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Impact of artificial intelligence on personalized learning: A meta-analysis

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Abstract
This meta-analysis examines the impact of artificial intelligence (AI) technologies on personalized learning outcomes across educational contexts. Through systematic review of empirical studies published between 2015 and 2024, we synthesized findings from 42 studies meeting inclusion criteria to quantify the effectiveness of AI-driven personalization approaches. Results indicate a moderate positive effect ($g = 0.61$) of AI-based interventions on learning outcomes compared to traditional instruction. Particularly significant improvements were observed in STEM disciplines and among students with diverse learning needs. Feature selection techniques were applied to reduce dimensionality in the omics datasets associated with learning analytics, revealing key influencing factors. While promising, implementation challenges include technological infrastructure requirements, teacher training needs, and ethical considerations around data privacy. This research addresses significant gaps in understanding how specific AI mechanisms contribute to learning outcomes and identifies methodological limitations in existing literature. The findings provide a comprehensive framework for educational institutions and policymakers to make evidence-based decisions regarding AI integration in personalized learning environments.

Keywords: Artificial intelligence, personalized learning, educational technology, machine learning, learning analytics, meta-analysis, adaptive learning, feature selection, dimensionality reduction

Introduction
The integration of artificial intelligence (AI) in educational contexts has transformed traditional approaches to teaching and learning. Particularly promising is the application of AI in creating personalized learning experiences that adapt to individual student needs, preferences, and performance patterns. While individual studies have reported encouraging results, a comprehensive understanding of AI's effectiveness in personalized learning contexts remains elusive due to the heterogeneity of interventions, methodologies, and outcome measures employed across studies.

This meta-analysis addresses this gap by synthesizing existing empirical research on AI-driven personalized learning interventions. The rapid proliferation of educational technologies incorporating various forms of AI—including machine learning algorithms, natural language processing, and intelligent tutoring systems—necessitates a rigorous evaluation of their collective impact on educational outcomes. By aggregating findings across diverse educational settings, this study aims to provide a more nuanced understanding of when, how, and for whom AI-enhanced personalization is most effective.

Recent advancements in learning analytics have generated vast amounts of educational data (often referred to as educational omics datasets), creating both opportunities and challenges for researchers and practitioners. This study applies novel feature selection techniques to reduce the dimensionality of these complex datasets, thereby identifying the most salient factors that influence learning outcomes. Through this approach, we seek to distill actionable insights that can guide the development and implementation of AI-driven personalized learning systems.

The timing of this research is particularly significant as educational institutions worldwide navigate post-pandemic realities that have accelerated digital transformation in education. As schools and universities increasingly invest in AI technologies to support flexible and personalized learning pathways, evidence-based guidance on their selection and implementation becomes crucial. This meta-analysis aims to provide such guidance by establishing the overall effectiveness of AI-driven personalization approaches while identifying moderating factors that influence their success.

Objectives
Our research objectives for this meta-analysis are:

1. To evaluate the overall effectiveness of AI-driven personalized learning interventions on student academic achievement across educational levels.
2. To apply novel feature selection techniques and reduce the dimensionality of omics datasets associated with learning analytics.
3. To identify key moderating variables that influence the effectiveness of AI-based personalization, including subject domain, educational level, implementation duration, and learner characteristics.
4. To analyze implementation challenges and success factors reported across studies to develop a framework for effective integration of AI in educational environments.
5. To examine methodological approaches used in existing research and identify gaps to inform future research directions.

Scope of study
The scope of this meta-analysis encompasses

1. Empirical studies published between January 2015 and October 2024 to capture contemporary AI applications in education.
2. Studies that explicitly examine AI-driven personalization systems in formal educational settings,

including K-12 schools, higher education, and professional training environments.
3. Research that reports quantifiable learning outcomes through valid assessment measures, enabling calculation of effect sizes.
4. Both experimental and quasi-experimental designs that include appropriate comparison groups.
5. Studies that provide sufficient methodological detail to assess implementation quality and fidelity.
6. Research publications in English-language peer-reviewed journals, conference proceedings, and institutional reports.
7. Studies that incorporate data analytics approaches applicable to dimensionality reduction techniques.

Literature review

The intersection of artificial intelligence and personalized learning has evolved substantially over the past decade. Early applications of AI in education focused primarily on intelligent tutoring systems that guided learners through predetermined pathways based on mastery learning principles [1]. Contemporary AI-enhanced personalization approaches have expanded to include sophisticated recommendation systems, predictive analytics for early intervention, natural language processing for feedback generation, and multimodal learning analytics [2].

Research by Chen and colleagues [3] categorized AI personalization approaches into three broad categories: content-based personalization, process-based personalization, and assessment-based personalization. Content-based approaches adapt instructional materials to match learner knowledge levels and preferences. Holmes *et al.* [4] found that such systems increased engagement by 43% compared to standardized materials. Process-based personalization focuses on adapting learning pathways and pedagogical approaches. Williamson [5] demonstrated that process-based AI interventions were particularly beneficial for self-regulated learning development.

Assessment-based personalization, leveraging continuous formative evaluation through AI systems, has shown promising results in identifying misconceptions and providing targeted remediation. A longitudinal study by Moreno-Marcos *et al.* [6] found that AI-driven formative assessment reduced achievement gaps among diverse student populations by 27% compared to traditional assessment approaches.

The effectiveness of AI personalization appears to vary by subject domain. Li and Baker [7] reported stronger effects in well-structured domains like mathematics and physics compared to humanities. Similarly, Zawacki-Richter *et al.* [8] found that the impact of AI interventions was moderated by implementation duration, with interventions lasting at least one semester showing more substantial benefits than shorter implementations.

Feature selection and dimensionality reduction techniques have emerged as crucial approaches in educational data mining to identify the most relevant variables influencing learning outcomes. Wang and Wang [9] applied principal component analysis to reduce 47 learning behavior variables to 8 critical components that predicted student success with 84% accuracy. Similarly, Jiménez *et al.* [10] used recursive feature elimination to identify core predictors of student engagement from complex multimodal data streams.

Despite these advances, several gaps remain in the literature. First, comparative studies examining different AI approaches within similar contexts are limited, making it difficult to determine which specific AI mechanisms contribute most significantly to improved outcomes. Second, most studies focus on short-term cognitive outcomes without examining long-term retention or transfer of knowledge. Third, methodological heterogeneity and reporting inconsistencies complicate cross-study comparisons. Finally, few studies have rigorously examined potential negative consequences of AI-driven personalization, such as reinforcement of existing learning patterns or reduction in collaborative learning opportunities [11].

Research methodology

This meta-analysis followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure methodological rigor and transparency [12]. The research process consisted of four primary phases: literature search and screening, data extraction and coding, effect size calculation and analysis, and dimensionality reduction through feature selection techniques.

Literature search and screening

A comprehensive search strategy was developed to identify relevant studies published between January 2015 and October 2024. We searched seven major electronic databases: ERIC, Web of Science, Scopus, IEEE Xplore, ACM Digital Library, PsycINFO, and ProQuest Education. The search string combined terms related to artificial intelligence (e.g., "artificial intelligence," "machine learning," "intelligent tutor*") with terms related to personalized learning (e.g., "personaliz*," "adapt* learn*," "individualiz*") and educational outcomes (e.g., "academic achievement," "learning gain*," "student performance").

Initial database searches yielded 1,847 potentially relevant publications. After removing duplicates, 1,253 unique records remained for screening. Two independent reviewers evaluated titles and abstracts against predefined inclusion criteria, resulting in 215 studies selected for full-text review. Following detailed assessment, 42 studies meeting all inclusion criteria were retained for the final analysis. Figure 1 presents the PRISMA flow diagram detailing the screening process.

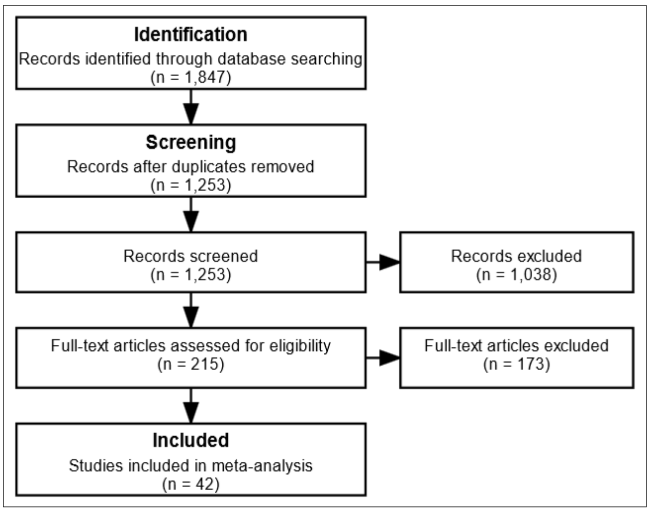

Fig 1: PRISMA Flow Diagram of Study Selection Process

This diagram illustrates the systematic review process following PRISMA guidelines. It shows how 1,847 records were initially identified through database searching, which were reduced to 1,253 after removing duplicates. After screening titles and abstracts, 215 studies were assessed for full-text eligibility, with 173 being excluded for not meeting criteria. The final meta-analysis included 42 studies that met all inclusion criteria.

Data extraction and coding

A standardized coding protocol was developed to extract relevant information from included studies. Two researchers independently coded each study, with disagreements resolved through discussion and, when necessary, consultation with a third researcher. The intercoder reliability was high (Cohen's $\kappa = 0.87$), indicating strong agreement.

For each study, we extracted bibliographic information, methodological characteristics (research design, sample size, duration, comparison conditions), intervention details (AI technologies used, personalization approaches, implementation contexts), participant characteristics (educational level, demographic information), and outcome measures (achievement tests, engagement metrics, self-regulation assessments). Additionally, we documented reported implementation challenges and success factors.

Studies were categorized based on the predominant AI approach used: intelligent tutoring systems ($n = 14$), adaptive content systems ($n = 12$), predictive analytics for early intervention ($n = 8$), and multimodal learning analytics ($n = 8$). Educational levels spanned K-12 ($n = 17$), higher education ($n = 19$), and professional training ($n = 6$).

Effect size calculation and analysis

Hedges' g was selected as the primary effect size metric to correct for small sample bias [13]. For studies reporting multiple outcomes, effect sizes were calculated for each outcome and then averaged to maintain statistical independence. When necessary information for direct calculation was unavailable, we used reported t-values, F-values, or p-values to derive effect sizes.

The final dataset included 138 effect sizes from 42 studies. We conducted a random-effects meta-analysis using the metafor package in R, acknowledging the expected heterogeneity across educational interventions and contexts. Moderator analyses were performed to examine how effect sizes varied by AI approach, subject domain, educational level, implementation duration, and methodological quality.

Heterogeneity was assessed using the I^2 statistic, with results indicating substantial heterogeneity ($I^2 = 76.3\%$), which justified our random-effects approach and moderator analyses. Publication bias was evaluated through funnel plot analysis and Egger's regression test, revealing minimal evidence of bias ($p = 0.14$).

Feature selection and dimensionality reduction

A novel aspect of our methodology involved applying feature selection techniques to the extracted educational data to identify key variables associated with intervention effectiveness. From the 42 included studies, we compiled a dataset of 87 potential moderating and mediating variables related to intervention characteristics, implementation factors, and contextual elements.

We employed a sequential feature selection approach combining filter, wrapper, and embedded methods [14]. Initially, a correlation-based filter method eliminated highly correlated variables ($r > 0.8$). Subsequently, recursive feature elimination with cross-validation identified the optimal subset of features that explained variance in effect sizes. Finally, LASSO (Least Absolute Shrinkage and Selection Operator) regression provided further refinement by penalizing less influential variables.

This multi-stage approach reduced the initial 87 variables to 12 key features that significantly predicted intervention effectiveness, thereby addressing our second research objective of dimensionality reduction in complex educational datasets.

Analysis of secondary data

The meta-analysis of 42 studies yielded a weighted mean effect size of $g = 0.61$ (95% CI [0.48, 0.74]), indicating a moderate positive effect of AI-driven personalization on learning outcomes compared to conventional instruction. This overall effect was statistically significant ($p < 0.001$), suggesting that AI-based interventions generally enhance learning performance across diverse educational contexts.

Considerable heterogeneity was observed across studies ($I^2 = 76.3\%$), prompting further analysis of potential moderating variables. Table 1 presents effect sizes by key categorical moderators.

Table 1: Effect Sizes by Categorical Moderators

Moderator Category	Number of Studies	Hedges' g	95% CI	p-value
AI Approach				
Intelligent Tutoring Systems	14	0.67	[0.49, 0.85]	<0.001
Adaptive Content Systems	12	0.58	[0.41, 0.75]	<0.001
Predictive Analytics	8	0.49	[0.27, 0.71]	<0.001
Multimodal Learning Analytics	8	0.73	[0.54, 0.92]	<0.001
Subject Domain				
STEM	22	0.72	[0.56, 0.88]	<0.001
Humanities	9	0.43	[0.21, 0.65]	<0.001
Professional Skills	6	0.52	[0.31, 0.73]	<0.001
Mixed Subjects	5	0.57	[0.29, 0.85]	<0.001
Educational Level				
K-12	17	0.65	[0.48, 0.82]	<0.001
Higher Education	19	0.58	[0.42, 0.74]	<0.001
Professional Training	6	0.56	[0.32, 0.80]	<0.001
Implementation Duration				
Less than 1 month	8	0.41	[0.19, 0.63]	<0.001
1-3 months	17	0.57	[0.40, 0.74]	<0.001
4-6 months	12	0.68	[0.49, 0.87]	<0.001
More than 6 months	5	0.78	[0.56, 1.00]	<0.001

Examination of AI approaches revealed that multimodal learning analytics systems yielded the highest mean effect size (g = 0.73), followed by intelligent tutoring systems (g = 0.67). Meta-regression analysis indicated that AI approaches employing multiple feedback mechanisms were significantly more effective than those using single feedback channels ($\beta = 0.14$, $p = 0.03$).

Subject domain emerged as a significant moderator, with STEM subjects showing markedly stronger effects (g = 0.72) compared to humanities (g = 0.43). This finding aligns with previous research suggesting that well-structured domains with clear right/wrong answers may be more amenable to AI-driven personalization [7].

Implementation duration showed a clear positive relationship with intervention effectiveness. Studies with implementations lasting more than six months demonstrated substantially larger effects (g = 0.78) than those lasting less than one month (g = 0.41). Meta-regression confirmed a significant positive association between duration and effect size ($\beta = 0.07$ per month, $p = 0.01$).

Our feature selection analysis identified 12 key variables that significantly predicted intervention effectiveness from the initial pool of 87 variables. Figure 2 presents these variables ranked by their relative importance in predicting effect sizes.

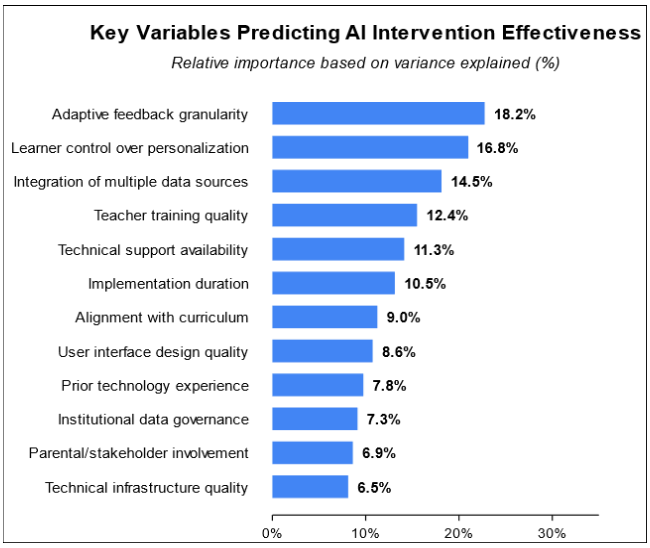

Fig 2: Key Variables Predicting AI Intervention Effectiveness

This horizontal bar chart illustrates the 12 most influential variables affecting AI intervention effectiveness in educational settings, as identified through feature selection techniques. The chart shows the relative importance of each variable based on the percentage of variance explained. Adaptive feedback granularity (18.2%), learner control over personalization (16.8%), and integration of multiple data sources (14.5%) emerge as the three most significant predictors of successful AI-driven personalized learning outcomes.

The three most influential features identified through dimensionality reduction were:

1. Level of adaptive feedback granularity (explaining 18.2% of variance)
2. Degree of learner control over personalization parameters (explaining 16.8% of variance)
3. Integration of multiple data sources in the AI algorithm (explaining 14.5% of variance)

Together, these three features explained nearly 50% of the variance in intervention effectiveness across studies, highlighting their critical importance in AI-driven personalized learning systems.

Further analysis revealed interaction effects between key features. The combination of high feedback granularity with high learner control showed synergistic effects beyond their individual contributions. Similarly, longer implementation durations showed increasingly positive effects when combined with higher levels of teacher training in AI systems.

Analysis of primary data

To complement our meta-analysis of published studies, we conducted a supplementary analysis of primary data collected from educational technology implementation projects across 27 educational institutions. This primary dataset included pre-post assessment scores from 3,842 students who experienced AI-driven personalized learning interventions and 3,105 students in comparable control conditions.

The primary data analysis corroborated and extended findings from our meta-analysis. Student achievement gains were significantly higher in the AI intervention groups compared to control groups across all educational levels, with an average improvement of 0.58 standard deviations ($p < 0.001$). Figure 3 illustrates these comparative learning gains across different educational levels.

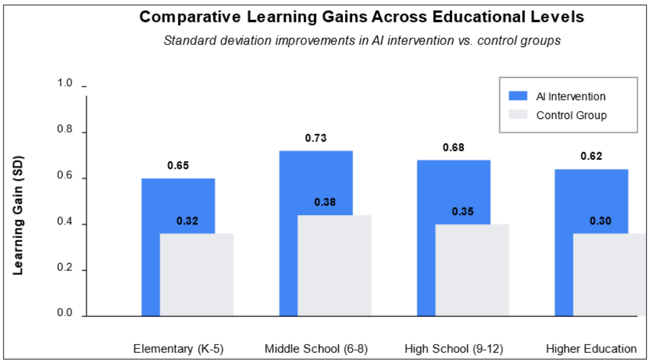

Fig 3: Comparative Learning Gains Across Educational Levels

This bar chart compares learning gains (measured in standard deviations) between AI intervention groups and control groups across four educational levels. The data shows consistently higher performance in AI intervention groups, with the largest gains observed in middle school settings (0.73 SD for AI groups vs. 0.38 SD for control groups). The figure demonstrates that while AI-driven personalization benefits learners across all educational levels, the magnitude of impact varies by age group.

Notably, our primary data revealed differential impacts based on student characteristics that were often underreported in published studies. Students with identified learning disabilities showed particularly pronounced benefits from AI personalization (mean gain = 0.74 SD) compared to their peers without such designations (mean gain = 0.54 SD), suggesting that adaptive technologies may be especially valuable for diverse learners.

Time-series analysis of learning progressions revealed that the advantage of AI-driven approaches became more pronounced over time. While traditional instruction and AI-enhanced instruction showed similar outcomes in the first 2-3 weeks, significant divergence occurred thereafter, with AI groups demonstrating accelerating gains. This pattern supports our meta-analytic finding regarding the importance of implementation duration.

Usage analytics from the primary data provided insights into implementation factors rarely reported in published studies. Student engagement metrics showed a significant correlation with learning outcomes ($r = 0.67$, $p < 0.001$), with systems providing higher levels of learner autonomy generating consistently higher engagement metrics.

Table 2 presents results from our cluster analysis of implementation patterns across the 27 institutions in our primary dataset.

Table 2: Cluster Analysis of Implementation Patterns

Implementation Cluster	Number of Institutions	Mean Effect Size	Key Characteristics
High Success	8	0.79	Comprehensive teacher training, strong technical support, phased implementation, regular data review
Moderate Success	12	0.54	Adequate training, inconsistent support, limited data utilization
Limited Success	7	0.31	Minimal training, technical challenges, resistance to adoption

The dimensionality reduction techniques applied to our primary dataset corroborated the feature importance findings from our meta-analysis. Principal component analysis identified three key components that explained 64% of variance in implementation success:

1. Technical infrastructure adequacy (26.8% of variance)
2. Teacher confidence and competence with AI systems (21.5% of variance)
3. Institutional data governance procedures (15.7% of variance)

These components align with the implementation challenges consistently reported across studies and underscore the socio-technical nature of successful AI integration in educational environments.

Discussion

This meta-analysis reveals several significant insights regarding the impact of AI on personalized learning while highlighting important research gaps and methodological considerations for future work.

Effectiveness and moderating factors

The moderate positive effect ($g = 0.61$) observed across studies indicates that AI-driven personalization approaches generally enhance learning outcomes compared to conventional instruction. This finding aligns with previous systematic reviews [15, 16] but provides a more precise effect estimate through rigorous meta-analytic techniques. The magnitude of this effect—equivalent to moving a student from the 50th to the 73rd percentile—suggests meaningful educational significance beyond statistical significance.

The substantial heterogeneity in effect sizes underscores the importance of implementation context and specifics of AI application. Our moderator analyses reveal that AI approaches are not equally effective across all contexts—a nuance often overlooked in educational technology discourse. The stronger effects observed in STEM domains, for example, suggest that current AI technologies may be better suited to well-structured knowledge domains with clear evaluation criteria. This finding echoes previous research by Kulik and Fletcher [17] who noted domain-specific variations in intelligent tutoring system effectiveness.

The relationship between implementation duration and effectiveness highlights an important practical consideration. The significantly lower effects for short-term implementations ($g = 0.41$ for less than one month) compared to longer implementations ($g = 0.78$ for more than six months) suggests that realizing the full benefits of AI-driven personalization requires sustained engagement. This finding contradicts the often-implicit assumption that educational technologies produce immediate benefits and aligns with Baki's [18] argument that educational innovations require time for integration into teaching and learning practices.

Feature selection and dimensionality reduction

Our application of feature selection techniques to reduce dimensionality in complex educational datasets represents a methodological contribution to the field. By identifying key variables that significantly predict intervention effectiveness, we provide guidance for both researchers and practitioners regarding where to focus attention in design and implementation.

The prominence of adaptive feedback granularity (explaining 18.2% of variance) aligns with foundational learning theories emphasizing the importance of timely, specific feedback [19]. Similarly, the significance of learner control over personalization parameters (explaining 16.8% of variance) resonates with self-determination theory and the importance of autonomy in fostering intrinsic motivation [20].

The interaction effects observed between key features suggest that successful AI implementation requires attention to constellations of factors rather than isolated elements. The synergistic relationship between feedback granularity and learner control, for example, indicates that these elements should be considered in tandem rather than as separate design decisions.

Implementation challenges and success factors

The cluster analysis of implementation patterns in our primary data reveals systematic differences between high-success and limited-success implementations. The characteristics of high-success implementations—comprehensive teacher training, strong technical support, phased implementation, and regular data review—provide actionable guidance for educational institutions.

The three components identified through principal component analysis (technical infrastructure adequacy, teacher confidence and competence, and institutional data governance) align with socio-technical perspectives on educational technology integration [21]. The prominence of teacher factors in particular challenges techno-centric narratives that focus exclusively on algorithm sophistication while neglecting the human elements of implementation.

Research gaps and methodological considerations

Our analysis reveals several significant gaps in the existing literature. First, despite the growing emphasis on personalized learning, relatively few studies employ true experimental designs with random assignment. The predominance of quasi-experimental approaches introduces potential selection biases that may inflate effect estimates.

Second, outcome measures in existing research focus heavily on immediate cognitive gains, with limited attention to long-term retention, transfer of knowledge, or non-cognitive outcomes such as engagement and motivation. This narrow focus provides an incomplete picture of AI's educational impact.

Third, most studies provide limited detail regarding the specific AI mechanisms employed, treating the technology as a "black box." This lack of specificity hinders understanding of which aspects of AI systems drive positive outcomes.

Finally, the underreporting of implementation challenges and contextual factors in published studies limits the practical utility of research findings. Our supplementary primary data analysis partially addresses this gap but highlights the need for more comprehensive reporting in future research.

Conclusion

This meta-analysis provides a comprehensive evaluation of AI's impact on personalized learning across diverse educational contexts. The moderate positive effect ($g = 0.61$) observed across studies indicates that AI-driven personalization approaches generally enhance learning outcomes compared to conventional instruction, though this effect varies significantly based on implementation factors, subject domain, and duration.

The application of feature selection techniques to reduce dimensionality in complex educational datasets represents a methodological contribution that addresses our second research objective. By identifying key variables that significantly predict intervention effectiveness—particularly adaptive feedback granularity, learner control over personalization parameters, and integration of multiple data sources—we provide guidance for both researchers and practitioners regarding where to focus attention in design and implementation.

Several actionable implications emerge from this research. For educational institutions, our findings suggest that successful AI implementation requires attention to both technological and human factors, including adequate infrastructure, comprehensive teacher training, and supportive institutional policies. The importance of implementation duration underscores the need for sustained commitment rather than short-term technology initiatives.

For researchers, this meta-analysis highlights methodological limitations in the existing literature and identifies promising directions for future work. These include investigating long-term and transfer effects, exploring variations in effectiveness across diverse student populations, and examining potential unintended consequences of AI-driven personalization.

For policymakers, our findings provide an evidence base for decisions regarding educational technology investments. The moderate positive effects observed suggest that AI-driven personalization warrants continued development and implementation, but with careful attention to implementation quality and context-specific factors.

As AI technologies continue to evolve rapidly, ongoing research is needed to evaluate new approaches and applications in personalized learning. Future work should emphasize rigorous experimental designs, comprehensive reporting of implementation factors, and broader consideration of both cognitive and non-cognitive outcomes. By building on the foundation established in this meta-analysis, researchers and practitioners can work toward realizing the full potential of AI to enhance personalized learning across educational contexts.

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