REVIEW

The Effect of Artificial Intelligence-Assisted Personalized Learning on Student Learning Outcomes: A Meta-Analysis Based on 31 Empirical Research Papers

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***Abstract**: The application of artificial intelligence in education has garnered more attention in academia, and its role in promoting student personalized learning has sparked a lot of discussion. Many researchers have emphasized the positive effect of intelligent technology in supporting student personalized learning; however, there is a lack of systematic data evidence in this regard. This article seeks to evaluate the effects of artificial intelligence-assisted personalized learning on student learning outcomes based on a meta-analysis of 36 experimental and quasi-experimental studies from 31 published papers. The analysis results show that artificial intelligence-assisted personalized learning has moderately positive effects on student learning outcomes in terms of knowledge, competence, and emotional development. Variables such as the type of Edutech applications, learning scenario, and duration of application can moderate the relationship between artificial intelligence-assisted personalized learning and student learning outcomes, whereas the education phase and disciplinary domain do not exhibit significant moderating effects on this relationship. The purpose of this study is to provide implications and references for further research and practical explorations of artificial intelligence application in education.*

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Introduction

TODAY, artificial intelligence (AI), one of the most popular terms among the public, has become the driver of the advances in many sectors. In the field of education, AI is also leveraged to create fresh solutions to teaching and learning challenges (Pedro et al., 2019). As a major branch of computer science, AI has multiple sub-areas such as machine learning, natural language processing, machine vision, and robotics. Technologies like these can be integrated into the processes of teaching, learning, and educational administration to enhance the experience of teachers and students (Chen et al., 2020). Specifically, they are employed to support personalized learning, improve instructional evaluation and assessment, analyze educational data, develop virtual learning environments, build smart campuses, and more (Chen et al., 2020; Huang et al., 2021). Recent years have witnessed an accelerated growth in the application of AI in instruction, with a focus on intelligent learning analytics, mechanisms for developing and sharing teaching resources, the construction of smart platforms for teaching management and evaluation, and the technical upgrading of learning environments (Hu & Wang, 2022). According to research, AI has the potential to assist with personalized learning because it enables students to learn at their own pace and in their own styles, resulting in improved learning outcomes (Harry & Sayudin, 2023).

To reveal AI's role and prospects in individualized education, some researchers have used the qualitative method to analyze existing research findings on AI's effects on personalized learning (Zhang et al., 2023). Nevertheless, there is a lack of quantitative analyses of the actual outcomes of AI-assisted personalized learning in the literature. To bridge this gap, we drew on relevant experimental and quasi-experimental research results to evaluate the effects of AI-assisted personalized learning on student learning outcomes, using the meta-analysis techniques.

Literature Review

Personalized learning is viewed as an inclusive, student-centered approach to learning that is aimed at meeting the needs of all students, especially those who struggle with learning (Zhang, 2023). The approach's centerpiece is its emphasis on adjusting teaching content, progression, and evaluation methods to the specific needs of each individual student as opposed to the traditional "one-size-fits-all" modality. With its principles of flexibility, adaptability, and respect for the students' agency, it can help create a vibrant educational environment (Ayeni et al., 2024). In certain studies, terms like adaptive learning, customized learning, and individualized teaching are also used to represent the concept of personalized learning (Shemshack & Spector, 2020).

A plurality of research findings has demonstrated that personalized learning has its advantage over conventional instructional methods in boosting student academic performance (Zhang et al., 2020). In the past, it was nearly impossible to realize personalized learning, especially across-the-board personalized learning, due to the limits of the teaching force and educational resources (van der Vorst & Jellic, 2019). Nowadays, the ever-increasing infusion of technology into education has provided avenues for reaching efficacious personalized learning (Shemshack & Spector, 2020). Particularly, AI applications in education can play a significant role in creating personalized learning experiences. Murtaza et al. (2022) argued that an effective system of personalized learning should contain certain core capabilities, including delivering knowledge suiting the learner's academic level, recommending and presenting teaching content according to their needs, and making ongoing evaluations of their performance. AI technology helps deliver these functions because AI algorithms can achieve adaptive content delivery by collecting and analyzing colossal amounts of data (including student academic performance, learning preferences, and learning processes), customizing educational experiences, and dynamically adjusting the levels of difficulty of teaching materials (Ayeni et al., 2024). In addition, AI facilitates personalized learning by providing real-time feedback to evaluate students' everyday assignment completion in a timely and targeted manner.

Currently, educational researchers have made a lot of efforts to leverage AI to support personalized learning. Among all educational technology (Edutech) applications for this end, the most used are the intelligent feedback mechanism, learning path recommendation, and personalized scaffolding. The intelligent feedback mechanism is different from the conventional one in that it automatically generates feedback through learning analytics while also dynamically adjusting feedback strategies in response to varying teaching scenarios and student behaviors, whereas the latter simply uses pre-set feedback strategies according to the type of error detected without the ability to handle instances beyond the predicted ones (Gutierrez & Atkinson, 2011; Chen et al., 2021). A learning path is a combination of purposeful education activities and resources aimed at facilitating the learner's acquisition of knowledge and skills in a certain subject area (Kong et al., 2020). The technology of learning path recommendation utilizes algorithms to select the most suitable path for the learner based on their distinctive characteristics and needs (Niknam & Thulasiraman, 2020). Scaffolding is an instructional strategy that aids students in internalizing knowledge and developing autonomous learning competences (Lim et al., 2023). The personalized scaffold dynamically modifies supporting strategies based on the monitoring of the student's learning progress, assisting the student in judging whether the current learning content is suitable for them (Su, 2020).

Furthermore, technologies like the adaptive learning system, intelligent tutoring system, smart education platform, and educational robot are integrated applications of AI-based Edutech, including the aforementioned three ones. An adaptive learning system typically concerns a complete cycle, including collecting data from the learner, using the data to estimate their learning progress, instantly recommending pertinent study activities for the learner, and providing targeted feedback. Following the learner's adaptation of their learning strategies based on the feedback, the system collects fresh data and initiates a new cycle (Wang et al., 2020). The adaptive system's algorithms typically make decisions by referring to a domain model of the knowledge to be learned, a student model of learners' background characteristics, and a task model that specifies features of the learning activities (Lee & Park, 2008). The intelligent tutoring system uses AI algorithms to mimic the methods of human teachers, offering customized guidance and support to students. It serves as additional teacher resources by offering students personalized feedback and directions according to their individually different learning styles (Ayeni et al., 2024). Some researchers noted that the intelligent tutoring system draws on the zone of proximal development theory and can enhance students' understanding by posing moderately challenging questions as human teachers do (Beal et al. 2010). Aside from the above two applications specializing in personalized services for students, the smart education platform, as a more comprehensive system, provides intelligent support services for both teachers and students using a wide range of AI technologies. It assists teachers in managing educational resources and organizing teaching and evaluation processes for more precise instruction, while also supplying students with interactive tools and learning resources that meet their needs based on the identification of their characteristics and automatically recording their learning process and assessing their learning outcomes (Luo, 2023; Deng & Wang, 2024). In this study, educational robots are not simply physical robots but also include software-based virtual ones, which were referred to as intelligent agents or assistants by some researchers (Wang et al., 2022). These educational robots can simulate human conversations through natural language processing, perceive student learning needs through interactive Q&A, and provide tailored teaching intervention and support accordingly (Zhang et al., 2023).

In addition, the researchers have also tried to combine AI with other technologies to strengthen the implementation of personalized learning. For instance, the integration of AI with virtual reality technology has the potential to create more diverse learning scenarios to meet the distinct needs of individuals (Zhang & Aslan, 2021). In some studies, the AI-enabled virtual-reality learning system is treated as a type of visual interactive system

(Zhang & Aslan, 2021; Zhang et al., 2023). Also, it must be emphasized that learning analytics is the technology underpinning all AI-based Edutech applications, albeit it is not separately discussed here.

To sum up, AI has been applied to a variety of applications that assist personalized learning. Many experimental and quasi-experimental studies have been conducted to explore the outcomes of AI-assisted personalized learning. A thorough understanding of its effectiveness and the optimization of its implementation necessitate more in-depth analysis of prior research findings. Multiple factors, such as the type of AI-based Edutech applications, application scenario, duration of application, disciplinary domain, and educational phase, can all influence the outcomes of AI-assisted personalized learning in students, which deserves further research.

Research Questions

We analyzed 36 relevant experimental and quasi-experimental studies using meta-analytic techniques to address the following questions:

1. Compared with traditional learning methods, can AI-assisted personalized learning significantly improve student learning outcomes?
2. What are the effects of a variety of AI-based Edutech applications on personalized learning outcomes?
3. How do the application scenario, application duration, disciplinary domain, and educational phase influence the effects of AI-assisted personalized learning on student learning outcomes?

Research Methodology

Literature Search and Screening

This study sourced relevant literature in Chinese from the China National Knowledge Infrastructure (CNKI) and publications in English from Web of Science and EBSCO, using search words "artificial intelligence," "AI," "personalized learning," "adaptive learning," "customized learning," and "individualized instruction." As of July 2024, 372 articles in Chinese and 1282 in English were retrieved. Moreover, the method of snowballing was adopted to conduct a secondary search in the literature retrieved and reference lists of certain systematic reviews to find additional 19 articles. Altogether, 1673 articles were obtained.

For literature screening, we set inclusion criteria as follows: (i) research topics concerned with AI-based educational technology and personalized learning; (ii) research design being experimental or quasi-experimental with the use of the experimental group (adopting AI-assisted personalized learning) and control group (using traditional learning methods);

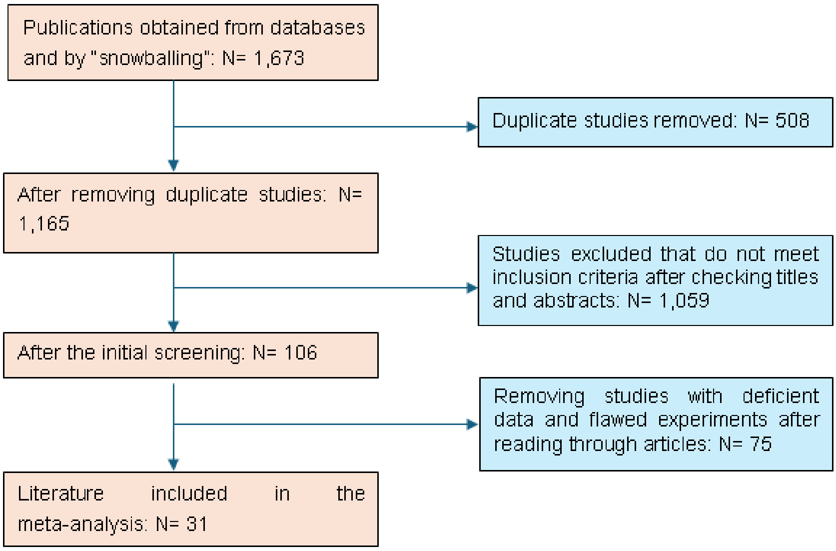

Figure 1. Literature Search and Screening Procedure.

(iii) Complete data including means (MD) and standard deviations (SD) for the computation of the mean and combined effect sizes. According to these criteria, 31 articles were selected and included in our meta-analysis, with six in Chinese and 25 in English. Five of them contain two independent studies; hence, the total number of experimental and quasi-experimental studies amounts to 36. **Figure 1** shows the literature search and screening processes of this study.

Literature Coding and Effect Size Estimation

For systematic analysis, we coded the characteristic values of the included 36 studies and extracted the following details: the first author, publication year, sample size, duration of experiment, educational phase, discipline domain, type of Edutech applications, application scenario, and student learning outcomes (**Table 1**). Disciplines involved in the studies were classified into science (e.g., mathematics, physics, and computer science) and non-science domains (e.g., language, arts, and management). Types of AI-based Edutech applications include the smart education platform, adaptive learning system, intelligent tutoring system, educational robot, intelligent feedback mechanism, learning path recommendation, personalized scaffolding, and virtual reality-based learning. Application scenarios included the offline classroom, digital platform, mobile platform, and virtual-reality learning environment. Student learning outcomes were

Table 1. Coding of the 37 Studies Included in the Meta-Analysis.

The First Author/Publication Year	Learning Outcomes	Types of Application	Application Scenarios	Educational Phases	Disciplinary Domains	Sample Sizes	Experiment Durations (months)
Ma(2023)	Knowledge	Smart education platform	Offline classroom	Primary	Science	103	3 - 6
Dai(2021)	Knowledge	Adaptive learning system	Offline classroom	Secondary	Science	98	3 - 6
Wang(2022)	Knowledge Emotion	Intelligent feedback mechanism	Offline classroom	Primary	Non-science	42	< 1
Kong(2020)	Knowledge Emotion	Learning path recommendation	Digital platform	Tertiary	Science	59	3 - 6
Yan(2020)	Knowledge	Intelligent tutoring system	Offline classroom	Secondary	Science	124	1 - 3
Luo(2023)	Knowledge Competence	Smart education platform	Offline classroom	Secondary	Science	94	1 - 3
Wang (2020)-1	Knowledge	Adaptive learning system	Offline classroom	Secondary	Science	155	< 1
Wang (2020)-2	Knowledge	Adaptive learning system	Offline classroom	Secondary	Science	84	< 1
Bahçeci (2016)	Knowledge	Intelligent tutoring system	Digital platform	Tertiary	Science	56	1 - 3
Beal (2010)	Knowledge	Intelligent tutoring system	Offline classroom	Secondary	Science	25	1 - 3
Chen (2009)	Knowledge	Learning path recommendation	Digital platform	Tertiary	Science	86	< 1
Deng (2023)	Knowledge	Smart education platform	Digital platform	Tertiary	Non-science	90	3 - 6
Divekar (2024)	Knowledge	Virtual reality-based learning	Virtual-reality learning environment	Tertiary	Non-science	20	1 - 3
Dolenc (2015)	Knowledge	Adaptive learning system	Digital platform	Secondary	Science	117	< 1
Hooshyar (2016)	Knowledge	Intelligent tutoring system	Digital platform	Tertiary	Science	58	1 - 3
Hwang (2020)	Knowledge Emotion	Adaptive learning system	Mobile platform	Primary	Science	109	< 1
Lang (2023)-1	Knowledge	Intelligent feedback mechanism	Mobile platform	Tertiary	Non-science	65	Not indicated
Lang (2023)-2	Knowledge	Intelligent feedback mechanism	Mobile platform	Primary	Non-science	593	Not indicated
Li (2017)	Knowledge	Intelligent feedback mechanism	Offline classroom	Secondary	Non-science	63	> 6
Lim (2024)	Knowledge	Personalized scaffolding	Digital platform	Tertiary	Science	59	< 1
Niknam (2020)	Knowledge	Learning path	Mobile platform	Tertiary	Science	50	1 - 3

		recommendation					
Su (2020)	Knowledge	Personalized scaffolding	Digital platform	Tertiary	Science	80	1 - 3
Wei (2023)	Knowledge Emotion Competence	Intelligent tutoring system	Mobile platform	Tertiary	Non-science	60	1 - 3
Wijekumar (2012)-1	Knowledge	Intelligent tutoring system	Digital platform	Primary	Non-science	130	3 - 6
Wijekumar (2012)-2	Competence	Intelligent tutoring system	Digital platform	Primary	Non-science	109	3 - 6
Xu (2014)	Knowledge Emotion	Intelligent tutoring system	Virtual-reality learning environment	Tertiary	Non-science	183	< 1
Qianjing & Lin (2021)	Knowledge	Adaptive learning system	Digital platform	Tertiary	Non-science	60	Not indicated
Julia (2016)	Competence	Educational robot	Offline classroom	Primary	Science	21	1 - 3
Goda (2014)-1	Emotion Competence	Educational robot	Digital platform	Tertiary	Non-science	63	< 1
Goda (2014)-2	Competence	Educational robot	Digital platform	Tertiary	Non-science	67	< 1
Serrano (2018)-1	Knowledge	Intelligent tutoring system	Digital platform	Secondary	Non-science	47	< 1
Serrano (2018)-2	Knowledge	Intelligent tutoring system	Digital platform	Primary	Non-science	68	< 1
Nugent (2010)	Emotion	Educational robot	Offline classroom	Primary	Science	269	< 1
Alfieri (2015)	Knowledge Emotion Competence	Educational robot	Virtual-reality learning environment	Secondary	Science	104	< 1
Zafar (2015)	Knowledge	Adaptive learning system	Digital platform	Tertiary	Science	57	< 1
Zhou (2023)	Knowledge	Smart education platform	Digital platform	Tertiary	Science	350	>6
					Non-science		

presented in three dimensions: knowledge development (measured by test results, academic progress, etc.), competence development (including the growth in critical thinking, problem-solving, and more), and emotional development (reflected by the improvements of learning motivation, self-efficacy, etc.). The coding was carried out by two researchers to ensure its accuracy. The Kappa value of the coding is 0.89, indicating a high level of agreement.

This study adopted Comprehensive Meta Analysis (CMA) 3.0 as the tool for data analysis. In a meta-analytic study, the effect size is estimated by Cohen’s d or Hedges’ g, which value to use depends on the sample size of the prior studies included. Cohen's d is applicable to all sample sizes, whereas Hedges' g is often opted for when the sample size is less than 20 because it is multiplied by a correction factor for small samples (Glass, 1976; Borenstein et al., 2021). Our literature coding shows that the sample sizes of the studies included in this meta-analysis are all above 20. Therefore, we used Cohen's d to estimate the effect sizes. In practical research, Cohen's d is commonly represented as SMD; in the software of CMA, "std diff in means" is the term for this value. Some of the studies included have more than one effect size because they evaluate student learning outcomes in various dimensions or disciplines. As a result, we extracted 54 effect sizes from the 36 studies.

Publication Bias Analysis

Publication bias is encountered when the significance and direction of research results bias the decision to publish on the part of researchers, reviewers, or editors (Ma & Liu, 2019). To evaluate the possibility of publication bias in the studies included in our meta-analysis, we conducted a comprehensive assessment using the funnel plot, fail-safe N, and Egger's regression analysis. As **Figure 2** shows, the majority of the 54 effect sizes are relatively evenly and symmetrically distributed on both sides of the average effect size; however, a small number of them fall outside the two sides of the funnel, indicating the possible presence of heterogeneity between studies. The fail-safe N is another indicator for evaluating the presence of publication bias. When the meta-analysis results show statistical significance, the larger the fail-safe N value, the lower the possibility of the meta-analytic conclusions being refuted, that is, the lower the possibility of publication bias (Hu & Wang, 2022). Using Rosenthal's (1979) computation method, we obtained a fail-safe N = 5312 (far greater than 5K+10=280, where K represents the number of effect sizes; in this study, it is 54), signaling a low possibility of publication bias in this study. The Egger's regression analysis results showed a t-value of 1.27 and a p-value of 0.209 > 0.05, also indicating that there was no significant publication bias in the literature included (Higgins et al., 2003). These analytic results suggest that the findings of our meta-analysis are reliable.

Heterogeneity Analysis

The purpose of heterogeneity analysis is to evaluate the combinability of research results from various studies for the generation of a combined effect

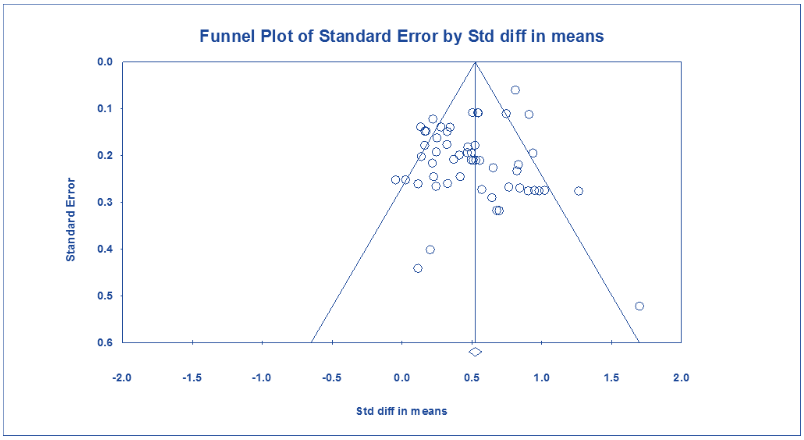

Figure 2. The Funnel Plot for Publication Bias Analysis.

Table 2. Results of Heterogeneity Analysis and the Estimation of Overall Effect Size.

Effects Models	Nos of Effect Sizes	Effect Sizes & 95% Confidence Intervals			Heterogeneity Tests			
		SMD	Standard Error	95% Confidence Intervals	Q Value	df	p Value	I^2
Fixed effects model	54	0.523	0.023	(0.477, 0.569)	138.194	53	0.000	61.648
Random effects model	54	0.490	0.041	(0.409, 0.571)				

size. Also, due to the presence of differences in the intervention, sample size, estimate results, and more between different studies, the results of heterogeneity analysis are crucial for the selection of the meta-analysis model. The commonly used statistical measures in heterogeneity analysis are the Cochran's Q and I^2 tests. The p-value is the primary indicator in the Cochran's Q test. A greater-than-0.1 p-value means the absence of heterogeneity, while a less-than-0.1 p-value indicates the presence of heterogeneity. According to Higgins et al. (2003), the I^2 values of 25%, 50%, and 75% represent low, medium, and high levels of heterogeneity, respectively. As **Table 2** shows, the overall effect size of this study has a Q value of 138.194 ($p < 0.001$) and an I^2 value of 61.648%, exhibiting statistically significant and medium-level heterogeneity between the studies included. Hence, a random effects model is employed for further analysis. Furthermore, these results of heterogeneity analysis indicate the presence of

Table 3. Differential Effects of AI-assisted Personalized Learning on Various Dimensions of Student Learning Outcomes.

Dimensions	Nos of Effect Sizes	Effect Sizes			Two-Sided Tests		Between-Group Effect
		SMD	Standard Error	95% Confidence Intervals	Z Value	p Value	
Knowledge	35	0.557	0.046	(0.467, 0.647)	12.121	0.000	Q=12.075 p=0.002
Emotion	9	0.268	0.070	(0.131, 0.405)	3.837	0.000	
Competence	10	0.436	0.106	(0.228, 0.643)	4.120	0.000	

Table 4. The Moderating Effect of the Type of Edutech Applications.

Types of Edutech Application	Nos of Effect Sizes	Effect Sizes			Two-Sided Tests		Between-Group Effect
		SMD	Standard Error	95% Confidence Intervals	Z value	p value	
Virtual reality-based learning	1	1.701	0.522	(0.678, 2.724)	3.260	0.001	Q=41.357 p=0.000
Personalized scaffolding	2	0.479	0.354	(-0.214, 1.172)	1.355	0.176	
Learning path recommendation	4	0.673	0.195	(0.291, 1.055)	3.455	0.001	
Intelligent feedback mechanism	4	0.776	0.055	(0.668, 0.885)	13.997	0.000	
Adaptive learning system	8	0.482	0.115	(0.255, 0.708)	4.172	0.000	
Educational robot	9	0.272	0.093	(0.089, 0.455)	2.918	0.004	
Smart education platform	11	0.610	0.053	(0.506, 0.713)	11.553	0.000	
Intelligent tutoring system	15	0.381	0.056	(0.271, 0.492)	6.784	0.000	

Table 5. The Moderating Effect of the Application Scenario.

Application Scenarios	Nos of Effect Sizes	Effect Sizes			Two-Sided Tests		Between-Group Effect
		SMD	Standard Error	95% Confidence Intervals	Z Value	p Value	
Virtual-reality learning environment	7	0.267	0.077	(0.116, 0.417)	3.447	0.001	Q=15.818 P=0.001
Mobile platform	8	0.599	0.093	(0.417, 0.781)	6.449	0.000	
Offline classroom	15	0.364	0.053	(0.269, 0.468)	6.886	0.000	
Digital platform	24	0.585	0.061	(0.466, 0.704)	9.639	0.000	

moderating variables that affect the effects of AI-assisted personalized learning on student learning outcomes. Thereby, we need to conduct moderation effect tests following the overall effect size estimation.

Research Results

The Overall Effect Size

According to Cohen (2013), the effect sizes of 0.8, 0.5, and 0.2 are large, medium, and minor, respectively. As shown in **Table 2**, the combined effect size in this study is 0.490, approximating 0.5, and the p-value is less than 0.001, indicating that AI-assisted personalized learning has a moderately positive effect on student learning outcomes.

We further delve into the effects of AI-assisted personalized learning on student knowledge, competence, and emotional development. The effect sizes are 0.557 ($p < 0.001$), 0.436 ($p < 0.001$), and 0.268 ($p < 0.001$) for the dimensions of knowledge, competence, and emotional development, respectively (**Table 3**). This reveals that AI-assisted personalized learning has moderately positive effects on students' knowledge and competence development, with a more significant impact on their knowledge development. Nevertheless, its impact on students' emotional development is much weaker. Moreover, the between-group effect size was 12.075 ($p < 0.005$), also displaying significant differences in the effects of AI-assisted personalized learning on various dimensions of student learning outcomes.

Moderating Variables

The Type of Edutech Applications

Table 4 shows the impact of the type of AI-based Edutech applications on the outcomes of personalized learning. The between-group effect size is 41.357 ($p < 0.001$), indicating heterogenous effects of distinct types of Edutech applications. Among the aforementioned applications, virtual reality-based learning produces the strongest effect (SMD = 1.701, $p < 0.005$). Nonetheless, there is only one effect size under this category; the results of this single study are not representative enough to evidence that personalized learning based on this application can generate the best learning outcomes. Except for personalized scaffolding (SMD = 0.479, $p > 0.005$), the rest of the Edutech applications all have positive effects on the outcomes of personalized learning ($p < 0.005$). Among them, the intelligent feedback mechanism shows the largest effect size (SMD = 0.776, $p<0.001$), followed by learning path recommendation (SMD = 0.673, $p<0.005$), the smart education platform (SMD = 0.610, $p < 0.001$), the adaptive learning system (SMD = 0.482, $p < 0.001$), the intelligent tutoring system (SMD = 0.381, $p < 0.001$), and the educational robot (SMD = 0.272, $p < 0.005$). According to the analysis results, personalized scaffolding does not exhibit a statistically significant effect on the outcomes of personalized learning. This may not be an accurate reflection of the actual impact of this application, as the estimation is based on a very small number of effect sizes (N = 2).

The Application Scenario

We also looked into the heterogenous effects of AI-assisted personalized learning on student learning outcomes in differential learning scenarios. The between-group effect size (15.818, $p < 0.005$) in **Table 5** exhibits significant heterogeneity in the impact of the learning setting on the outcomes of AI-assisted personalized learning. The mobile platform (SMD = 0.599, $p < 0.001$) and the digital platform (SMD = 0.585, $p < 0.001$) had more significantly positive impacts than the offline classroom (SMD = 0.364, $p < 0.001$) and the virtual-reality learning environment (SMD = 0.267, $p < 0.005$).

The Educational Phase and Disciplinary Domains

As displayed in **Table 6**, there are modest differences between the effects of AI-assisted personalized learning on learning outcomes of tertiary education students (SMD = 0.573, $p < 0.001$), primary education students (SMD = 0.437, $p < 0.001$), and secondary education students (SMD = 0.385, $p < 0.001$). Yet, the impact of age is not significant, as indicated by the between-group effect size (5.069, $p > 0.05$).

Table 7 shows that AI-assisted personalized learning has moderately positive effects on student learning outcomes in both science (SMD = 0.481, $p < 0.001$) and non-science (SMD = 0.502, $p < 0.001$) disciplines. The disciplinary differences had no significant impact on the outcomes of AI-assisted personalized learning, as supported by the between-group effect size (0.065, $p = 0.798 > 0.05$).

The Duration of Experiment

Table 8 presents the moderating effects of varied durations of experiments. Three of the studies are excluded from the effect size test on this moderating variable because they do not specify the durations of their intervention. The between-group effect size ($Q = 11.200$, $p < 0.05$) produced by this test indicates statistically significant heterogeneity in the impact of the application duration on the outcomes of AI-assisted personalized learning.

Table 6. The Moderating Effect of the Educational Phase.

Educational Phases	Nos of Effect Sizes	Effect Sizes			Two-Sided Tests		Between-Group Effect
		SMD	Standard Error	95% Confidence Intervals	Z Value	p Value	
Primary	12	0.437	0.094	(0.254, 0.621)	4.674	0.000	Q=5.069 p=0.079
Secondary	15	0.385	0.057	(0.274, 0.496)	6.776	0.000	
Tertiary	27	0.573	0.062	(0.451, 0.695)	9.193	0.000	

Table 7. The Moderating Effect of the Disciplinary Domain.

Disciplinary Domains	Nos of Effect Sizes	Effect Sizes			Two-Sided Tests		Between-Group Effect
		SMD	Standard Error	95% Confidence Intervals	Z Value	p Value	
Science	29	0.481	0.055	(0.373, 0.589)	8.706	0.000	Q=0.065 p=0.798
Non-science	25	0.502	0.063	(0.379, 0.625)	8.018	0.000	

Table 8. The Moderating Effect of the Duration of Experiment.

Experiment Durations (months)	Nos of Effect Sizes	Effect Sizes			Two-Sided Tests		Between-Group Effect
		SMD	Standard Error	95% Confidence Intervals	Z Value	P Value	
<1	23	0.339	0.053	(0.236，0.443)	6.410	0.000	Q=11.200 P= 0.011
1 - 3	15	0.579	0.065	(0.452，0.707)	8.892	0.000	
3 - 6	7	0.545	0.117	(0.315，0.775)	4.642	0.000	
> 6	6	0.590	0.088	(0.419，0.762)	6.739	0.000	

Experiments lasting 1-3 months (SMD = 0.579, $p < 0.001$), 3-6 months (SMD = 0.545, $p < 0.001$), and more than 6 months (SMD = 0.590, $p < 0.001$) have moderately positive impacts, as opposed to the modestly positive impacts of the experiments shorter than one month (SMD = 0.339, $p < 0.001$).

Discussion

According to our statistical analysis results, AI-assisted personalized learning can improve the overall learning outcomes of the student, which is supported by the findings of previous studies on this topic (Hu & Wang, 2022; Zhang et al., 2023). The successful integration of AI technology into personalized learning can provide students with a more individualized learning experience, meeting the individually different needs and preferences among them. Our research finding justifies the broad implementation of personalized learning in the context of the widespread application of AI technology.

The meta-analytic results demonstrate that AI-assisted personalized learning has positive effects on knowledge, competence, and emotional development of the student. Specifically, its effect is the most prominent on student knowledge development but the weakest on student emotional development. One possible reason for this gap is that the design and development of educational AI applications are more targeted at facilitating student knowledge acquisition and academic success, resulting in the ongoing optimization of the roles of these applications in enhancing the students' learning outcomes in the dimension of content knowledge development. Another reason may be that current research tends to adopt the self-report questionnaire survey in gathering information for the evaluation of student emotional development. The information is subject to the subjective biases and memory failures of the respondents as well as the influence of social expectations, leading to inaccurate or incomplete research results in this regard. On the contrary, the evaluation of student knowledge development can be conducted by quantitative methods like the standardized test, which has helped increase researchers' interest in this area. In addition, although a few of the studies included in the meta-analysis established emotional variables, such as learning motivation, self-efficacy, and learning satisfaction, for the examination of student emotional development, only one of them (Nugent et al., 2010) made this dimension a focal point of its research. This may be emblematic of the neglect in academia of the effect of AI-assisted personalized learning on student emotional development.

This study also finds that factors, such as the type of Edutech applications, application scenario, and duration of application, can impact the outcomes of AI-assisted personalized learning. This suggests that the improvement of student learning outcomes in personalized study is contingent on a combination of multiple factors. Our meta-analysis shows that the effect sizes of apps that only use one technology, like learning path recommendation and the intelligent feedback mechanism, are slightly bigger than those that use more than one technology, like the adaptive learning system, smart education platform, and intelligent tutoring system. This finding implies that Edutech applications based on integrated technologies may encounter more challenges in data integration, which considerably compromises their overall effectiveness, and that their effects are more likely to be affected by other factors like students' preferences of technology use and teacher engagement, as opposed to the better reception of single-technology-based applications among students because of their easy use and specific focuses. Furthermore, this study finds that the intelligent feedback mechanism is the most effective in boosting the outcomes of personalized learning among all the single technology-based applications. It highlights the significance of instant, individualized feedback for student academic progress, which deserves more in-depth research. Among integrated technology-based applications, the smart education platform has the most prominent positive effect on the outcomes of personalized learning. As stated earlier in the study, the smart education platform helps the teacher administer precision instruction. Hence, teacher engagement may be the primary factor for the outstanding performance of this application. More research efforts are needed to explore the roles of teacher engagement in AI-assisted personalized learning. It is also found that the educational robot has a minor positive impact on the outcomes of personalized learning. Some researchers pointed out that this may be due to the insufficient sensitivity of the data analysis method, leading to the inability to spot the variations between the experimental and control groups (Gode et al., 2014), or due to the inordinately short durations of intervention (Nugent et al., 2010). We suggest that the researchers and educators should extend the time of interaction between the student and educational robot when introducing the latter into personalized learning.

Among the four learning scenarios, the offline classroom has less influence on the outcomes of AI-assisted personalized learning compared with the digital platform and mobile platform. This is because the student enjoys less freedom in learning (e.g., the time limit and susceptibility to disruptions from peers) in the traditional classroom environment, resulting in the constrained effects of the technological intervention on student learning (Beal et al., 2010). In contrast, the student has more autonomy in learning on the digital platform and mobile platform, where they can experience more private and flexible learning patterns. The analysis results show that the virtual-reality learning environment has the least influence on the outcomes of AI-assisted personalized learning, which can be linked to overly short periods of the experiments (most of them only lasted for one week). With such a condition, it is almost impossible to determine the genuine impact of the virtual-reality learning environment on students' long-term learning behavior and outcomes (Divekar et al., 2024). In examining the impact of the duration of the experiment as a moderating variable, we also discovered that duration of less than one month has the smallest effect on the outcomes of AI-assisted personalized learning. Therefore, it is important that educators prescribe adequate lengths of application when using AI technology in student personalized learning to ensure its outcomes.

On the other hand, the meta-analysis results demonstrate that the educational phase and disciplinary domain have little impact on the outcomes of AI-assisted personalized learning. This finding indicates that the role of AI-assisted educational technology in promoting personalized learning is stable and generalizable. It provides justifications for increasing AI application in all disciplines at all educational levels to further enhance instructional quality and student achievements.

Conclusion

This study analyzed the research results of 36 studies in 31 publications using meta-analytic techniques. The research findings show that AI-assisted personalized learning has positive effects on the overall learning outcomes of the student, particularly in the dimension of knowledge development, and those factors, such as the type of AI-based Edutech applications, application scenario, and duration of application, can also impact the outcomes of personalized learning. An important implication of this study is that educators need to pay regard to multi-faceted factors when introducing and implementing AI-assisted personalized learning to reach optimal results. First, they should adopt the type of Edutech application pertinent to the specific needs of the student and characteristics of the discipline to make best use of the application's benefits. Second, it is important to remove disruptive factors in certain learning scenarios in order to improve the outcomes of personalized learning. Third, the application duration of technologies deserves serious consideration; an appropriate length of application is beneficial for the thorough evaluation of the long-term effect of the technology on student learning outcomes.

It is noteworthy that AI-based Edutech applications adopted in personalized learning are far more than these mentioned in our study, but empirical research in this area is inadequate, warranting more attention from academia. Also, the roles of AI-assisted personalized learning in interdisciplinary instruction, which were not addressed in this study, deserve thorough exploration. Furthermore, for more effective application of AI technologies in personalized learning and their deeper integration into the field of education across the board, it is imperative for the researchers to investigate the issues of privacy, security, and digital divides. Equally important is to encourage continuous practical explorations among teachers to improve the implementation tactics for AI-assisted personalized learning to promote the cognitive and non-cognitive development of the student.

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(The studies included in the meta-analysis are marked with asterisks)

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