



The Impacts of Intelligent Feedback on Learning Achievements and Learning Perceptions in Inquiry-Based Science Learning: A Meta-Analysis of Studies from 2013 to 2023

Lanqin Zheng¹ · Zhe Shi¹ · Zhixiong Fu¹ · Shuqi Liu¹

Accepted: 1 February 2025 / Published online: 18 February 2025
© The Author(s), under exclusive licence to Springer Nature B.V. 2025

Abstract

In recent years, in the era of digital intelligence, intelligent feedback has received increasing attention. However, few studies have explored the impacts of intelligent feedback on learning achievements and learning perceptions in inquiry-based science learning. To address these research gaps, this study examined the overall impacts of intelligent feedback on learning achievements and learning perceptions on the basis of a meta-analysis of studies conducted from 2013 to 2023. In total, 42 articles featuring 4554 participants were included in and analyzed as part of this study. The results revealed that intelligent feedback had moderate impacts on learning achievements and learning perceptions. In addition, sample level, feedback technique, feedback timing, and control over feedback significantly moderated the effects of intelligent feedback in this context, as revealed by an analysis of 14 moderators. The findings of this research, alongside its practical and theoretical implications, are discussed in depth.

Keywords Intelligent feedback · Inquiry-based learning · Meta-analysis · Learning achievement · Learning perception

Introduction

Recently, intelligent feedback has received increasing attention, and researchers have increasingly applied intelligent feedback in the field of education. Intelligent feedback can help track learning trajectories (Tacoma et al., 2020), rectify learners' errors (Fossati et al., 2015), and facilitate deep comprehension of the subject matter (Yang et al., 2023). Intelligent feedback has positive impacts on students' learning achievements, attitudes, engagement, and higher-order

thinking skills (Fernández-Alemán et al., 2016; Liu et al., 2020).

Prior studies have investigated how inquiry-based science learning can be notably enhanced by intelligent feedback (Wang et al., 2023; Wongwatkit et al., 2017). Some studies have reported that intelligent feedback can help improve students' learning achievements (Afzaal et al., 2024) and learning perceptions (Drissi et al., 2024). Other studies have reported that intelligent feedback is not helpful with respect to learning achievements (Schmidt et al., 2018) or even harmful to learning perceptions (Sun et al., 2019). Therefore, previous studies have presented contradictory results, and the impacts of intelligent feedback require clarification. In addition, comprehensive meta-analyses of intelligent feedback in inquiry-based science learning remain lacking.

Meta-analysis can synthesize previous findings with the goals of identifying the total effect size among multiple studies (Borenstein et al., 2011) and helping mitigate potential biases (Kates et al., 2018). Moreover, meta-analyses yield results that exhibit stronger statistical power, higher levels of external validity, and broader generalizability than do the results of individual studies (Konstantopoulos, 2008). In addition, the analysis of moderating variables can facilitate the examination of the relationships between moderators

✉ Lanqin Zheng
bnuzhenglq@bnu.edu.cn

Zhe Shi
202321010189@mail.bnu.edu.cn

Zhixiong Fu
202322010214@mail.bnu.edu.cn

Shuqi Liu
202322010225@mail.bnu.edu.cn

¹ School of Educational Technology, Faculty of Education, Beijing Normal University, No. 19, XinJieKouWai Street, HaiDian District, Beijing 100875, China

and learning outcomes (Chen et al., 2018). The current study focuses on a thorough meta-analysis of research on this topic with the goal of investigating the impacts of intelligent feedback on both learning achievements and learning perceptions in inquiry-based science learning. The current meta-analysis thus helps elucidate the role and effectiveness of intelligent feedback with respect to both learning achievements and learning perceptions in inquiry-based science learning. This meta-analysis also provides insights into the various moderators that shape the impacts of intelligent feedback in inquiry-based science learning.

In this study, intelligent feedback is defined as the use of artificial intelligence technologies to track learners' behaviors, interpret learners' natural language responses, and provide appropriate prompts and guidance in the form of feedback information. In the current study, learning perception is conceptualized in terms of students' experiences with inquiry-based science learning, such as their learning attitudes, learning stratification, and self-efficacy. Learning achievements are assessed on the basis of standardized tests designed by educators or researchers to evaluate students' knowledge and skills (Sung et al., 2015).

Literature Review

Inquiry-based learning

In recent years, inquiry-based learning has become the focus of research in the field of education (Kurtén & Henriksson, 2021). Inquiry-based learning has been defined in terms of a variety of instructional methods that can promote learning through student-centered investigations of questions and problem-solving (Aditomo et al., 2013). Inquiry-based learning is a student-driven learning method that emphasizes practice, inquiry, and innovation (Kamarudin et al., 2024; Rönnebeck et al., 2016). Inquiry-based learning enables students to draw themes from various subject areas or real life, actively collect and process information, communicate with their peers, and learn by doing with the goals of acquiring knowledge, improving abilities, and developing a creative spirit (Bevins & Price, 2016; Lazonder & Harmsen, 2016). Typically, inquiry-based learning includes four stages, namely, orientation, conceptualization, investigation, and conclusion (Pedaste et al., 2015).

Inquiry-based learning is rooted in constructivism learning theory and discovery learning theory. Constructivism learning theory emphasizes learners' active construction and dynamic generation of knowledge (Andrini, 2016). Discovery learning theory posits that learners acquire knowledge through their own inquiry and discovery (Balm, 2009). Furthermore, previous studies have proposed different inquiry-based learning models. For instance, Bybee et al. (2006)

introduced a 5E inquiry-based learning cycle model consisting of five phases, namely, engagement, exploration, explanation, elaboration, and evaluation. Chen (2022) introduced a POED (predict-observe-explain-demonstrate) model in the context of scientific inquiry learning, which is an extension of the POE model and provides a new perspective for science educators.

Inquiry-based learning has been widely used in science education and achieved positive results. For instance, Razaq et al. (2020) applied inquiry-based learning to mathematics and reported that this approach improved high school students' mathematics learning performance and learning motivation. Rodríguez-Martínez et al. (2023) used an intelligent agent system to guide learners' inquiry-based science learning, thereby improving their learning achievements and attitudes. Although various kinds of technologies can help promote inquiry-based learning, only limited research has investigated the overall effects of intelligent feedback on inquiry-based science learning achievements and perceptions.

Intelligent Feedback

Intelligent feedback is a type of feedback that is generated with the aid of natural language processing technology (Golonka et al., 2014). Intelligent feedback focuses on using advanced technologies such as artificial intelligence technology to provide information regarding one's understanding or performance (Biswas & Bhattacharya, 2024; Hattie & Timperley, 2007). The benefits of intelligent feedback lie in its ability to provide customized feedback and suggestions after processing and analyzing a large amount of data (Yang et al., 2024). Intelligent feedback can improve learning efficiency and effectiveness more than can traditional manual feedback (Sun et al., 2019). Intelligent feedback has also been reported to be helpful with regard to enhancing learning engagement. For instance, Sun et al. (2019) reported that the combined use of intelligent encouragement and warning feedback can improve students' interest and engagement.

Intelligent feedback has been widely used in inquiry-based science learning. For instance, Chou et al. (2022) applied intelligent feedback in the context of physics inquiry-based learning by providing students with corrective feedback and reported that intelligent feedback can significantly improve students' learning achievements. Fang et al. (2023) provided students with a self-regulated learning system involving intelligent feedback in the context of science, technology, engineering, and mathematics (STEM) education and reported that intelligent feedback can significantly improve their STEM skills. Drissi et al. (2024) examined the effects of intelligent feedback on students' learning outcomes and reported that intelligent feedback can improve students' learning motivation and learning achievements.

Nevertheless, studies on the comprehensive effects of intelligent feedback on learning achievements and learning perceptions remain scarce.

Previous Reviews and Meta-Analyses

Various descriptions of efforts to adopt inquiry-based learning have been provided by previous reviews and meta-analyses. For instance, Pedaste et al. (2015) conducted a literature review with the goal of summarizing the core characteristics of inquiry-based learning and identified five inquiry phases. Lazonder and Harmsen (2016) used a meta-analytical approach to examine the effectiveness of guidance in inquiry-based learning and reported that guidance has significant positive impacts on inquiry-based learning activities, performance success, and learning outcomes. Herranen and Aksela (2019) systematically reviewed students' questions in the context of inquiry-based learning and proposed an inquiry model based on these questions. Liu et al. (2021) conducted a systematic literature review of 31 empirical studies with the goal of investigating mobile technology-supported inquiry-based learning, revealing that most such studies have focused on open and guided inquiry. Urdanivia Alarcon et al. (2023) systematically reviewed the literature on inquiry-based learning and teaching and concluded that teachers must master various strategies that can be used to implement open inquiry-based learning. Vo and Simmie (2024) examined scientific inquiry assessment trends and techniques on the basis of a review of studies conducted from 2000 to 2024 and reported that performance assessments and independent tests have been the most frequently used methods in this context.

In addition, previous studies have focused mainly on adaptive feedback, automatic feedback, and personalized feedback. For instance, Bimba et al. (2017) reviewed adaptive feedback in computer-based learning environments and divided feedback implementations into different categories. Deeva et al. (2021) reviewed 109 automated feedback systems and developed a new classification framework for automatic feedback systems. Cavalcanti et al. (2021) reviewed automatic feedback in online learning environments and reported that automatic feedback can improve student performance. Maier and Klotz (2022) revealed that most studies on this topic have provided personalized feedback on the basis of students' behavioral data and present knowledge levels on the basis of a review of 39 studies. However, very few studies have conducted systematic meta-analyses of intelligent feedback in inquiry-based science learning.

Research Gaps

Although previous studies have analyzed and evaluated various techniques for providing intelligent feedback

(Rodríguez-Martínez et al., 2023; Song and Kim, 2021; Zacharia, 2015), these studies have exhibited several shortcomings. First, systematic meta-analyses that contain comprehensive examinations of the impacts of intelligent feedback on learning achievements in inquiry-based science learning from 2013 to 2023 remain lacking. Second, systematic meta-analyses of the overall impact of intelligent feedback on learning perceptions in the context of inquiry-based learning from 2013 to 2023 remain scarce. Third, studies regarding the influence of different moderators on the effects of intelligent feedback in the context of inquiry-based learning remain lacking. Finally, studies concerning how intelligent feedback can be integrated into inquiry-based learning with the goal of maximizing learning performance have been very limited. The present study was designed to bridge these research gaps and address the following research questions on the basis of a systematic meta-analysis:

RQ1: What are the comprehensive impacts of intelligent feedback on both learning achievements and learning perceptions in inquiry-based science learning?

RQ2: How do diverse moderating variables influence the efficacy of intelligent feedback in inquiry-based science learning?

Methodology

The present study was performed on the basis of the preferred reporting items for systematic reviews and meta-analyses (PRISMA) specification and statement (Page et al., 2021). The following section describes the data sources, screening criteria, coding scheme, and method for calculating effect sizes used in this research.

Data Sources

The data used in this study were obtained from high-quality databases, including Scopus, Web of Science, Eric, and Google Scholar. Three groups of keywords were used in the searches: (1) keywords related to inquiry-based learning, including “inquiry-based learning,” “inquiry experiments,” “science inquiry,” “science inquiry learning,” and “educational inquiry experiments”; (2) keywords related to intelligent feedback, including “automatic feedback,” “intelligent feedback,” “intelligent feedback tools,” and “intelligent feedback technology”; and (3) keywords related to learning achievements and learning perceptions, including “learning achievement,” “learning outcome,” “achievement,” “outcome,” “learning performance,” “academic achievement,” “academic performance,” “learning perception,” “perception,” “learning experiences,” “learning attitude,” “learning motivation,” and satisfaction. The Boolean operator “AND”

was used to combine several groups of keywords, whereas the operator “OR” was employed to connect several sets of keywords.

Screening Criteria

In line with the PRISMA screening process and the corresponding criteria, the first round of the search yielded 8947 journal articles from the Web of Science, 7822 articles from Scopus, 198 articles from Eric, and 2980 articles from Google Scholar; these articles were published from 2013 to 2023. The inclusion and exclusion criteria used in this research are as follows.

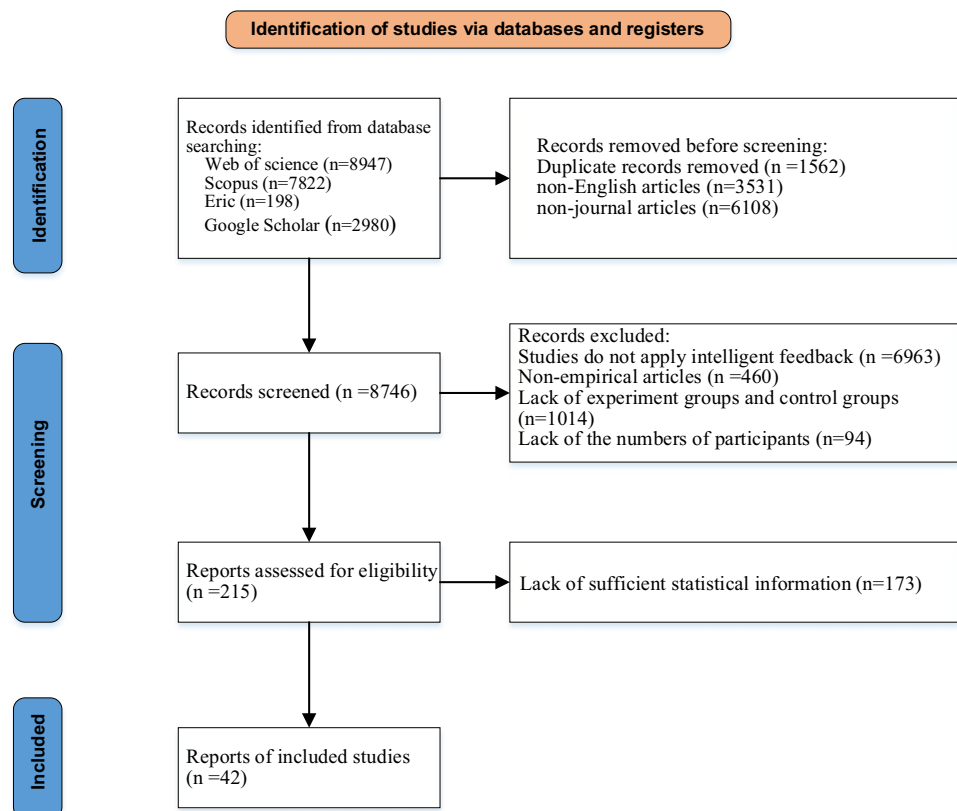
1. Only journal articles published in English were included. News, conference papers, book reviews, editorials, and abstracts were excluded.
2. The research topic of the articles were required to be related to inquiry-based science learning and intelligent feedback.
3. The studies were required to apply intelligent feedback technology to the task of facilitating inquiry-based science learning.
4. The articles were required to report empirical studies that included both control and experimental groups, in which context the experimental group received an inter-

vention involving intelligent feedback, while the control group received conventional methods that lacked intelligent feedback.

5. The studies were required to include both pretests and posttests and to report the learning achievements and learning perceptions of both the experimental and control groups.
6. The articles were required to provide complete data that could be used to estimate the effect size, such as means, standard deviation, t values or p values, as well as the number of participants.

On the basis of these screening criteria, 3531 non-English articles, 6108 nonjournal articles, and 1562 duplicate articles were excluded. Among the remaining articles, the research topics of 6963 articles were irrelevant to intelligent feedback. In total, 1014 articles did not include both experimental and control groups. Furthermore, a total of 460 articles did not involve empirical studies. A total of 94 articles did not report the number of participants. In total, 173 articles did not report complete data that could be used to calculate effect sizes. Finally, 42 articles that featured 4554 participants were included in the current study, as illustrated in Fig. 1. The Appendix presents a list of the 42 articles thus selected.

Fig. 1 Search processes and results



Coding Scheme

To examine the impacts of intelligent feedback on learning achievements and learning perceptions in inquiry-based science learning, a specific coding scheme was adapted from Zheng et al. (2023) and Deeva et al. (2021). The coding scheme included 14 moderators (see Table 1). The five methodological moderators included sample level, sample size, research design, learning settings, and types of organization. The nine substantive feature moderators included the type of feedback, feedback timing, feedback techniques, the adaptability of feedback, feedback generation models, the data sources used to provide feedback, technical ways of providing feedback, control over feedback, and the purpose of the feedback. We selected these moderators for several reasons. First, previous studies have reported that sample level (Fleckenstein et al., 2023), sample size (Jongsma et al., 2023), research design (Lv et al., 2021), learning setting (Cai et al., 2023), and type of organization (Jongsma et al., 2023) impact the effectiveness of feedback. Second, the types of feedback (Cen & Zheng, 2024), feedback timing (Cornide-Reyes et al., 2020), feedback techniques (Liao et al., 2024), adaptability of feedback (Cai et al., 2023), feedback generation models (Deeva et al., 2021), data sources used to provide feedback (Shi & Aryadoust, 2024), technical ways of providing feedback (Deeva et al., 2021), control over feedback (Deeva et al., 2021), and the purpose of the feedback (Cavalcanti et al., 2021) have been shown to influence the efficacy of such feedback. Therefore, these 14 moderators are crucial and necessary for this attempt to understand and examine the impacts of intelligent feedback on learning achievements and learning perceptions. Furthermore, all 42 articles included in this research were analyzed independently by two coders. Divergence was resolved through face-to-face discussions. The interrater reliability, which was calculated via the kappa value, achieved a value of 0.865, thus indicating a high degree of reliability.

Effect Size Calculation

The effect size is an indicator that measures the size of the experimental effect, and commonly used measures of effect size include Cohen's d and Hedges' g (Borenstein et al., 2011). This study strictly followed the five steps proposed by Borenstein et al. (2011) to measure the effect sizes accurately by reference to Hedges' g . The first step involved computing the effect size for each study. In the second step, Hedges' g method was used to compute the total weighted effect size. In the third step, the confidence interval of the average effect size was determined with the help of the random effects model. In the fourth step, the Q_B value was used to explore the influence of various moderators on the effect size. In the fifth step, Rosenthal's fail-safe N method (Rosenthal, 1979)

and Orwin's fail-safe N method (Orwin, 1983) were used to test publication bias. If the fail-safe N value is greater than $5k + 10$ (where k refers to the number of studies), unpublished studies have little effect on the effect size.

Results

Descriptive Information

Table 2 presents descriptive information regarding the 42 selected articles. The findings revealed that higher education accounted for the highest percentage among the four sample levels. Furthermore, most of the studies selected 51–100 participants to test the effects of intelligent feedback in inquiry-based learning. Most of the studies used quasi-experimental designs to test the effects of intelligent feedback. Blended learning or flipped classroom learning settings were investigated in most studies. Most of the studies implemented intelligent feedback interventions at the individual level. In terms of the types of feedback, mixed types of feedback were the most prevalent, and the feedback often included multiple pieces of information. With respect to feedback timing, most studies provided real-time feedback to learners. With respect to feedback techniques, most studies implemented intelligent feedback via online inquiry-based learning platforms. The dominance of student adaptation in terms of adaptability of feedback suggested that practitioners were more inclined to consider student adaptations in the process of generating feedback. In addition, most feedback systems focused on data-driven feedback and relied more heavily on students' behavioral data to generate feedback. Feedback systems more frequently took the form of plug-ins for learning platforms or other tools. Furthermore, a lack of feedback control on the part of learners was often present in these studies; that is, the learners did not have many choices regarding the ways in which feedback was received or selected. Moreover, feedback serves multiple purposes, such as providing evaluations, advice or guidance to learners or motivating them. The appendix presents the 42 articles selected for this research.

RQ1: Overall Sizes of the Effects on Learning Achievements and Learning Perceptions

According to the merged effect sizes pertaining to the random effects model (as presented in Table 3), the overall effect of intelligent feedback on learning achievements reached 0.706, thus indicating a positive and substantial impact. The 95% confidence interval was 0.536–0.875. The heterogeneity test results revealed heterogeneity in terms of the effect size ($Q_{\text{total}} = 336.702$, $z = 8.159$, $p < 0.001$). Therefore, this study revealed that intelligent feedback in

Table 1 Coding scheme

Variables	Category
Sample levels	<ol style="list-style-type: none"> 1. Elementary school 2. Junior and senior high school 3. Higher education 4. Mixed
Sample size	<ol style="list-style-type: none"> 1. 1–50 2. 51–100 3. More than 100
Research design	<ol style="list-style-type: none"> 1. True experimental design 2. Quasiexperimental design
Learning settings	<ol style="list-style-type: none"> 1. Laboratory 2. Classroom 3. Distance/online learning settings 4. Blended/flipped classroom 5. Outdoor
Types of organization used in the treatment	<ol style="list-style-type: none"> 1. Individual 2. Group
Types of feedback	<ol style="list-style-type: none"> 1. Corrective feedback 2. Suggestive feedback 3. Informative feedback 4. Motivational feedback 5. Mixed
Feedback timing	<ol style="list-style-type: none"> 1. Real-time feedback 2. Delayed feedback 3. Mixed
Feedback technique	<ol style="list-style-type: none"> 1. Online inquiry learning platform 2. Intelligent agent system or artificial intelligence (AI) technology 3. Augmented reality (AR) or virtual reality (VR) 4. Mobile software 5. Mixed
Adaptability of feedback	<ol style="list-style-type: none"> 1. Student-adaptive 2. Nonadaptive
Feedback generation model	<ol style="list-style-type: none"> 1. Data-driven 2. Expert-driven 3. Mixed
Data source used to provide feedback	<ol style="list-style-type: none"> 1. Learning achievements 2. Behavior data 3. Mixed
Technical ways of providing feedback	<ol style="list-style-type: none"> 1. Standalone 2. Plug-in
Control of feedback	<ol style="list-style-type: none"> 1. Lack of control over feedback 2. Moderate control over feedback 3. Strong control over feedback
Purpose of feedback	<ol style="list-style-type: none"> 1. Provide evaluation results 2. Provide advice and guidance 3. Provide recommendations 4. Stimulate learning motivation and enthusiasm 5. Mixed

Table 2 Categories and proportions of the 42 articles included in this research

Variable	Category	No. of studies	Proportion of studies
Sample levels	1. Elementary school	13	0.31
	2. Junior and senior high school	12	0.29
	3. Higher education	16	0.38
	4. Mixed	1	0.02
Sample size	1. 1–50	6	0.14
	2. 51–100	21	0.50
	3. More than 100	15	0.36
Research design	1. True experimental design	6	0.14
	2. Quasi-experimental design	36	0.86
Learning settings	1. Laboratory	6	0.14
	2. Classroom	13	0.31
	3. Distance/online learning settings	6	0.14
	4. Blended/flipped classroom	16	0.38
	5. Outdoor	1	0.02
Types of organization used in the treatment	1. Individual	33	0.79
	2. Group	9	0.21
Types of feedback	1. Corrective feedback	4	0.10
	2. Suggestive feedback	3	0.07
	3. Informative feedback	9	0.21
	4. Motivational feedback	3	0.07
	5. Mixed	23	0.55
Feedback timing	1. Real-time feedback	37	0.88
	2. Delayed feedback	2	0.05
	3. Mixed	3	0.07
Feedback technique	1. Online inquiry learning platform	28	0.67
	2. Intelligent agent system or artificial intelligence (AI) technology	4	0.10
	3. Augmented reality (AR) or virtual reality (VR)	5	0.12
	4. Mobile software	1	0.02
	5. Mixed	4	0.10
Adaptability of feedback	1. Student-adaptive	30	0.71
	2. Nonadaptive	12	0.29
Feedback generation model	1. Data-driven	37	0.88
	2. Expert-driven	1	0.02
	3. Mixed	4	0.10
Data source used to provide feedback	1. Learning achievements	15	0.36
	2. Behavior data	17	0.40
	3. Mixed	10	0.24
Technical ways of providing feedback	1. Standalone	6	0.14
	2. Plug-in	36	0.86
Control of feedback	1. Lack of control over feedback	28	0.67
	2. Moderate control over feedback	12	0.29
	3. Strong control over feedback	2	0.05
Purpose of feedback	1. Provide evaluation results	11	0.26
	2. Provide advice and guidance	3	0.07
	3. Provide recommendations	2	0.05
	4. Stimulate learning motivation and enthusiasm	3	0.07
	5. Mixed	23	0.55

Table 3 Overall effect sizes regarding learning achievements

	K	ES	SE	σ^2	95% CI		Test of mean		Test of heterogeneity		
					Lower	Upper	Z	p	Q	df	p
Fixed	42	0.499	0.029	0.001	0.443	0.556	17.369	0.000	336.702	41	0.000
Random	42	0.706	0.087	0.007	0.536	0.875	8.159	0.000			

ES, effect size; CI, confidence interval; SE, standard error; df, degrees of freedom

inquiry-based science learning had a moderate positive effect on students' learning achievements. These findings indicate that the use of intelligent feedback to facilitate inquiry-based science learning can help improve learning achievements. The appendix (as shown in Table 8) presents the effect sizes reported in the 42 selected articles.

According to the merged effect sizes pertaining to the random effects model (as presented in Table 4), the overall size of the effect on learning perceptions reached 0.641, thus indicating a moderate positive impact. The 95% confidence interval was 0.467–0.814. The results of the heterogeneity test revealed heterogeneity in the effect size ($Q_{\text{total}} = 124.065$, $z = 7.244$, $p < 0.001$). Therefore, this study revealed that intelligent feedback in inquiry-based science learning had a moderate positive effect on students' learning perceptions. The use of intelligent feedback to facilitate inquiry-based science learning was helpful with regard to promoting students' learning perceptions.

RQ2: Effect Sizes Pertaining to Learning Achievements According to the Moderators

This study analyzed the ways in which intelligent feedback was moderated by 14 variables. Table 5 presents the results concerning these 14 moderators with respect to learning achievements. At the sample level, the effect size was greater in higher education than in primary school and junior or senior high school. In addition, the results revealed substantial differences in effect size across different sample levels ($Q_B = 9.852$, $df = 3$, $p = 0.020$). Therefore, the sample level had a significant positive effect on intelligent feedback in inquiry-based science learning.

With respect to sample size, a sample size of 1–50 was associated with the largest effect size, while a sample size of more than 100 was associated with the smallest effect size. However, no significant differences were observed based on sample size ($Q_B = 4.535$, $df = 2$, $p = 0.104$). In terms of

research design, the quasiexperimental design entailed a greater effect size than did the true experimental design. No substantial differences in effect size were observed across different research designs ($Q_B = 2.528$, $df = 1$, $p = 0.112$).

With respect to learning settings, the results revealed a greater effect size in online learning settings than in other learning settings, although no significant differences in effect size were observed across learning settings ($Q_B = 2.443$, $df = 4$, $p = 0.655$). Concerning the types of organization used in the treatment, the results revealed that the implementation of intelligent feedback in a group setting entail a greater effect size than did targeting individuals, but no significant differences in effect size were observed in this context ($Q_B = 0.627$, $df = 1$, $p = 0.429$).

In terms of feedback type, no significant differences were observed in effect size across different types of feedback ($Q_B = 0.401$, $df = 4$, $p = 0.982$). Furthermore, real-time feedback was associated with a greater effect size than was delayed feedback. Significant differences were observed among the different feedback timings ($Q_B = 9.330$, $df = 2$, $p = 0.009$).

The results demonstrated that the hybrid feedback technique were associated with the largest effect size, and significant differences were observed across the different feedback techniques ($Q_B = 14.333$, $df = 4$, $p = 0.006$). With respect to feedback adaptations, although feedback based on student adaptations entailed a greater effect size than did nonadaptive feedback, no significant differences were observed among the different feedback adaptation styles ($Q_B = 2.587$, $df = 1$, $p = 0.108$).

The findings revealed that both data-driven feedback and expert-driven feedback achieved the highest effect sizes, but no significant differences were observed among the different feedback generation models ($Q_B = 1.300$, $df = 2$, $p = 0.522$). With regard to the data sources used to provide feedback, the behavioral data were associated with larger effect sizes than were the other data sources. These results revealed

Table 4 Overall effect sizes regarding learning perceptions

	K	ES	SE	σ^2	95% CI		Test of mean		Test of heterogeneity		
					Lower	Upper	Z	p	Q	df	p
Fixed	20	0.522	0.033	0.001	0.457	0.586	15.820	0.000	124.065	19	0.000
Random	20	0.641	0.088	0.008	0.467	0.814	7.244	0.000			

ES, effect size; CI, confidence interval; SE, standard error; df, degrees of freedom

Table 5 Results regarding the moderators

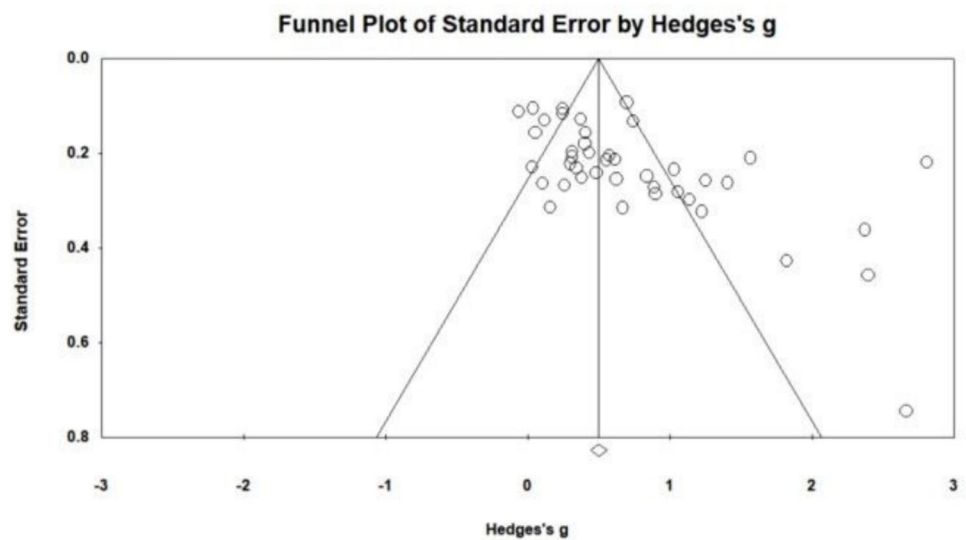
Categories	<i>k</i>	<i>g</i>	<i>z</i>	95% CI	Q_B	<i>df</i>
Sample levels					9.852*	3
1. Elementary school	13	0.454	5.620***	[0.296, 0.612]		
2. Junior and senior high school	12	0.604	4.663***	[0.350, 0.858]		
3. Higher education	16	1.027	5.637***	[0.670, 1.384]		
4. Mixed	1	0.312	1.586	[−0.074, 0.698]		
Sample size					4.535	2
1. 1–50	6	1.379	3.719***	[0.652, 2.105]		
2. 51–100	21	0.700	6.789***	[0.498, 0.902]		
3. More than 100	15	0.545	3.912***	[0.272, 0.818]		
Research design					2.528	1
1. True experimental design	6	0.439	2.553*	[0.102, 0.777]		
2. Quasi-experimental design	36	0.754	7.744***	[0.563, 0.944]		
Learning settings					2.443	4
1. Laboratory	6	0.653	4.122***	[0.343, 0.964]		
2. Classroom	13	0.753	5.735***	[0.495, 1.010]		
3. Distance/online learning settings	6	0.872	3.316**	[0.357, 1.388]		
4. Blended/flipped classroom	16	0.640	3.932***	[0.321, 0.959]		
5. Outdoor	1	0.433	2.165*	[0.041, 0.824]		
Types of organization used in the treatment					0.627	1
1. Individual	33	0.648	7.676***	[0.482, 0.813]		
2. Group	9	0.871	3.236**	[0.343, 1.398]		
Types of feedback					0.401	4
1. Corrective feedback	4	0.791	1.653	[−0.147, 1.728]		
2. Suggestive feedback	3	0.776	1.739	[−0.099, 1.651]		
3. Informative feedback	9	0.656	5.619***	[0.428, 0.885]		
4. Motivational feedback	3	0.821	2.529*	[0.185, 1.457]		
5. Mixed	23	0.647	6.524***	[0.452, 0.841]		
Feedback timing					9.330**	2
1. Real-time feedback	37	0.770	7.442***	[0.567, 0.973]		
2. Delayed feedback	2	0.248	1.728	[−0.033, 0.528]		
3. Mixed	3	0.442	2.546*	[0.102, 0.783]		
Feedback technique					14.333**	4
1. Online inquiry learning platform	28	0.574	6.898***	[0.411, 0.737]		
2. Intelligent agent system or artificial intelligence (AI) technology	4	0.905	3.126**	[0.338, 1.473]		
3. Augmented reality (AR) or virtual reality (VR)	5	0.429	3.727***	[0.204, 0.655]		
4. Mobile software	1	1.409	5.360***	[0.894, 1.924]		
5. Mixed	4	1.434	2.080*	[0.083, 2.785]		
Adaptability of feedback					2.587	1
1. Student-adaptive	30	0.786	7.226***	[0.572, 0.999]		
2. Nonadaptive	12	0.513	3.936***	[0.257, 0.768]		
Feedback generation model					1.300	2
1. Data-driven	37	0.644	8.193***	[0.490, 0.798]		
2. Expert-driven	1	0.484	1.998*	[0.009, 0.959]		
3. Mixed	4	1.150	2.118*	[0.086, 2.215]		
Data source used to provide feedback					1.349	2
1. Learning achievements	15	0.708	4.038***	[0.364, 1.044]		
2. Behavior data	17	0.776	5.680***	[0.508, 1.044]		
3. Mixed	10	0.564	4.457***	[0.316, 0.812]		
Technical ways of providing feedback					2.518	1
1. Standalone	6	0.503	4.348***	[0.276, 0.730]		

Table 5 (continued)

Categories	<i>k</i>	<i>g</i>	<i>z</i>	95% CI	Q_B	<i>df</i>
2. Plug-in	36	0.743	7.644***	[0.552, 0.933]	15.867***	2
Control of feedback						
1. Lack of control over feedback	28	0.643	5.878***	[0.428, 0.857]		
2. Moderate control over feedback	12	0.969	5.665***	[0.634, 1.305]		
3. Strong control over feedback	2	0.245	2.486*	[0.052, 0.439]		
Purpose of feedback					1.331	4
1. Provide evaluation results	11	0.661	3.111**	[0.245, 1.078]		
2. Provide advice and guidance	3	0.776	1.739	[−0.099, 1.651]		
3. Provide recommendations	2	1.208	2.260*	[0.160, 2.255]		
4. Stimulate learning motivation and enthusiasm	3	0.821	2.529*	[0.185, 1.457]		
5. Mixed	23	0.647	6.524***	[0.452, 0.841]		

* $p < .05$; ** $p < .01$; *** $p < .001$

Fig. 2 Funnel plot by effect size



no significant differences across different data sources ($Q_B = 1.349$, $df = 2$, $p = 0.510$).

In terms of the technical methods used to provide feedback, plug-in technology entailed a greater effect size than did standalone methods. No substantial differences in effect size were observed across different technical methods ($Q_B = 2.518$, $df = 1$, $p = 0.113$). In terms of learner control over feedback, moderate control over feedback was associated with a greater effect size. The results of the present study revealed significant differences among different degrees of control ($Q_B = 15.867$, $df = 2$, $p = 0.000$). Thus, the degree of learner control over feedback had a positive effect on intelligent feedback. Moreover, no significant differences were observed in effect size due to the purpose of feedback ($Q_B = 1.331$, $df = 4$, $p = 0.856$).

Publication Bias

This study used the funnel plot method, Orwin's fail-safe N test, and Rosenthal's fail-safe N test to assess publication

bias comprehensively. A funnel plot of the 42 effect sizes included in this study is illustrated in Fig. 2. The effect sizes of the majority of studies were uniformly and symmetrically distributed on both sides of the average effect value, thus providing a preliminary indication that the possibility of publication bias in this context was relatively small. Moreover, the classic fail-safe N primarily assesses how many unpublished studies are needed to achieve an overall effect value that is not significant with regard to published studies. The measurement standard is $5*n + 10$, where n represents the number of studies included in the meta-analysis, as indicated in Table 6. In this study, this number was 4230, i.e., much greater than 220 ($42*5 + 10$). Table 7 presents the results regarding Orwin's fail-safe N . The results indicated that 2055 missing studies would be needed to decrease Hedges' g to a trivial level. This indicator revealed that the effect size values of unpublished studies had little impact on the overall effect values of the published studies. Thus, according to these three testing methods, the results of the

Table 6 Classic fail-safe N

Items	Value
Z value for observed studies	19.766
p value for observed studies	0.000
Alpha	0.050
Tails	2.000
Z for alpha	1.959
Number of observed studies	42.000
Number of missing studies that would increase the p value to a level $>$ alpha	4230.000

Table 7 Orwin's fail-safe N

Items	Value
Hedges's g in observed studies	0.499
Criterion for a "trivial" Hedges's g	0.010
Mean Hedges's g in missing studies	0.000
Number of missing studies needed to reduce Hedges's g to a level $<$ 0.01	2055.000

meta-analysis were stable, and the phenomenon of publication bias was not obvious in this context.

Discussion

Effects of Intelligent Feedback

The present study revealed that, in comparison with traditional methods, intelligent feedback had moderate impacts on learning achievements and learning perceptions in inquiry-based science learning. Therefore, learners who received intelligent feedback exhibited better learning achievements and learning perceptions than did learners who did not receive intelligent feedback in inquiry-based science learning. The findings further suggested that intelligent feedback in inquiry-based science learning is a promising way of improving learning achievements and developing learners' perceptions. The main reason for this finding is that intelligent feedback provides learners with more opportunities to engage in self-reflection and self-correction, thereby helping improve their science learning performance (Biswas & Bhattacharya, 2024). In addition, learning environments that offer intelligent feedback could increase learners' interest in learning and enable them to learn in a fully enjoyable and engaging state (Herbert et al., 2018). Learners can receive intelligent feedback immediately after providing responses, thus promoting their self-regulation and positive learning perceptions (Afzaal et al., 2024).

Moderator Analysis

The current study revealed substantial difference in effect size across diverse sample levels. Higher levels of education were associated with the strongest effects at all sample levels. This result could be explained by the fact that individual differences may influence learners' acceptance of and responses to intelligent feedback, thereby impacting their learning outcomes (Mertens et al., 2022). Younger learners may process feedback differently than do undergraduate students or adults (Swart et al., 2019).

The results indicated no significant differences among the various sample sizes. Therefore, the effect of intelligent feedback was relatively stable and not dependent on sample size. In addition, a small sample size was associated with a larger effect size than was a large sample size. A possible reason for this finding is that a small sample size produced fewer sources of variation than did a large sample size (Slavin & Smith, 2009).

With respect to the research design, no substantial differences in effect size were observed between the quasi-experimental design and the true experimental design. However, the quasi-experimental design was associated with a greater effect size than was the true experimental design. This result can be explained by the fact that quasi-experimental designs are more flexible than are true experimental designs; furthermore, the former can be used to examine the effectiveness of independent variables under natural conditions, thereby decreasing threats to the validity of such research (Singh, 2021).

With respect to learning settings, the present study demonstrated that online learning settings were associated with a larger effect size than were other learning settings. No substantial differences in effect size were observed across different learning settings. The primary reason for these findings might be the fact that online learning environments allow students to learn anywhere and anytime, thus enabling them to improve their learning performance by integrating science information with thinking skills in the context of online inquiry-based learning (Jha et al., 2024).

In terms of organization type, the results revealed that when intelligent feedback was provided in groups, it was associated with a larger effect size. However, no substantial differences in effect size were observed depending on whether intelligent feedback was provided to groups or individuals. Therefore, intelligent feedback can be provided at either the group or individual level.

This study revealed no noteworthy differences in effect size among several types of feedback. Thus corrective feedback, suggestive feedback, informative feedback, motivational feedback, or mixed feedback could be provided depending on learners' needs.

With respect to feedback timing, the present study revealed significant differences in effect sizes between different such timings. Real-time feedback was associated with a greater effect size than was delayed feedback. This conclusion is corroborated by the findings of Fleckenstein et al. (2023), who reported that timely feedback can promote learning outcomes in educational settings very effectively.

With respect to feedback techniques, the current study demonstrated that hybrid feedback techniques yielded the highest effect size, and noteworthy differences were observed among the different feedback techniques. This result can be attributed to the fact that the use of mixed feedback techniques can produce a synthesis of the benefits of online inquiry learning platforms, intelligent agent systems or artificial intelligence technologies, augmented reality, virtual reality, and mobile applications. The employment of a variety of feedback techniques can offer learners more comprehensive and multifaceted feedback (Martin, 2020), thus helping improve their learning achievements and learning perceptions.

The current study revealed no significant differences in effect size between adaptive feedback and nonadaptive feedback. However, adaptive feedback was associated with a greater effect size than was nonadaptive feedback. The primary reason for this finding is that adaptive feedback can be adjusted to suit the learner's performance and needs, facilitate the learner's understanding of subject knowledge (Sailer et al., 2023), and enable the learner to monitor and regulate their learning processes (Mejeh et al., 2024). Colliot et al. (2024) also suggested that adaptive feedback can help improve learning performance.

The present study revealed no substantial differences in effect size among the three types of feedback generation models. Both data-driven feedback and expert-driven feedback achieved the highest effect sizes. The main reason for this finding is that expert-driven feedback can provide a useful structure for learners (Kroeze et al., 2021), while data-driven feedback can help students self-regulate their learning and improves their learning achievements (Afzaal et al., 2021). Therefore, the integration of data-driven feedback and expert-driven feedback could lead to the best effect. In addition, this study revealed no substantial differences in effect size across different data sources. Therefore, researchers and practitioners should select different data sources when providing intelligent feedback to learners.

In terms of the technical methods used to provide feedback, plug-in technologies were associated with a greater effect size than were standalone technologies. Moreover, no significant differences were observed between these two methods. This finding may be due to the fact that intelligent feedback based on plug-in technologies is more flexible, scalable, and customizable than is stand-alone intelligent feedback (He et al., 2014). Therefore, the integration of plug-in technologies into inquiry-based learning systems with the goals of increasing feedback and enhancing personalized recommendations

or intelligent questions and answers (and thus meeting the diverse learning needs of learners) is recommended.

Furthermore, noteworthy differences in effect size were observed among different degrees of control over feedback. Moderate control over feedback was associated with the greatest effect size. This finding implies that learners have a certain degree of autonomy with respect to adjusting their learning strategies and progress when they receive feedback. Deeva et al. (2021) reported that allowing students to adjust feedback delivery according to their own preferences and needs can promote the most effective feedback. Therefore, learners should be empowered to select whether they want to view the feedback, and they should be able to adjust the feedback when feedback mechanisms are designed.

Finally, the effect size did not differ considerably due to the purpose of the feedback. This finding might suggest that intelligent feedback systems could be effective for any such purposes, such as providing evaluation results, offering advice and guidance, making recommendations, or stimulating learning motivation and enthusiasm.

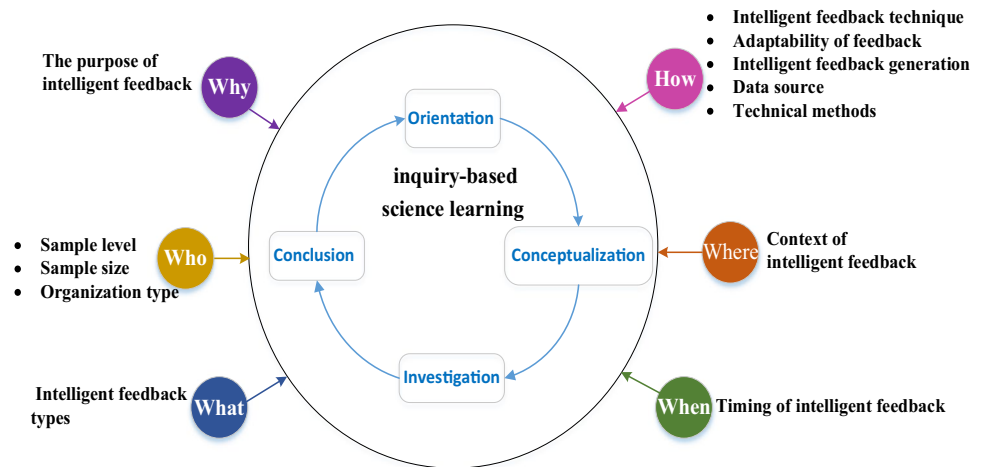
Implications

The results of the current meta-analysis have several implications for practitioners and researchers. First, this study demonstrated that intelligent feedback had significant positive impacts on students' learning achievements and learning perceptions in inquiry-based science learning. Consequently, educators and practitioners should use intelligent feedback to improve students' learning performance in inquiry-based science learning.

Second, the present study indicated that feedback timing, feedback techniques, and control over feedback significantly moderated the effectiveness of such feedback with respect to learning achievements. The timing of feedback is crucial (Cornide-Reyes et al., 2020), and Yang et al. (2024) reported that immediate feedback can help correct learners' mistakes and enhance their self-efficacy and learning performance. In addition, Liao et al. (2024) reported that feedback techniques moderate the relationship between learning motivation and performance. The degree of control over feedback influences learning performance (Deeva et al., 2021). Therefore, the design of these moderators plays a crucial role in the process of increasing the effectiveness of intelligent feedback.

Third, the present study has theoretical implications with regard to inquiry-based science learning. In this study, a "6W" framework for the implementation of intelligent feedback-supported inquiry-based science learning was proposed, as illustrated in Fig. 3. The proposed framework included six crucial elements, namely, "why, who, what, when, where, and how". First, the purpose of intelligent feedback should be considered carefully, as this purpose determines how the feedback should be provided. Feedback is provided with the aim of evaluating, advising, guiding, recommending, or stimulating learning

Fig. 3 The 6W framework for intelligent feedback-supported inquiry-based science learning



motivation, and enthusiasm. Second, the users of intelligent feedback should be considered in advance, and particular consideration should be given to learners' interactions with intelligent feedback, which are important with respect to their learning performance. The sample level, sample size, and organization type are vital with regard to the effectiveness of intelligent feedback. Third, the type of intelligent feedback provided to learners is very important. The various types of intelligent feedback include corrective feedback, suggestive feedback, informative feedback, motivational feedback, and mixed feedback. Fourth, the timing of the provision of intelligent feedback is crucial. Feedback can be provided in real time or delayed. Fifth, the context of intelligent feedback should be considered in advance. Such contexts include laboratories, classrooms, online learning, blended learning, and outdoor settings. Finally, the manner in which intelligent feedback is provided has important impacts on the effects of such feedback. The feedback technique, adaptability of feedback, feedback generation model, data sources used for the feedback thus provided, and technical methods used to provide feedback should be designed carefully. Overall, the framework proposed in this research not only contributes to our understanding of the effects of intelligent feedback on inquiry-based science learning but also explains how intelligent feedback should be designed and applied with the goal of promoting inquiry-based science learning.

Limitations and Directions for Future Research

Although the findings of this study have significant potential to shape the future implementation of intelligent feedback in inquiry-based learning, some limitations of the current study limit the generalizability of its conclusions. First, only 42 articles met the criteria for inclusion in this study after full-text screening. Therefore, further research should broaden the data sources used in such analysis to obtain a more comprehensive understanding of the effects of intelligent feedback on inquiry-based science learning. Second, this study examined the impacts of 14

moderators on the effectiveness of intelligent feedback. Future research should examine the impacts of additional moderators on intelligent feedback in inquiry-based science learning.

Conclusions

The present study provided substantial evidence regarding the positive effects of intelligent feedback and highlighted the diverse variables that moderate the effectiveness of intelligent feedback in inquiry-based science learning. This study revealed that intelligent feedback had moderate impacts on learning achievements and learning perceptions. Additionally, the sample level, feedback technique, feedback time, and control over feedback significantly moderated the effect of intelligent feedback. The use of a combination of multiple feedback technologies achieved better results than did the use of a single feedback technology. Real-time feedback was more effective than delayed feedback. Moderating students' control over feedback led to better learning achievements.

The main contributions of this study are twofold. One contribution of this research lies in the fact that it provides solid empirical evidence regarding the effectiveness of intelligent feedback in inquiry-based science learning on the basis of a synthesis and analysis of data drawn from 42 articles. Another contribution lies in the fact that identifies the key factors that impact the effectiveness of intelligent feedback, including feedback timing, feedback techniques, and feedback control. Overall, the results of this study can deepen our understanding of intelligent feedback mechanisms in the context of inquiry-based science learning. The present study elucidates how intelligent feedback should be employed (in light of the moderating effects of different variables) to maximize achievements in and perceptions of inquiry-based science learning. The current study thus offers insights to researchers and practitioners regarding how they should design and implement intelligent feedback in inquiry-based science learning efficiently and effectively.

The Appendix

Table 8 The effect size, standard error, and 95% confidence interval of 42 articles

No	Year	Paper title	Journal	Authors	Effect size	Standard error	95% confidence interval
1	2015	Data Driven Automatic Feedback Generation in the iList Intelligent Tutoring System	Tech., Inst., Cognition and Learning	Davide Fossati, Barbara Di Eugenio, Stellan Ohlsson, Christopher Brown, and Lin Chen	7.444	0.094	0.515 0.883
2	2014	BEETLE II: Deep Natural Language Understanding and Automatic Feedback Generation for Intelligent Tutoring in Basic Electricity and Electronics	Artificial Intelligent Education	Myroslava Dzikovska, Natalie Steinhäuser, Elaine Farrow, Johanna Moore, and Gwendolyn Campbell	12.753	0.220	2.378 3.241
3	2016	The evaluation of i-SIDRA—a tool for intelligent feedback—in a course on the anatomy of the locomotor system	International Journal of Medical Informatics	Fernández-Alemán, J. L., Lopez-Gonzalez, L., Gonzalez-Sequeros, O., Jayne, C., López-Jiménez, J. J., & Toval, A	2.572	0.157	0.096 0.714
4	2020	Effects of an Immersive Virtual Reality-Based Classroom on Students' Learning Performance in Science Lessons	British Journal of Educational Technology	Ruixue Liu, Lei Wang, Jing Lei, Qiu Wang, and Youqun Ren	2.863	0.214	0.193 1.033
5	2017	Evaluating an Intelligent Tutoring System for Personalized Math Teaching	International Symposium on Educational Technology	Bilan Zhang, Jiyou Jia	1.342	0.223	-0.138 0.736
6	2013	Fundamentals of the Design and the Operation of an Intelligent Tutoring System for the Learning of the Arithmetical and Algebraic Way of Solving Word Problems	Computers & Education	David Arnau, Miguel Arevalillo-Herráez, Luis Puig, José Antonio González-Calero	4.845	0.258	0.745 1.757
7	2022	The Impacts of Online Skeuomorphic Physics Inquiry-Based Learning With and Without Simulation on 8th Graders' Scientific Inquiry Performance	Journal of Science Education and Technology	Ren-Jye Chou, Chih-Ping Liang, Li-yu Huang, Hsiao-Ching She	0.898	0.130	-0.138 0.373
8	2022	An Integrated Concept Mapping and Image Recognition Approach to Improving Students' Scientific Inquiry Course Performance	British Journal of Educational Technology	Hsiu-Ling Huang, Gwo-Jen Hwang, Pei-Ying Chen	3.758	0.324	0.591 1.859
9	2023	Effects of a Contextualized Reflective Mechanism-Based Augmented Reality Learning Model on Students' Scientific Inquiry Learning Performances, Behavioral Patterns, and Higher Order Thinking	Interactive Learning Environments	Xiao-Fan Lin, Gwo-Jen Hwang, Jing Wang, Yue Zhou, Wenyi Li, Jiachun Liu, Zhong-Mei Liang	4.402	0.235	0.573 1.493

Table 8 (continued)

No	Year	Paper title	Journal	Authors	Effect size	Standard error	95% confidence interval
10	2022	Developing a Cycle-Mode Poed Model and using Scientific Inquiry for a Practice Activity to Improve Students' Learning Motivation, Learning Performance, and Hands-on Ability	Interactive Learning Environments	Jyun-Chen Chen	0.390	0.264	-0.414 0.620
11	2021	Integrating Smartphone-Controlled Paper Airplane Into Gamified Science Inquiry for Junior High School Students	Journal of Educational Computing Research	Mengmeng Cheng, Chien-Yuan, Su Kinshuk	5.360	0.263	0.894 1.924
12	2022	Effects of a BCI-Based AR Inquiring Tool on Primary Students' Science Learning: A Quasi-Experimental Field Study	Journal of Science Education and Technology	Su Cai, Zifeng Liu, Changhao Liu, Haitao Zhou, Jiangxu Li	2.125	0.315	0.052 1.288
13	2016	Computational Scientific Inquiry With Virtual Worlds and Agent-Based Models: New Ways of Doing Science to Learn Science	Interactive Learning Environments	Michael J. Jacobson Charlotte E. Taylor, Deborah Richards	3.151	0.286	0.340 1.460
14	2014	Supporting Scientific Experimentation and Reasoning in Young Elementary School Students	Journal of Science Education and Technology	Keisha Varma	1.499	0.252	-0.116 0.873
15	2023	Effects of Developing Prompt Scaffolding to Support Collaborative Scientific Argumentation in Simulation-Based Physics Learning	Interactive Learning Environments	Fan-Jun Yang, Chien-Yuan Su, Wen-Wen Xu, Yue Hu	0.959	0.268	-0.268 0.782
16	2015	Exploring the Impacts of Cognitive and Metacognitive Prompting on Students' Scientific Inquiry Practices Within an E-Learning Environment	International Journal of Science Education	Wen-Xin Zhang, Ying-Shao Hsu, Chia-Yu Wang, Yu-Ting Ho	3.819	0.298	0.554 1.722
17	2023	Investigating Student-Generated Questioning in a Technology-Enabled Elementary Science Classroom: A Case Study	Education Sciences	Longkai Wu, Yaohuizhuo Liu, Meng-Leong How, Sujin He	1.998	0.242	0.009 0.959
18	2019	Enhancing Digital Simulated Laboratory Assessments: A Test of Pre-Laboratory Activities with the Learning Error and Formative Feedback Model	Journal of Science Education and Technology	Man-Wai Chu, Jacqueline P. Leighton	2.892	0.129	0.121 0.628
19	2016	Designing Automated Guidance for Concept Diagrams in Inquiry Instruction	Journal of Research in Science Teaching	Kihyun Ryoo, Marcia C. Linn	2.116	0.117	0.018 0.476

Table 8 (continued)

No	Year	Paper title	Journal	Authors	Effect size	Standard error	95% confidence interval
20	2018	The Effects of Computer-Supported Self-Regulation in Science Inquiry on Learning Outcomes, Learning Processes, and Self-Efficacy	Educational Technology Research and Development	Chiu-Lin Lai, Gwo-Jen Hwang, Yi-Hsuan Tu	3.745	0.282	0.503 1.609
21	2022	Evaluation of an Inquiry-Based Virtual Lab for Junior High School Science Classes	Journal of Educational Computing Research	Ting-Ling Lai, You-Sheng Lin, Chi-Yin Chou, Hsiu-Ping Yueh	2.583	0.214	0.134 0.974
22	2021	Enhancing Scientific Discovery Learning by Just-in-Time Prompts in a Simulation-Assisted Inquiry Environment	European Journal of Educational Research	Shiva Hajian, Misha Jain, Arita L. Liu, Teeba Obaid, Mari Fukuda, Philip H. Winne, John C. Nesbit	3.580	0.745	1.206 4.126
23	2018	A negotiation-Based Adaptive Learning System for Regulating Help-Seeking Behaviors	Computers & Education	Chih-Yueh Choua, K. Robert Laia, Po-Yao Chaob, Shu-Fen Tsengc, and Ting-Yi Liaa	0.496	0.314	-0.460 0.772
24	2016	A Solution-Based Intelligent Tutoring System Integrated with an Online Game-Based Formative Assessment: Development and Evaluation	Education Tech Research Dev	Danial Hooshyar, Rodina Binti Ahmad, Moslem Yousefi, Moein Fathi, Abbas Abdollahi, Shi-Jinn Horng, Heuiseok Lim	3.276	0.272	0.358 1.424
25	2016	Applying an Online Game-Based Formative Assessment in a Flowchart-Based Intelligent Tutoring System for Improving Problem-Solving Skills	Computers & Education	Danial Hooshyar, Rodina Binti Ahmad, Moslem Yousefi, Moein Fathi, Shi-Jinn Horng, and Heuiseok Lim	6.571	0.362	1.667 3.084
26	2023	Building Personalised Homework from a Learning Analytics Based Formative Assessment: Effect on Fifth-Grade Students' Understanding of Fractions	British Journal of Educational Technology	José Antonio Rodríguez-Martínez, José Antonio González-Calero, Javier del Olmo-Muñoz, David Arnaú, Sergio Tirado-Olivares	1.484	0.209	-0.099 0.719
27	2023	Developing a Gamified Artificial Intelligence Educational Robot to Promote Learning Effectiveness and Behavior in Laboratory Safety Courses for Undergraduate Students	International Journal of Educational Technology in Higher Education	Qi-Fan Yang, Li-Wen Lian and Jia-Hua Zhao	3.372	0.249	0.352 1.329
28	2016	Sensor-Augmented Virtual Labs: Using Physical Interactions with Science Simulations to Promote Understanding of Gas Behavior	Journal of Science Education and Technology	Jie Chao, Jennifer L. Chiu, Crystal J. DeJaegher, Edward A. Pan	4.272	0.427	0.987 2.660
29	2017	Influence of an Integrated Learning Diagnosis and Formative Assessment-Based Personalized Web Learning Approach on Students Learning Performances and Perceptions	Interactive Learning Environments	Charoentai, Wongwatkit, Niwat Srisawasdi, Gwo-Jen Hwang, and Patcharin Panjaburee	2.447	0.255	0.124 1.124

Table 8 (continued)

No	Year	Paper title	Journal	Authors	Effect size	Standard error	95% confidence interval
30	2023	Learning with Digital Technology-Facilitated Empathy: an Augmented Reality Approach to Enhancing Students' Flow Experience, Motivation, and Achievement in a Biology Program	Interactive Learning Environments	Xiao-Ming Wang, Qing-Nan Hu, Gwo-Jen Hwang, and Xiao-Han Yu	0.135	0.230	-0.420 0.482
31	2014	Exploring Feedback and Student Characteristics Relevant for Personalizing Feedback Strategies	Computers & Education	Susanne Narciss, Sergey Sosnovsky, Lenka Schaubert, Eric Andrés, Anja Eichelmann, George Gogvadze, and Erica Melis	1.586	0.197	-0.074 0.698
32	2020	The Effect of Automated Feedback on Revision Behavior and Learning Gains in Formative Assessment of Scientific Argument Writing	Computers & Education	Mengxiao Zhu, Ou Lydia Liu, Hee-Sun Lee	0.342	0.106	-0.171 0.244
33	2023	Informative Feedback and Explainable AI-Based Recommendations to Support Students' Self-regulation	Technology, Knowledge and Learning	Muhammad Afzaal, Aayesha Zia, Jalal Nouri, Uno Fors	2.294	0.106	0.035 0.452
34	2023	Rdsai: An Intelligent Tool for Data Science Assignments	Multimedia Tools and Applications	Pierpaolo Vittorini, Alessandra Galassi	2.787	0.206	0.170 0.978
35	2020	Intelligent Feedback on Hypothesis Testing	International Journal of Artificial Intelligence in Education	Sietske Tacoma, Bastiaan Heeren, Johan Jeuring, and Paul Drijvers	-0.590	0.113	-0.287 0.154
36	2014	Implementation of a Model-Tracing-Based Learning Diagnosis System to Promote Elementary Students' Learning in Mathematics	Educational Technology & Society	Yian-Shu Chu, Haw-Ching Yang, Shian-Shyong Tseng, and Che-Ching Yang	2.232	0.180	0.049 0.756
37	2017	Influences of an Inquiry-Based Ubiquitous Gaming Design on Students' Learning Achievements, Motivation, Behavioral Patterns, and Tendency Towards Critical Thinking and Problem Solving	British Journal of Educational Technology	Gwo-Jen Hwang Chih-Hung Chen	2.165	0.200	0.041 0.824
38	2015	Development of an Inquiry-Based Learning Support System Based on an Intelligent Knowledge Exploration Approach	Educational Technology & Society	Ji-Wei Wu, Judy C. R. Tseng, Gwo-Jen Hwang	5.590	0.133	0.483 1.005
39	2018	SITS: A Solution-Based Intelligent Tutoring System for Students' Acquisition of Problem-Solving Skills in Computer Programming	Innovations in Education and Teaching International	Danial Hooshyar, Rodina Binti Ahmad, Moslem Yousefi, Moein Fathi, Shinn, Horng and Heuiseok Lim	5.245	0.457	1.502 3.295

Table 8 (continued)

No	Year	Paper title	Journal	Authors	Effect size	Standard error	95% confidence interval
40	2023	A Complex Systems Approach to Analyzing Pedagogical Agents' Scaffolding of Self-Regulated Learning Within an Intelligent Tutoring System	Metacognition and Learning	Daryn A. Dever, Nathan A. Sonnenfeld, Megan D. Wiedbusch, S. Grace Schmorrow, Mary Jean Amon, Roger Azevedo	7.454	0.210	1.156 1.980
41	2023	Effect of Augmented Reality-Based Virtual Educational Robotics on Programming Students' Enjoyment of Learning, Computational Thinking Skills, and Academic Achievement	Computers & Education	Fang-Chuan Ou Yang, Hui-Mim Lai, Yen-Wen Wang	1.476	0.231	-0.112 0.795
42	2023	A Concept Mapping-Based Self-Regulated Learning Approach to Promoting Students' Learning Achievement and Self-regulation in STEM Activities	Interactive Learning Environments	Jian-Wen Fang, Li-Yuan He, Gwo-Jen Hwang, Xiu-Wei Zhu, Chu-Nu Bian, and Qing-Ke Fu	0.345	0.157	-0.254 0.363

Author Contribution Lanqin Zheng: conceptualization; methodology; writing original draft; review; editing. Zhe Shi, Zhixiong Fu, Shuqi Liu: data curation; formal analysis; writing original draft. All of the authors have approved this manuscript.

Funding This study is supported by the National Key Research & Development program of China (2023YFC3341200).

Data Availability The data that support the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethical Approval Not applicable.

Research Involving Human Participants and/or Animals Not applicable.

Consent to Participate Not applicable.

Consent for Publication Not applicable.

Informed Consent Not applicable.

Competing Interests The authors declare no competing interests.

References

- Aditomo, A., Goodyear, P., Bliuc, A. M., & Ellis, R. A. (2013). Inquiry-based learning in higher education: Principal forms, educational objectives, and disciplinary variations. *Studies in Higher Education, 38*(9), 1239–1258. <https://doi.org/10.1080/03075079.2011.616584>
- Afzaal, M., Zia, A., Nouri, J., & Fors, U. (2024). Informative feedback and explainable AI-based recommendations to support students' self-regulation. *Technology, Knowledge and Learning, 29*(1), 331–354. <https://doi.org/10.1007/s10758-023-09650-0>
- Andrini, V. S. (2016). The effectiveness of inquiry learning method to enhance students' learning outcome: A theoretical and empirical review. *Journal of Education and Practice, 7*(3), 38–42. <https://files.eric.ed.gov/fulltext/EJ1089825.pdf>
- Balm, A. (2009). The effects of discovery learning on students' success and inquiry learning skills. *Eurasian Journal of Educational Research (EJER), 9*(35), 1–20.
- Bevins, S., & Price, G. (2016). Reconceptualising inquiry in science education. *International Journal of Science Education, 38*(1), 17–29. <https://doi.org/10.1080/09500693.2015.1124300>
- Bimba, A. T., Idris, N., Al-Hunaiyyan, A., Mahmud, R. B., & Shuib, N. L. B. M. (2017). Adaptive feedback in computer-based learning environments: A review. *Adaptive Behavior, 25*(5), 217–234. <https://doi.org/10.1177/1059712317727590>
- Biswas, U., & Bhattacharya, S. (2024). ML-based intelligent real-time feedback system for blended classroom. *Education and Information Technologies, 29*(4), 3923–3951. <https://doi.org/10.1007/s10639-023-11949-5>
- Borenstein, M., Hedges, L. V., Higgins, J. P. T., & Rothstein, H. R. (2011). *Introduction to meta-analysis*. Wiley.
- Bybee, R. W., Taylor, J. A., Gardner, A., Van Scotter, P., Powell, J. C., Westbrook, A., & Landes, N. (2006). The BSCS 5E instructional model: Origins and effectiveness. *Colorado Springs, Co: BSCS, 5*(88–98). <https://fremontmonths.org/ourpages/auto/2008/5/11/1210522036057/bscs5efullreport2006.pdf>

- Cai, Z., Gui, Y., Mao, P., Wang, Z., Hao, X., Fan, X., & Tai, R. H. (2023). The effect of feedback on academic achievement in technology-rich learning environments (TREs): A meta-analytic review. *Educational Research Review*, 39, 100521. <https://doi.org/10.1016/j.edurev.2023.100521>
- Cavalcanti, A. P., Barbosa, A., Carvalho, R., Freitas, F., Tsai, Y. S., Gašević, D., & Mello, R. F. (2021). Automatic feedback in online learning environments: A systematic literature review. *Computers and Education: Artificial Intelligence*, 2, 100027. <https://doi.org/10.1016/j.caeai.2021.100027>
- Cen, Y., & Zheng, Y. (2024). The motivational aspect of feedback: A meta-analysis on the effect of different feedback practices on L2 learners' writing motivation. *Assessing Writing*, 59, 100802. <https://doi.org/10.1016/j.asw.2023.100802>
- Chen, J. C. (2022). Developing a cycle-mode POED model and using scientific inquiry for a practice activity to improve students' learning motivation, learning performance, and hands-on ability. *Interactive Learning Environments*, 30(7), 1252–1264. <https://doi.org/10.1080/10494820.2020.1716023>
- Chen, J., Wang, M., Kirschner, P. A., & Tsai, C. C. (2018). The role of collaboration, computer use, learning environments, and supporting strategies in CSCL: A meta-analysis. *Review of Educational Research*, 88(6), 799–843. <https://doi.org/10.3102/0034654318791584>
- Chou, R. J., Liang, C. P., Huang, L. Y., & She, H. C. (2022). The impacts of online skeuomorphic physics inquiry-based learning with and without simulation on 8th graders' science inquiry performance. *Journal of Science Education and Technology*, 31(3), 357–371. <https://doi.org/10.1007/s10956-022-09960-5>
- Colliot, T., Krichen, O., Girard, N., Anquetil, É., & Jamet, É. (2024). What makes tablet-based learning effective? A study of the role of real-time adaptive feedback. *British Journal of Educational Technology* (pp. 1–18). <https://doi.org/10.1111/bjet.13439>
- Cornide-Reyes, H., Riquelme, F., Monsalves, D., Noel, R., Cechinel, C., Villarreal, R., ... & Munoz, R. (2020). A multimodal real-time feedback platform based on spoken interactions for remote active learning support. *Sensors*, 20(21), 6337. <https://doi.org/10.3390/s20216337>
- Deeva, G., Bogdanova, D., Serral, E., Snoeck, M., & De Weerd, J. (2021). A review of automated feedback systems for learners: Classification framework, challenges and opportunities. *Computers & Education*, 162, 104094. <https://doi.org/10.1016/j.compedu.2020.104094>
- 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. *Education and Information Technologies*, 29, 15463–15500. <https://doi.org/10.1007/s10639-024-12477-6>
- Fang, J. W., He, L. Y., Hwang, G. J., Zhu, X. W., Bian, C. N., & Fu, Q. K. (2023). A concept mapping-based self-regulated learning approach to promoting students' learning achievement and self-regulation in STEM activities. *Interactive Learning Environments*, 31(10), 7159–7181. <https://doi.org/10.1080/10494820.2022.2061013>
- Fernández-Alemán, J. L., Lopez-Gonzalez, L., Gonzalez-Sequeros, O., Jayne, C., López-Jiménez, J. J., & Toval, A. (2016). The evaluation of i-SIDRA—a tool for intelligent feedback—in a course on the anatomy of the locomotor system. *International Journal of Medical Informatics*, 94, 172–181. <https://doi.org/10.1016/j.ijmedinf.2016.07.00>
- Fleckenstein, J., Liebenow, L. W., & Meyer, J. (2023). Automated feedback and writing: A multi-level meta-analysis of effects on students' performance. *Frontiers in Artificial Intelligence*, 6, 1162454. <https://doi.org/10.3389/fraci.2023.1162454>
- Fossati, D., Di Eugenio, B., Ohlsson, S. T. E. L. A. N., Brown, C., & Chen, L. (2015). Data driven automatic feedback generation in the iList intelligent tutoring system. *Technology, Instruction, Cognition and Learning*, 10(1), 5–26. <https://www.oldcitypublishing.com/wp-content/uploads/2016/02/TICLv10n1p5-26Fossati.pdf>
- Golonka, E. M., Bowles, A. R., Frank, V. M., Richardson, D. L., & Freynik, S. (2014). Technologies for foreign language learning: A review of technology types and their effectiveness. *Computer Assisted Language Learning*, 27(1), 70–105. <https://doi.org/10.1080/09588221.2012.700315>
- Hattie, J., & Timperley, H. (2007). The power of feedback. *Review of Educational Research*, 77(1), 81–112. <https://doi.org/10.3102/003465430298487>
- He, Z., Shen, Z., & Zhu, S. (2014). Design and implementation of an internet-based electrical engineering laboratory. *ISA Transactions*, 53(5), 1377–1382. <https://doi.org/10.1016/j.isatra.2013.12.035>
- Herbert, B., Ens, B., Weerasinghe, A., Billingham, M., & Wigley, G. (2018). Design considerations for combining augmented reality with intelligent tutors. *Computers & Graphics*, 77, 166–182. <https://doi.org/10.1016/j.cag.2018.09.017>
- Herranen, J., & Aksela, M. (2019). Student-question-based inquiry in science education. *Studies in Science Education*, 55(1), 1–36. <https://doi.org/10.1080/03057267.2019.1658059>
- Jha, N. K., Bhowmik, P. K., & Bhagat, K. K. (2024). Online inquiry-based learning systems for argumentation: A systematic review. *Educational Technology & Society*, 27(3), 1–28. [https://doi.org/10.30191/ETS.202407_27\(3\)](https://doi.org/10.30191/ETS.202407_27(3))
- Jongsma, M. V., Scholten, D. J., van Muijlwijk-Koezen, J. E., & Meeter, M. (2023). Online versus offline peer feedback in higher education: A meta-analysis. *Journal of Educational Computing Research*, 61(2), 329–354. <https://doi.org/10.1177/07356331221114181>
- Kamarudin, M. Z., Mat Noor, M. S. A., & Omar, R. (2024). A scoping review of the effects of a technology-integrated, inquiry-based approach on primary pupils' learning in science. *Research in Science & Technological Education*, 42(3), 828–847. <https://doi.org/10.1080/02635143.2022.2138847>
- Kates, A. W., Wu, H., & Coryn, C. L. (2018). The effects of mobile phone use on academic performance: A meta-analysis. *Computers & Education*, 127, 107–112. <https://doi.org/10.1016/j.compedu.2018.08.012>
- Konstantopoulos, S. (2008). An introduction to meta-analysis. In J. W. Osborne (Ed.), *Best practices in quantitative methods* (pp. 177–194). Sage.
- Kroeze, K. A., Van Den Berg, S. M., Veldkamp, B. P., & De Jong, T. (2021). Automated assessment of and feedback on concept maps during inquiry learning. *IEEE Transactions on Learning Technologies*, 14(4), 460–473. <https://doi.org/10.1109/TLT.2021.3103331>
- Kurtén, B., & Henriksson, A. C. (2021). A model for continued professional development with focus on inquiry-based learning in science education. *LUMAT: International Journal on Math, Science and Technology Education*, 9(1), 208–234. <https://doi.org/10.31129/LUMAT.9.1.1448>
- Lazonder, A. W., & Harmsen, R. (2016). Meta-analysis of inquiry-based learning: Effects of guidance. *Review of Educational Research*, 86(3), 681–718. <https://doi.org/10.3102/0034654315627366>
- Liao, M., Zhu, K., & Wang, G. (2024). Can human-machine feedback in a smart learning environment enhance learners' learning performance? A meta-analysis. *Frontiers in Psychology*, 14, 1288503. <https://doi.org/10.3389/fpsyg.2023.1288503>
- Liu, R., Wang, L., Lei, J., Wang, Q., & Ren, Y. (2020). Effects of an immersive virtual reality-based classroom on students' learning performance in science lessons. *British Journal of Educational Technology*, 51(6), 2034–2049. <https://doi.org/10.1111/bjet.13028>
- Liu, C., Zowghi, D., Kearney, M., & Bano, M. (2021). Inquiry-based mobile learning in secondary school science education: A systematic review. *Journal of Computer Assisted Learning*, 37(1), 1–23. <https://doi.org/10.1111/jcal.12505>

- Lv, X., Ren, W., & Xie, Y. (2021). The effects of online feedback on ESL/EFL writing: A meta-analysis. *The Asia-Pacific Education Researcher*, 30(6), 643–653. <https://doi.org/10.1007/s40299-021-00594-6>
- Maier, U., & Klotz, C. (2022). Personalized feedback in digital learning environments: Classification framework and literature review. *Computers and Education: Artificial Intelligence*, 3, 100080. <https://doi.org/10.1016/j.caeai.2022.100080>
- Martin, D. (2020). Providing Students with multimodal feedback experiences. *Journal of Curriculum, Teaching, Learning and Leadership in Education*, 5(1), 2. <https://digitalcommons.unomaha.edu/cgi/viewcontent.cgi?article=1082&context=ctlle>
- Mejeh, M., Sarbach, L., & Hascher, T. (2024). Effects of adaptive feedback through a digital tool—a mixed-methods study on the course of self-regulated learning. *Education and Information Technologies*, 29, 1–43. <https://doi.org/10.1007/s10639-024-12510-8>
- Mertens, U., Finn, B., & Lindner, M. A. (2022). Effects of computer-based feedback on lower-and higher-order learning outcomes: A network meta-analysis. *Journal of Educational Psychology*, 114(8), 1743–1772. <https://doi.org/10.1037/edu0000764>
- Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., ... & Moher, D. (2021). The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *International Journal of Surgery*, 88, 105906. <https://doi.org/10.1016/j.ijssu.2021.105906>
- Pedaste, M., Mäeots, M., Siiman, L. A., De Jong, T., Van Riesen, S. A., Kamp, E. T., ... & Tsourlidaki, E. (2015). Phases of inquiry-based learning: Definitions and the inquiry cycle. *Educational research review*, 14, 47–61. <https://doi.org/10.1016/j.edurev.2015.02.003>
- Razzaq, R., Ostrow, K. S., & Heffernan, N. T. (2020). Effect of immediate feedback on math achievement at the high school level. In *International conference on artificial intelligence in education* (pp. 263–267). Cham: Springer International Publishing. https://doi.org/10.1007/978-3-030-52240-7_48
- Rodríguez-Martínez, J. A., González-Calero, J. A., del Olmo-Muñoz, J., Arnau, D., & Tirado-Olivares, S. (2023). Building personalised homework from a learning analytics based formative assessment: Effect on fifth-grade students' understanding of fractions. *British Journal of Educational Technology*, 54(1), 76–97. <https://doi.org/10.1111/bjet.13292>
- Rönnebeck, S., Bernholt, S., & Ropohl, M. (2016). Searching for a common ground—A literature review of empirical research on scientific inquiry activities. *Studies in Science Education*, 52(2), 161–197. <https://doi.org/10.1080/03057267.2016.1206351>
- Sailer, M., Bauer, E., Hofmann, R., Kiesewetter, J., Glas, J., Gurevych, I., & Fischer, F. (2023). Adaptive feedback from artificial neural networks facilitates pre-service teachers' diagnostic reasoning in simulation-based learning. *Learning and Instruction*, 83, 101620. <https://doi.org/10.1016/j.learninstruc.2022.101620>
- Schmidt, M., Mousavi, A., Squires, V., & Wilson, K. (2018). Assessing the effectiveness of automated personalized feedback in an undergraduate biology course. In *Proceedings of Hawaii international conference science, technology & engineering, arts, mathematics & education* (pp. 1–17).
- Shi, H., & Aryadoust, V. (2024). A systematic review of AI-based automated written feedback research. *ReCALL*, 36(2), 187–209. <https://doi.org/10.1017/S0958344023000265>
- Singh, A. (2021). Quasi experimental design in scientific psychology. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3793568>
- Slavin, R. E., & Smith, D. (2009). The relationship between sample sizes and effect sizes in systematic reviews in education. *Educational Evaluation and Policy Analysis*, 31(4), 500–506. <https://doi.org/10.3102/0162373709352369>
- Song, D., & Kim, D. (2021). 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>
- Sun, J. C. Y., Yu, S. J., & Chao, C. H. (2019). Effects of intelligent feedback on online learners' engagement and cognitive load: The case of research ethics education. *Educational Psychology*, 39(10), 1293–1310. <https://doi.org/10.1080/01443410.2018.1527291>
- Sung, Y. T., Chang, K. E., & Yang, J. M. (2015). How effective are mobile devices for language learning? A meta-analysis. *Educational Research Review*, 16, 68–84. <https://doi.org/10.1016/j.edurev.2015.09.001>
- Swart, E. K., Nielen, T. M. J., & Sikkema-de Jong, M. T. (2019). Supporting learning from text: A meta-analysis on the timing and content of effective feedback. *Educational Research Review*, 28, 100296. <https://doi.org/10.1016/j.edurev.2019.100296>
- Tacoma, S., Heeren, B., Jeurig, J., & Drijvers, P. (2020). Intelligent feedback on hypothesis testing. *International Journal of Artificial Intelligence in Education*, 30(4), 616–636. <https://doi.org/10.1007/s40593-020-00218-y>
- Urdanivia Alarcon, D. A., Talavera-Mendoza, F., Rucano Paucar, F. H., Cayani Caceres, K. S., & Machaca Viza, R. (2023). Science and inquiry-based teaching and learning: A systematic review. *Frontiers in Education*, 8, 1170487. <https://doi.org/10.3389/fecl.2023.1170487>
- Vo, D. V., & Simmie, G. M. (2024). Assessing scientific inquiry: A systematic literature review of tasks, tools and techniques. *International Journal of Science and Mathematics Education* (pp. 1–36). <https://doi.org/10.1007/s10763-024-10498-8>
- Wang, X. M., Hu, Q. N., Hwang, G. J., & Yu, X. H. (2023). Learning with digital technology-facilitated empathy: An augmented reality approach to enhancing students' flow experience, motivation, and achievement in a biology program. *Interactive Learning Environments*, 31(10), 6988–7004. <https://doi.org/10.1080/10494820.2022.2057549>
- Wongwatkit, C., Srisawasdi, N., Hwang, G. J., & Panjaburee, P. (2017). Influence of an integrated learning diagnosis and formative assessment-based personalized web learning approach on students learning performances and perceptions. *Interactive Learning Environments*, 25(7), 889–903. <https://doi.org/10.1080/10494820.2016.1224255>
- Yang, F. J., Su, C. Y., Xu, W. W., & Hu, Y. (2023). Effects of developing prompt scaffolding to support collaborative science argumentation in simulation-based physics learning. *Interactive Learning Environments*, 31(10), 6526–6541. <https://doi.org/10.1080/10494820.2022.2041673>
- Yang, G., Zhou, W., Zhou, H., Li, J., Chen, X., & Tu, Y. F. (2024). An empirical study of the effects of intelligent cognitive diagnostic feedback strategy on L2 writing performance, epistemic structure, and transferability. *Education and Information Technologies*, 29(2), 2183–2216. <https://doi.org/10.1007/s10639-023-11905-3>
- Zacharia, Z. C. (2015). Examining whether touch sensory feedback is necessary for science learning through experimentation: A literature review of two different lines of research across K-16. *Educational Research Review*, 16, 116–137. <https://doi.org/10.1016/j.edurev.2015.10.001>
- Zheng, L., Niu, J., Zhong, L., & Gyasi, J. F. (2023). The effectiveness of artificial intelligence on learning achievement and learning perception: A meta-analysis. *Interactive Learning Environments*, 31(9), 5650–5664.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Springer Nature or its licensor (e.g. a society or other partner) holds exclusive rights to this article under a publishing agreement with the author(s) or other rightsholder(s); author self-archiving of the accepted manuscript version of this article is solely governed by the terms of such publishing agreement and applicable law.