. V., & **Olkin, I.** (2014). *Statistical methods for meta-analysis*. Academic press.

Herodotou, C., Muirhead, D. K., Aristeidou, M., Hole, M. J., Kelley, S., Scanlon, E., & **Duffy, M.** (2018). Blended and online learning: a comparative study of virtual microscopy in Higher Education. *Interactive Learning Environments*, *28*(6), 713–728. https://doi.org/10.1080/10494820.2018.1552874

Hodges, G. W., Flanagan, K, Lee, J., Cohen, A., Krishnan, S., & **Ward, C.** (2020). A quasi-experimental study comparing learning gains associated with serious educational gameplay and hands-on science in elementary classrooms. *J Res Sci Teach*, *57*, 1460–1489. https://doi.org/10.1002/tea.21661

Hoke, T. (2024). AI with a heart: Integrating emotional intelligence and sustainability in smart education for 21st-century learners. In *Proceedings of the International Conference on Sustainability: Developments and Innovations* (pp. 458–465). Springer Nature Singapore, Singapore. https://doi.org/10.1007/978-981-97-8348-9_56

Holmes, W., Bialik, M., & **Fadel, C.** (2019). *Artificial intelligence in education: Promises and implications for teaching and learning.* Center for Curriculum Redesign.

Hsu, T.-C., Huang, H.-L., Hwang, G.-J., & **Chen, M.-S.** (2023). Effects of Incorporating an Expert Decision-making Mechanism into Chatbots on Students' Achievement, Enjoyment, and Anxiety. *Educational Technology & Society*, *26*(1), 218–231. https://www.jstor.org/stable/48707978

Huang, A. Y. Q., Lu, O. H. T., & **Yang, S. J. H.** (2023). Effects of artificial Intelligence–Enabled personalized recommendations on learners' learning engagement, motivation, and outcomes in a flipped classroom. *Computers & Education*, *194*, 104684. ISSN 0360-1315. https://doi.org/10.1016/j.compedu.2022.104684

Huang, H.-L., Hwang, G.-J., & **Chen, P.-Y.** (2022). An integrated concept mapping and image recognition approach to improving students' scientific inquiry course performance. *British Journal of Educational Technology*, *53*, 706–727. https://doi.org/10.1111/bjet.13177

Hu, Y. H. (2022). Effects and acceptance of precision education in an AI-supported smart learning environment. *Education and Information Technologies, 27*(2), 2013–2037. https://doi.org/10.1007/s10639-021-10664-3

Huang, R., Ritzhaupt, A. D., Sommer, M., Zhu, J., Stephen, A., Valle, N., … & **Li, J.** (2020). The impact of gamification in educational settings on student learning outcomes: A meta-analysis. *Educational Technology Research and Development, 68*, 1875–1901. https://doi.org/10.1007/s11423-020-09807-z

Hwang, S. (2016). *Meta-analysis using R.* Hakjisa.

Imran, M., Almusharraf, N., & **Abbasova, M. Y.** (2025). Digital learning transformation: A study of teachers' post-COVID-19 experiences. *Social Sciences & Humanities Open, 11*, 101228. https://doi.org/10.1016/j.ssaho.2024.101228

Javaid, M., Haleem, A., & **Pratap, R.** (2023). ChatGPT's role in automating educational tasks. *Journal of AI and Learning, 18*, 72–84. https://doi.org/10.1016/j.ject.2023.08.001

Kulik, J. A., & **Fletcher, J. D.** (2016). Effectiveness of intelligent tutoring systems: A meta-analytic review. *Review of Educational Research, 86*(1), 42–78. https://doi.org/10.3102/0034654315581420

Lai, Y. H., Chen, S. Y., Lai, C. F., Chang, Y. C., & **Su, Y. S.** (2019). Study on enhancing AIoT computational thinking skills by plot image-based VR. *Interactive Learning Environments*, *29*(3), 482–495. https://doi.org/10.1080/10494820.2019.1580750

Lampropoulos, G. (2024). Extended reality and the metaverse in education: Towards immersive collaborative learning. In *Augmented and virtual reality in the metaverse* (pp. 101–111). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-57746-8_6

Lee, D., & **Kwon, H.** (2024). Meta-analysis on effects of artificial intelligence education in K-12 South Korean classrooms. *Education and Information Technologies*, 1–36. https://doi.org/10.1007/s10639-024-12738-4

Lee, Y. F., Hwang, G. J., & **Chen, P. Y.** (2022). Impacts of an AI-based chabot on college students' after-class review, academic performance, self-efficacy, learning attitude, and motivation. *Education Tech Research Dev*, *70*, 1843–1865. https://doi.org/10.1007/s11423-022-10142-8

Liew, T. W., Pang, W. M., Leow, M. C., & **Tan, S. M.** (2022). Anthropomorphizing malware, bots, and servers with human-like images and dialogues: The emotional design effects in a multimedia learning environment. *Smart Learning Environments*, *9*(1), 5. https://doi.org/10.1186/s40561-022-00187-w

Lin, C. J., Wang, W. S., Lee, H. Y., Huang, Y.-M., & **Wu, T.-T.** (2024). Recognitions of image and speech to improve learning diagnosis on STEM collaborative activity for precision education. *Educ Inf Technol*, *29*, 13859-13884. https://doi.org/10.1007/s10639-023-12426-9

Lin, Y.-T. (2023). Learning Performances towards the BookRoll E-Book System for Flipped Classrooms in Software Engineering Education. *Educational Technology & Society*, *26*(3), 190–202. https://www.jstor.org/stable/48734330

Lipsey, M. W., & **Wilson, D. B.** (2017). The efficacy of psychological, educational, and behavioral treatment: Confirmation from meta-analysis. In *Quantitative methods in criminology* (pp. 65–93). https://doi.org/10.4324/9781315089256-4

Lin, X.-F., Wang, Z., Zhou, W., Luo, G., Hwang, G.-J., Zhou, Y., Wang, J., Hu, Q., Li, W., Liang, Z.-M. (2023). Technological support to foster students' artificial intelligence ethics: An augmented reality-based contextualized dilemma discussion approach. *Computers & Education*, *201*, 104813. ISSN 0360–1315. https://doi.org/10.1016/j.compedu.2023.104813

Liu W. I., Liu, C. H., Liao, C. Y., Chao, P. R., & **Chu, K. C.** (2020). Mobile community learning programme's effectiveness in case management for psychiatric nurses: A preliminary randomised controlled trial. *Nurse Educ Today*, *85*, 104259. https://doi.org/10.1016/j.nedt.2019.104259

Liu, Z-M, Fan, X., Liu, Y., & **Ye, X.-d.** (2022). Effects of immersive virtual reality cardiopulmonary resuscitation training on prospective kindergarten teachers' learning achievements, attitudes and self-efficacy. *British Journal of Educational Technology*, *53*, 2050–2070. https://doi.org/10.1111/bjet.13237

Li, W., Wang, F., Mayer, R. E., & **Liu, T.** (2022). Animated pedagogical agents enhance learning outcomes and brain activity during learning. *Journal of Computer Assisted Learning*, *38*(3), 621–637. https://doi.org/10.1111/jcal.12634

Liyanawatta, M., Yang, S. H., Liu, Y. T., Zhuang, Y., & **Chen, G. D.** (2022). Audience participation digital drama-based learning activities for situational learning in the classroom. *British Journal of Educational Technology*, *53*(1), 189–206. https://doi.org/10.1111/bjet.13160

Lo, C.-M., Han, J., Wong, E. S. W., & **Tang, C.-C.** (2021). Flexible learning with multicomponent blended learning mode for undergraduate chemistry courses in the pandemic of COVID-19. *Interactive Technology and Smart Education*, *18*(2), 175–188. https://doi.org/10.1108/ITSE-05-2020-0061

Luckin, R., & **Holmes, W.** (2016). *Intelligence unleashed: An argument for AI in education.*

Ma, Y., Zhang, L., & **Wu, M.** (2022). Research on the influence of virtual reality on the learning effect of technical skills of science and engineering college students: Meta-analysis based on 32 empirical studies. *International Journal of Digital Multimedia Broadcasting, 2022*, e6202370. https://doi.org/10.1155/2022/6202370

Mhlanga, D. (2023). Open AI in education: The responsible and ethical use of ChatGPT towards lifelong learning. In *FinTech and artificial intelligence for sustainable development: The role of smart technologies in achieving development goals* (pp. 387–409). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-37776-1_17

Morocco-Clarke, A., Sodangi, F. A., & **Momodu, F.** (2024). The implications and effects of ChatGPT on academic scholarship and authorship: A death knell for original academic publications? *Information & Communications Technology Law, 33*(1), 21–41. https://doi.org/10.1080/13600834.2023.2239623

Nabulsi, L., Nguyen, A., & **Odeleye, O. A.** (2021). Comparison of the Effects of Two Different Online Homework Systems on Levels of Knowledge Retention in General Chemistry Students. *J Sci Educ Technol*, *30*, 31–39. https://doi.org/10.1007/s10956-020-09872-2

Ng, D. T. K., Su, J., & **Chu, S. K. W.** (2024). Fostering Secondary School Students' AI Literacy through Making AI-Driven Recycling Bins. *Educ Inf Technol*, *29*, 9715–9746. https://doi.org/10.1007/s10639-023-12183-9

Noor, U., Younas, M., Saleh Aldayel, H., Menhas, R., & **Qingyu, X.** (2022). Learning behavior, digital platforms for learning, and its impact on university students' motivations and knowledge development. *Frontiers in Psychology, 13*, 933974. https://doi.org/10.3389/fpsyg.2022.933974

Oh, S. S. (2002). *Meta-analysis: Theory and practice*. Konkuk University.

Ouyang, F., Zheng, L., & **Jiao, P.** (2022). Artificial intelligence in online higher education: A systematic review of empirical research from 2011 to 2020. *Education and Information Technologies, 27*(6), 7893–7925. https://doi.org/10.1007/s10639-022-10925-9

Özer, M. (2024). Potential benefits and risks of artificial intelligence in education. *Bartın University Journal of Faculty of Education*, *13*(2), 232–244. https://doi.org/10.14686/buefad.1416087

Pham, S. T., & **Sampson, P. M.** (2022). The development of artificial intelligence in education: A review in context. *Journal of Computer Assisted Learning*, *38*(5), 1408–1421. https://doi.org/10.1111/jcal.12687

Roose, K. (2022). The brilliance and weirdness of ChatGPT. *The New York Times*, 5.

Serpil, H., & **Kesim, E.** (2024). Understanding the application of AI in higher education systems: Global perspectives from a local AI ecosystem. *Open Praxis, 16*(4), 645–662. https://doi.org/10.55982/openpraxis.16.4.725

Schmidgall, S. P., Scheiter, K., & **Eitel, A.** (2020). Can we further improve tablet-based drawing to enhance learning? An empirical test of two types of support. *Instr Sci*, *48*, 453–474. https://doi.org/10.1007/s11251-020-09513-6

Schoeb, D. S., Schwarz, J., Hein, S., Schlager, D., Pohlmann, P. F., Frankenschmidt, A., Gratzke, C., & **Miernik, A.** (2020). Mixed reality for teaching catheter placement to medical students: a randomized single-blinded, prospective trial. *BMC Med Educ*, *20*, 510. https://doi.org/10.1186/s12909-020-02450-5

Shih, W. L., & **Tsai, C. Y.** (2020). Effect of Flipped Classroom with BOPPPS Model on Learners' Learning Outcomes and Perceptions in a Business Etiquette Course. *Asia-Pacific Edu Res*, *29*, 257–268. https://doi.org/10.1007/s40299-019-00475-z

Shrivastava, R. (2023). Role of artificial intelligence in the future of education. *International Journal of Professional Business Review, 8*(1), 2. https://doi.org/10.26668/businessreview/2023.v8i1.840

Sichterman, B., van Ginkel, S., van Halteren, M., van Tilborg, R., & **Noroozi, O.** (2023). The Effects of a Constructively Aligned Virtual Reality Setting on Professionals' Knowledge, Motivation and Perceptions. *International Journal of Technology in Education*, *6*(4), 561–582. https://doi.org/10.46328/ijte.462

Song, D., & **Kim, D.** (2020). Effects of self-regulation scaffolding on online participation and learning outcomes. *Journal of Research on Technology in Education*, *53*(3), 249–263. https://doi.org/10.1080/15391523.2020.1767525

Tang, K. Y., Chang, C. Y., & **Hwang, G. J.** (2021). Trends in artificial intelligence-supported e-learning: A systematic review and co-citation network analysis (1998–2019). *Interactive Learning Environments*, 1–19. https://doi.org/10.1080/10494820.2021.1875001

Taskıran, A., & **Goksel, N.** (2022). Automated feedback and teacher feedback: Writing achievement in learning English as a foreign language at a distance. *Turkish Online Journal of Distance Education*, *23*(2), 120–139. https://doi.org/10.17718/tojde.1096260

Timms, M. J. (2016). Letting artificial intelligence in education out of the box: Educational cobots and smart classrooms. *International Journal of Artificial Intelligence in Education, 26*, 701–712. https://doi.org/10.1007/s40593-016-0095-y

Tlili, A., Garzón, J., Salha, S., Huang, R., Xu, L., Burgos, D., … & **Wiley, D.** (2023). Are open educational resources (OER) and practices (OEP) effective in improving learning achievement? A meta-analysis and research synthesis. *International Journal of Educational Technology in Higher Education, 20*(1), 54. https://doi.org/10.1186/s41239-023-00424-3

van Alten, D. C. D., Phielix, C., Janssen, J., & **Kester, L.** (2020). Self-regulated learning support in flipped learning videos enhances learning outcomes. *Computers & Education*, *158*, 104000. ISSN 0360–1315. https://doi.org/10.1016/j.compedu.2020.104000

van den Berg, G. (2024). Generative AI and educators: Partnering in using open digital content for transforming education. *Open Praxis, 16*(2), 130–141. https://doi.org/10.55982/openpraxis.16.2.640

van der Meij, H., Veldkamp, S., & **Leemkuil, H.** (2020). Effects of scripting on dialogues, motivation and learning outcomes in serious games. *Br J Educ Technol*, *51*, 459–472. https://doi.org/10.1111/bjet.12851

Wang, X., Huang, R. "Tammy", Sommer, M., Pei, B., Shidfar, P., Rehman, M. S., Ritzhaupt, A. D., & **Martin, F.** (2024). The efficacy of artificial intelligence-enabled adaptive learning systems from 2010 to 2022 on learner outcomes: A meta-analysis. *Journal of Educational Computing Research, 62*(6). https://doi.org/10.1177/07356331241240459

Wang, X., Younas, M., Jiang, Y., Imran, M., & **Almusharraf, N.** (2025). A systematic review on blockchain in education: Solutions and challenges. *IEEE Access*. https://ieeexplore.ieee.org/document/10804766

Williamson, B., & **Eynon, R.** (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology, 45*, 223–235. https://doi.org/10.1080/17439884.2020.1798995

Wu, L. J., & **Chang, K. E.** (2020). Effect of embedding a cognitive diagnosis into the adaptive dynamic assessment of spatial geometry learning. *Interactive Learning Environments*, *31*(2), 890–907. https://doi.org/10.1080/10494820.2020.1815216

Wu, R., & **Yu, Z.** (2024). Do AI chatbots improve students' learning outcomes? Evidence from a meta-analysis. *British Journal of Educational Technology, 55*(1), 10–33. https://doi.org/10.1111/bjet.13334

Yang, C., Zhang, J., Hu, Y., Yang, X., Chen, M., Shan, M., & **Li, L.** (2024). The impact of virtual reality on practical skills for students in science and engineering education: A meta-analysis. *International Journal of STEM Education, 11*(1), 28. https://doi.org/10.1186/s40594-024-00487-2

Yang, F.-C. O., Lai, H.-M., Wang, Y.-W. (2023). Effect of augmented reality-based virtual educational robotics on programming students' enjoyment of learning, computational thinking skills, and academic achievement. *Computers & Education*, *195*, 104721. ISSN 0360–1315. https://doi.org/10.1016/j.compedu.2022.104721

Yang, Q. F., Lian, L. W., & **Zhao, J. H.** (2023). Developing a gamified artificial intelligence educational robot to promote learning effectiveness and behavior in laboratory safety courses for undergraduate students. *Int J Educ Technol High Educ*, *20*, 18. https://doi.org/10.1186/s41239-023-00391-9

Yang, Y. T. C., Chen, Y. C., & **Hung, H. T.** (2020). Digital storytelling as an interdisciplinary project to improve students' English speaking and creative thinking. *Computer Assisted Language Learning*, *35*(4), 840–862. https://doi.org/10.1080/09588221.2020.1750431

Younas, M., El-Dakhs, D. A. S., & **Jiang, Y.** (2025). A comprehensive systematic review of AI-driven approaches to self-directed learning. *IEEE Access*. https://doi.org/10.1109/ACCESS.2025.3546319

Younas, M., Noor, U., Zhou, X., Menhas, R., & **Qingyu, X.** (2022). COVID-19, students' satisfaction about e-learning, and academic achievement: Mediating analysis of online influencing factors. *Frontiers in Psychology, 13*, 948061. https://doi.org/10.3389/fpsyg.2022.948061

Yousef, A. M. F. (2021). Augmented reality assisted learning achievement, motivation, and creativity for children of low-grade in primary school. *J Comput Assist Learn*, *37*, 966–977. https://doi.org/10.1111/jcal.12536

Zhang, L., & **Ma, Y.** (2023). A study of the impact of project-based learning on student learning effects: A meta-analysis study. *Frontiers in Psychology, 14*, 1202728. https://doi.org/10.3389/fpsyg.2023.1202728

Zhan, Z., Tong, Y., Lan, X., & **Zhong, B.** (2024). A systematic literature review of game-based learning in artificial intelligence education. *Interactive Learning Environments, 32*(3), 1137–1158. https://doi.org/10.1080/10494820.2022.2115077

Zhou, X., Younas, M., Omar, A., & **Guan, L.** (2022). Can second language metaphorical competence be taught through instructional intervention? A meta-analysis. *Frontiers in Psychology, 13*, 1065803. https://doi.org/10.3389/fpsyg.2022.1065803

Zulnaidi, H., Oktavika, E., & **Hidayat, R.** (2020). Effect of use of GeoGebra on achievement of high school mathematics students. *Educ Inf Technol*, *25*, 51–72. https://doi.org/10.1007/s10639-019-09899-y

TO CITE THIS ARTICLE:
Younas, M., Ismayil, I., El-Dakhs, D. A. S., & Anwar, B. (2025). Exploring the Impact of Artificial Intelligence in Advancing Smart Learning in Education: A Meta-Analysis with Statistical Evidence. *Open Praxis*, *17*(3), pp. 594–610. DOI: https://doi.org/10.55982/openpraxis.17.3.842

Submitted: 06 February 2025
Accepted: 06 March 2025
Published: 11 August 2025

Open Praxis is a peer-reviewed open access journal published by International Council for Open and Distance Education.