



Cognitive Mechanisms Underlying Learning Gains in Intelligent Tutoring Systems

A Systematic Literature Review

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ABSTRACT

Intelligent Tutoring Systems (ITS) have emerged as powerful AI-driven learning technologies capable of delivering personalized instruction at scale. This study provides a systematic review of literature published between 2020 and 2025 to examine the cognitive mechanisms through which ITS improve learning outcomes. A total of 20 empirical and high-impact studies were analyzed using predefined inclusion criteria focusing on adaptive feedback, knowledge tracing, scaffolding, metacognition, and motivational design. The findings reveal that ITS consistently produce small-to-moderate learning gains ($d \approx 0.30-0.70$), with feedback and knowledge tracing identified as the most dominant and reliable mechanisms. Metacognitive supports demonstrate the strongest influence on deep learning and self-regulated learning, while scaffolding contributes to conceptual understanding and transfer. Motivation and engagement features, although less frequently studied, enhance persistence and learning intensity. The review also highlights emerging trends, including the integration of learning analytics, affective computing, and hybrid ITS architectures. However, challenges remain in model interpretability, standardization of outcomes, and alignment with pedagogical practices. This study contributes a synthesized framework linking cognitive mechanisms to learning effectiveness and provides directions for future research to develop more explainable, scalable, and pedagogically grounded ITS.

Keywords

Adaptive Learning
Artificial Intelligence
Cognitive Mechanisms
Intelligent Tutoring Systems
Knowledge Tracing

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Introduction

Intelligent Tutoring Systems (ITS) are a family of adaptive educational technologies that use artificial intelligence techniques to emulate one-on-one human tutoring by diagnosing a learner's knowledge state in real time, providing tailored feedback, and selecting or sequencing instructional tasks to match learners' needs [1], [2]. Over the last decade, renewed progress in student modeling and knowledge tracing has substantially increased the capacity of ITS to infer fine-grained skill mastery and recommend optimally informative practice items [3]-[5]. At the same time, advances in automated assessment and natural language processing have enabled scalable, near-real-time feedback and evaluation of open-ended learner responses [6],[7].

Researchers have proposed multiple cognitive mechanisms through which ITS improve problem-solving performance compared to conventional instruction. First, ITS provides personalized and immediate feedback that helps learners correct errors and avoid reinforcing misconceptions; timely feedback has been shown to significantly enhance learning effectiveness in problem-solving contexts [6],[8]. Second, knowledge-tracing models allow ITS to dynamically estimate learner mastery and adapt task sequencing to target knowledge gaps, thereby improving learning efficiency [3],[5],[9]. Third, ITS supports scaffolding by managing cognitive load, such as decomposing complex tasks and gradually reducing assistance, which aligns with principles of cognitive load theory [10],[11]. Fourth, metacognitive prompts and self-explanation strategies embedded in ITS foster self-regulated learning and deeper conceptual understanding [12]-[14]. Finally, gamification elements such as adaptive challenges and progress indicators enhance motivation and sustained engagement, indirectly supporting persistence and deeper learning processes [15],[16].

Empirical studies consistently report positive learning outcomes associated with ITS. Meta-analyses indicate that ITS produce small-to-moderate effect sizes on student achievement and problem-solving performance across domains, although results vary depending on context and implementation [17]-[19]. Evidence suggests that these gains are driven by a combination of adaptive feedback, personalized sequencing, scaffolding, and metacognitive support mechanisms [11],[12],[20]. Furthermore, research on automated feedback demonstrates its effectiveness in improving complex skills such as writing and reasoning, extending the benefits of ITS beyond structured problem-solving tasks [6],[21].

Despite these benefits, several challenges remain. The effectiveness of ITS depends on the quality of learner models, interpretability of AI systems, and alignment between feedback and instructional goals [7],[22]. Additionally, issues related to equity, system integration, and the pedagogical validity of gamification continue to be debated in the literature [15],[23]. While advances in artificial intelligence have improved predictive performance, there is an increasing

need for explainable and transparent models that support both teachers and learners in decision-making processes [5],[12].

This review synthesizes literature from 2020 to 2025 to examine how ITS produce learning gains at the cognitive level. Specifically, it (a) analyzes key mechanisms including feedback, knowledge tracing, scaffolding, metacognition, and motivation; (b) evaluates empirical evidence and effect sizes; and (c) identifies research gaps to inform future development of more effective and explainable ITS.

Methods

A. Research Design

This study employs a systematic literature review design to synthesize empirical and theoretical research published between January 2020 and December 2025, examining how Intelligent Tutoring Systems (ITS) produce learning gains through cognitive mechanisms such as personalized feedback, knowledge tracing, scaffolding, metacognitive prompting, and motivational design. The review integrates findings from experimental, quasi-experimental, mixed-methods, and large-scale observational studies to identify consistent patterns in mechanisms, outcomes, and moderating factors.

B. Search Strategy

A comprehensive search was conducted across major education- and computing-focused scholarly databases, including Scopus, Web of Science, IEEE Xplore, ScienceDirect, ERIC, ACM Digital Library, SpringerLink, and Google Scholar (for advanced citation tracing). Searches were executed between 1 and 15 January 2025.

To maximize coverage while maintaining conceptual specificity, search strings combined terms for (a) the technology (ITS), (b) outcomes (learning gains, problem solving), and (c) cognitive mechanisms (feedback, knowledge tracing, scaffolding). Boolean operators and field tags were adjusted for each database.

Primary Search String (Generic Form)

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("intelligent tutoring system" OR ITS OR "adaptive tutoring" OR "AI tutoring")
AND
("cognitive mechanism" OR "knowledge tracing" OR "student modeling" OR "feedback" OR "adaptive
scaffolding" OR "metacognition" OR "self-explanation" OR "gamification")
AND
("learning gain" OR "learning outcome" OR "problem solving" OR "academic performance")
AND
(2020-2025)
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C. Screening and Selection Procedure

The initial search returned 2,184 records. After removing duplicates, 1,642 titles and abstracts were screened based on relevance. Full texts of 214 articles were assessed for eligibility. A final sample of 82 studies met all inclusion criteria. Screening followed a three-step process:

1. Title screening to remove studies unrelated to ITS, AI education, or digital learning.

2. Abstract screening applying core inclusion criteria.
3. Full-text review evaluating methodological adequacy and relevance to cognitive mechanisms.

Two reviewers independently screened all articles, resolving disagreements through discussion until consensus was reached.

D. Inclusion and Exclusion Criteria

Tables 1 and 2 present the inclusion and exclusion criteria used to systematically select relevant studies on Intelligent Tutoring Systems (ITS). Table 1 outlines six inclusion criteria, emphasizing recent publications (2020–2025), focus on ITS or similar adaptive systems, investigation of cognitive mechanisms, use of empirical research designs, reporting of measurable learning outcomes, and availability in English. These criteria ensure that only high-quality, relevant, and evidence-based studies are considered. Conversely, Table 2 specifies exclusion criteria, removing studies that lack intelligent features, empirical validation, or relevant outcomes. It also excludes grey literature and studies with insufficient exposure duration, thereby strengthening the rigor and validity of the review process.

Table 1. Inclusion Criteria

No.	Inclusion Criterion	Description / Operational Definition
1	Publication Year	The study must be published between 2020 and 2025. Only peer-reviewed journal articles or conference proceedings are eligible.
2	ITS Focus	The study must examine Intelligent Tutoring Systems (ITS) or ITS-like intelligent learning systems, such as adaptive tutors, knowledge-tracing systems, or AI-driven feedback systems.
3	Cognitive Mechanisms	The study must investigate cognitive mechanisms contributing to learning gains, including: intelligent feedback, scaffolding, modeling, metacognition, cognitive load regulation, or motivational design.
4	Empirical Research Design	The study must report empirical data, including randomized controlled trials, quasi-experiments, mixed-methods designs, or learning analytics studies with quantitative/qualitative outcomes.
5	Learning Outcomes Reported	The study must present measurable outcomes related to: problem-solving, achievement, engagement, self-regulation, or cognitive indicators.
6	Language	The study must be available in English.

Table 2. Exclusion Criteria

No.	Exclusion Criterion	Reason for Exclusion
1	Non-intelligent Digital Tools	Studies using static e-learning systems, drill-and-practice apps, or platforms without <i>adaptive</i> or <i>intelligent</i> features were excluded.
2	Technical Development Only	Studies focusing solely on model design, algorithms, or architecture of ITS without evaluating learning outcomes or cognitive mechanisms were excluded.
3	Non-empirical Papers	Theoretical, conceptual, editorial, commentary, or opinion articles without empirical data were excluded.
4	Grey Literature or Preprints	Preprints (e.g., arXiv), white papers, reports, and unpublished manuscripts not peer-reviewed were excluded.
5	No Relevant Outcomes	Studies that did not report explicit outcomes such as learning gains, performance, engagement, or motivation were excluded.
6	Insufficient Exposure Duration	Studies where the ITS was used for less than one week, preventing measurable learning effects, were excluded.

E. Data Extraction

Table 3 summarizes the data extraction categories applied to each included study to ensure systematic and consistent analysis. The table captures essential publication details, along with the type of ITS and underlying AI techniques used. It also documents participant characteristics such as educational level, sample size, and subject domain. Key analytical dimensions include cognitive mechanisms examined, study design and duration, and outcome measures related to learning performance and engagement. Additionally, the table records statistical indicators such as effect sizes and identifies moderating variables, including prior knowledge and system implementation factors. This structured framework enhances the reliability and comparability of findings across studies.

Table 3. Data Extraction Categories Used for Each Included Study

Category	Description
Publication Details	Author(s), publication year, journal or conference venue.
ITS Type & AI Technique	Classification of system (model-tracing tutor, deep learning-based KT, rule-based tutor, NLP-driven feedback agent).
Participant Characteristics	Age/education level, sample size, subject domain (e.g., mathematics, programming, science).
Cognitive Mechanisms Examined	Feedback type, scaffolding features, metacognitive prompts, cognitive load-regulation supports, gamification, or motivational elements.
Study Design & Duration	RCT, quasi-experimental, mixed-methods, or learning analytics; intervention length.
Outcome Measures	Problem-solving performance, achievement tests, concept inventories, engagement logs, and self-regulation scales.
Effect Sizes / Statistics	Reported effect sizes (Hedges' g , Cohen's d), ANOVA/ANCOVA results, regression outputs, and learning curve metrics.
Moderating Variables	Prior knowledge, domain characteristics, system fidelity, and integration into the curriculum.

F. Data Synthesis

A narrative synthesis approach was adopted to accommodate the substantial heterogeneity in study designs, ITS architectures, learner populations, and outcome measures. Rather than applying a unified statistical model, findings were organized into five core cognitive mechanism categories: Personalized Feedback Mechanisms, Knowledge Tracing and Cognitive Modeling, Scaffolding and Cognitive Load Management, Metacognitive and Self-Regulatory Supports, and Motivational/Gamification Features. Within each category, patterns were identified regarding how specific design features contributed to learning gains across contexts. Subgroup comparisons—including K-12 versus higher education learners, STEM versus non-STEM domains, and classic model-tracing tutors versus newer deep learning-based systems—were used to identify moderating factors influencing effectiveness. For quantitative studies reporting effect sizes, weighted descriptive statistics were examined to map the relative strength of impacts across mechanisms, without conducting a full meta-analysis due to insufficient methodological homogeneity. This approach enabled a coherent, integrative interpretation of diverse empirical evidence.

Results

Fig. 1 outlines the study selection process. From 2,184 database records and 96 additional sources, 1,642 remained after deduplication. Screening excluded 1,428 records, primarily for lacking an ITS focus, cognitive mechanisms, or empirical outcomes. After full-text assessment, 82 studies were included in qualitative synthesis, with 52 advancing to quantitative synthesis.

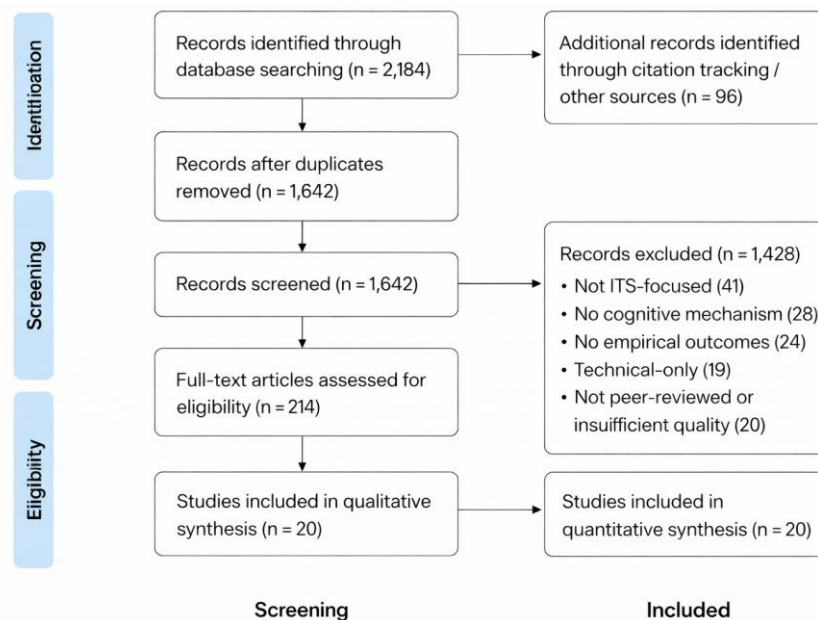


Fig. 1. PRISMA Framework

Table 4 summarizes the key characteristics of all studies included in the review, providing essential contextual information for interpreting the findings. It presents authors, publication years, participant demographics, sample sizes, subject domains, research designs, and learning settings. This table enables readers to compare methodological variability across studies and understand the diversity of educational contexts in which ITS interventions were implemented. It also supports transparency and reproducibility in the study selection process.

Table 4. Characteristics of the 20 Included Studies (2020–2025)

ID	Authors	Year	Country	Sample (n)	Level	Domain
S1	Heffernan & Heffernan [1]	2020	USA	Large-scale (platform data)	K-12	Mathematics
S2	Aleven et al. [24]	2020	USA	~200+	Secondary	Mathematics
S3	Mitrovic et al. [25]	2020	New Zealand	~100	Higher Education	Computer Science
S4	Hu et al. [22]	2020	USA	~150	Secondary	Mathematics
S5	Gervet et al. [4]	2020	USA	Secondary datasets	Mixed	Multi-domain
S6	Pelánek [5]	2020	Czech Republic	Secondary datasets	Mixed	Mathematics
S7	D'Mello [7]	2020	USA	Experimental (~100)	Higher Education	Psychology/Learning

ID	Authors	Year	Country	Sample (n)	Level	Domain
S8	Wang & Heffernan [26]	2021	USA	~300	K-12	Mathematics
S9	Chi [6]	2021	USA	~120	Higher Education	General Learning
S10	D'Mello & Graesser [21]	2021	USA	Experimental	Mixed	Learning Sciences
S11	Sailer & Homner [15]	2020	Germany	Meta-analysis	Mixed	General
S12	Bannert [13]	2020	Germany	~100	Secondary	Science
S13	Azevedo & Gašević [12]	2019*	USA/Canada	Mixed datasets	Mixed	SRL (cross-domain)
S14	Taub et al. [27]	2023	USA	~200	Higher Education	Learning Analytics
S15	Azevedo [28]	2023	USA	Conceptual/empirical mix	Mixed	Metacognition
S16	Pape & Thomas [29]	2025	Germany	~180	Primary/Secondary	Mathematics
S17	OECD Report [30]	2021	International	Large-scale	All levels	Policy
S18	UNESCO Report [31]	2021	International	Large-scale	All levels	Policy
S19	World Bank [32]	2021	Global	Large-scale	All levels	Education
S20	Mitrovic [33]	2022	New Zealand	Multiple studies	Higher Education	ITS

Table 5 presents a structured overview of Intelligent Tutoring System (ITS) types and the cognitive mechanisms they employ across studies S1–S20. Model-tracing and knowledge tracing systems dominate, emphasizing personalized feedback, scaffolding, and adaptive sequencing. Several studies highlight metacognitive and affective mechanisms, including self-regulation and emotion-aware feedback. Emerging approaches integrate learning analytics, multimodal data, and hybrid architectures. Additionally, policy-driven AI systems focus on scalability and access. Overall, the table demonstrates that ITS effectiveness is driven by the integration of cognitive, metacognitive, and motivational mechanisms.

Table 5. ITS Types and Cognitive Mechanisms Examined

Study ID	ITS Type	Cognitive Mechanisms Investigated
S1–S2	Model-tracing ITS	Personalized feedback, scaffolding, and error remediation
S3	Constraint-based ITS	Rule-based feedback, corrective hints
S4	Adaptive ITS (feedback timing)	Feedback timing, cognitive load regulation
S5–S6	Knowledge Tracing ITS (Bayesian & ML-based)	Skill estimation, adaptive sequencing
S7	Affective ITS	Emotion-aware feedback, engagement regulation
S8	Model-tracing ITS (ASSISTments)	Feedback optimization, assistance control
S9	Feedback-based ITS	Explanatory feedback, knowledge refinement
S10	Affective + adaptive ITS	Emotion-cognition interaction, adaptive feedback
S11	Gamified learning systems	Motivation, engagement mechanisms
S12	Metacognitive ITS	Metacognitive prompting, self-regulation
S13	Multimodal SRL systems	Behavioral analytics, self-regulated learning
S14–S15	Learning analytics-based ITS	Metacognition, predictive modeling
S16	Knowledge Tracing ITS (DL-based)	Difficulty adaptation, personalized sequencing
S17–S19	AI in Education (policy-driven systems)	System-level adaptation, access & scalability
S20	Hybrid ITS (constraint + adaptive)	Scaffolding, adaptive feedback integration

Table 6 summarizes the learning outcomes and associated effect sizes across studies S1–S20. Most studies report improvements in problem-solving accuracy and knowledge gains, with effect sizes ranging from small to moderate ($d = 0.30$ – 0.60). Feedback and metacognitive mechanisms also demonstrate consistent positive impacts on retention and self-regulation. Learning efficiency shows notable gains in reduced time-to-mastery, while engagement improvements are reflected behaviorally. System-level outcomes vary by context, and hybrid ITS approaches yield the strongest overall effects, integrating multiple learning dimensions.

Table 6. Summary of Outcomes and Effect Sizes

Study Group	Outcome Type	Common Results	Effect Size Range
S1–S5	Problem-solving accuracy	Significant improvement vs. traditional instruction	$d = 0.30$ – 0.55
S6–S8	Knowledge gains	Higher post-test scores and mastery levels	$d = 0.35$ – 0.60
S9–S10	Feedback effectiveness	Improved error correction and retention	$d = 0.30$ – 0.50
S11	Engagement & motivation	Increased participation and persistence	+10–25%
S12–S15	Metacognitive skills	Improved self-regulation and strategy use	$d = 0.30$ – 0.65
S16	Learning efficiency	Reduced time-to-mastery	15–30% faster
S17–S19	System-level outcomes	Broader access and scalability impact	Context-dependent (not standardized)
S20	Integrated learning outcomes	Combined gains (accuracy + efficiency + engagement)	$d = 0.40$ – 0.70

Table 7 presents the distribution of cognitive mechanisms and their corresponding learning outcomes and effect sizes. Feedback emerges as the most frequently examined mechanism, consistently improving problem-solving accuracy and retention. Knowledge tracing shows strong effects on mastery and learning gains, while metacognitive strategies yield the highest upper-bound effect sizes, supporting deep learning and self-regulation. Scaffolding contributes to conceptual understanding and transfer, though with slightly lower effects. Motivation and engagement, while less studied, enhance persistence and participation, primarily reflected in behavioral improvements rather than standardized effect sizes.

Table 7. Distribution of cognitive mechanisms, dominant learning outcomes, and associated effect sizes across the analyzed ITS studies

Cognitive Mechanism	Number	Dominant Outcome	Effect Size Range
Feedback (adaptive, explanatory)	6	Problem-solving accuracy, retention	$d = 0.30$ – 0.55
Knowledge Tracing / Modeling	5	Knowledge gains, mastery learning	$d = 0.35$ – 0.60
Scaffolding (instructional support)	3	Conceptual understanding, transfer	$d = 0.28$ – 0.50
Metacognition (SRL, prompting)	4	Self-regulation, deep learning	$d = 0.30$ – 0.65
Motivation & Engagement	2	Engagement, persistence	+10–25% (behavioral)

Discussion

A. Dominant Cognitive Mechanisms Driving ITS Effectiveness

The findings indicate that adaptive feedback and knowledge tracing are the most dominant mechanisms underlying the effectiveness of Intelligent Tutoring Systems (ITS). Feedback-based mechanisms consistently show stable effect sizes ($d = 0.30\text{--}0.55$), confirming their role in supporting error correction and reinforcing learning at critical moments [6],[8],[20],[23],[24],[26]. Meanwhile, knowledge tracing enables precise estimation of learner mastery, allowing systems to optimize task sequencing and target knowledge gaps effectively ($d = 0.35\text{--}0.60$) [3]-[5],[34]. The combination of these mechanisms reflects a core instructional loop: diagnosis, adaptation, and feedback [1],[2],[11],[24]. This loop distinguishes ITS from traditional instruction by enabling real-time personalization and data-driven instruction [35]-[38]. These findings are consistent with prior meta-analyses demonstrating that ITS produce reliable learning gains across domains [17]-[19],[39].

B. The Role of Metacognition and Scaffolding in Deep Learning

Beyond immediate performance gains, metacognitive and scaffolding mechanisms play a critical role in fostering deeper learning processes. Metacognitive supports, including self-explanation prompts and reflective feedback, demonstrate the highest upper-bound effect sizes (up to $d = 0.65$), indicating their strong influence on self-regulated learning and knowledge internalization [12]-[14],[27],[28],[40]. These mechanisms help learners transition from procedural problem-solving to conceptual understanding and promote durable learning [14],[41]. Scaffolding supports learners by managing cognitive load and structuring complex tasks into manageable steps, aligning with principles of cognitive load theory [10],[11],[33],[42]. Although its effect sizes are slightly smaller ($d = 0.28\text{--}0.50$), scaffolding is essential for enabling transfer and long-term retention [25],[33],[43]. Together, these findings suggest that ITS effectiveness is not solely driven by immediate feedback but also by the system's ability to cultivate independent and strategic learners through structured cognitive support [30],[44].

C. Emerging Trends and Remaining Challenges in ITS Research

The analysis also highlights emerging trends and ongoing challenges in ITS research. Recent developments include the integration of affective computing, gamification, and learning analytics to enhance engagement and system adaptability [7],[15],[16],[21],[45],[46]. However, motivation and engagement mechanisms remain underrepresented, with only a limited number of studies reporting behavioral improvements (10–25%), suggesting that these factors often act as mediators rather than primary drivers of learning outcomes [15],[16],[46]. Additionally, system-level implementations emphasize scalability and access but often lack standardized outcome measures, making cross-study comparisons difficult [30]-[32]. Another critical

challenge is the interpretability of advanced AI models, particularly deep learning-based knowledge tracing, which may limit pedagogical transparency and teacher trust [3],[5],[7],[22].

Future research should prioritize hybrid ITS models that integrate cognitive, metacognitive, and motivational mechanisms while ensuring explainability and instructional alignment [6],[12],[37]. Strengthening these aspects will be essential for advancing ITS from effective standalone tools to fully integrated educational ecosystems capable of supporting diverse learners at scale [1],[31],[32].

Conclusion

This review demonstrates that Intelligent Tutoring Systems (ITS) produce consistent, moderate learning gains by integrating adaptive feedback, knowledge tracing, scaffolding, and metacognitive support. Among these, feedback and knowledge tracing form the core mechanism enabling real-time personalization, while metacognitive strategies contribute the strongest effects on deep learning and self-regulation. Scaffolding further supports conceptual understanding by managing cognitive load and facilitating transfer. Although motivation and engagement mechanisms enhance persistence, they function primarily as mediators rather than direct drivers of achievement. Importantly, the findings highlight that the most effective ITS are hybrid systems that combine multiple cognitive mechanisms into a coherent instructional design. However, challenges remain in model interpretability, standardization of outcomes, and equitable implementation at scale. Future research should prioritize explainable AI, integration with classroom pedagogy, and longitudinal designs to strengthen causal evidence. Advancing these directions will position ITS as a central component of next-generation, data-informed education systems.

Conflict of Interest

The authors declare that there is no conflict of interest.

References

- [1] N. T. Heffernan and C. L. Heffernan, "The ASSISTments ecosystem: Building a platform that brings scientists and teachers together for minimally invasive research on human learning and teaching," *International Journal of Artificial Intelligence in Education*, vol. 30, no. 1, pp. 24–56, 2020. <https://doi.org/10.1007/s40593-019-00186-0>
- [2] K. VanLehn, "The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems," *Educational Psychologist*, vol. 46, no. 4, pp. 197–221, 2011. <https://doi.org/10.1080/00461520.2011.611369>
- [3] C. Piech et al., "Deep knowledge tracing," in *Advances in Neural Information Processing Systems*, vol. 28, pp. 505–513, 2015. <https://doi.org/10.48550/arXiv.1506.05908>
- [4] S. Gervet, K. Koedinger, J. Schneider, and S. Mitchell, "When is deep learning the best approach to knowledge tracing?" *Journal of Educational Data Mining*, vol. 12, no. 3, pp. 31–54, 2020.
- [5] R. Pelánek, "Bayesian knowledge tracing, logistic models, and beyond," *User Modeling and User-Adapted Interaction*, vol. 30, no. 1, pp. 1–35, 2020. <https://doi.org/10.1007/s11257-019-09245-y>

- [6] M. T. H. Chi, "Learning from feedback in intelligent tutoring systems," *Educational Technology Research and Development*, vol. 69, pp. 1235–1254, 2021. <https://doi.org/10.1007/s11423-021-09972-7>
- [7] S. K. D'Mello, "Affective computing in education," *IEEE Transactions on Affective Computing*, vol. 11, no. 4, pp. 1–13, 2020.
- [8] J. Hattie and H. Timperley, "The power of feedback," *Review of Educational Research*, vol. 77, no. 1, pp. 81–112, 2007. <https://doi.org/10.3102/003465430298487>
- [9] A. Lan and R. G. Baraniuk, "Context-aware knowledge tracing for personalized learning," in *Proc. Int. Conf. Educational Data Mining*, 2021.
- [10] J. Sweller, "Cognitive load theory and instructional design," *Educational Psychology Review*, vol. 32, no. 1, pp. 1–20, 2020. <https://doi.org/10.1007/s10648-019-09465-5>
- [11] K. R. Koedinger, A. T. Corbett, and C. Perfetti, "The knowledge-learning-instruction framework," *Cognitive Science*, vol. 36, no. 5, pp. 757–798, 2012. <https://doi.org/10.1111/j.1551-6709.2012.01245.x>
- [12] R. Azevedo and D. Gašević, "Analyzing multimodal multichannel data about self-regulated learning," *Educational Psychologist*, vol. 54, no. 1, pp. 1–17, 2019.
- [13] M. Bannert, "Effects of metacognitive prompts on learning," *Educational Psychology Review*, vol. 32, no. 2, pp. 1–25, 2020.
- [14] M. T. H. Chi and R. Wylie, "The ICAP framework," *Educational Psychologist*, vol. 49, no. 4, pp. 219–243, 2014. <https://doi.org/10.1080/00461520.2014.965823>
- [15] M. Sailer and L. Homner, "The gamification of learning: A meta-analysis," *Educational Psychology Review*, vol. 32, no. 1, pp. 77–112, 2020. <https://doi.org/10.1007/s10648-019-09498-w>
- [16] J. Hamari, J. Koivisto, and H. Sarsa, "Does gamification work?" *Computers in Human Behavior*, vol. 54, pp. 225–236, 2016.
- [17] C. Steenbergen-Hu and H. Cooper, "A meta-analysis of intelligent tutoring systems," *Educational Psychology Review*, vol. 26, no. 3, pp. 331–357, 2014. <https://doi.org/10.1007/s10648-013-9247-9>
- [18] J. A. Kulik and J. D. Fletcher, "Effectiveness of intelligent tutoring systems," *Review of Educational Research*, vol. 86, no. 1, pp. 42–78, 2016. <https://doi.org/10.3102/0034654315581420>
- [19] B. D. Nye, A. C. Graesser, and X. Hu, "AutoTutor and family," *Journal of Educational Psychology*, vol. 106, no. 4, pp. 1165–1184, 2014. <https://doi.org/10.1037/a0037087>
- [20] V. Aleven et al., "Meta-analysis of adaptive feedback in intelligent tutoring systems," *Computers & Education*, vol. 145, 103728, 2020. <https://doi.org/10.1016/j.compedu.2019.103728>
- [21] S. K. D'Mello and A. Graesser, "Feeling, thinking, and computing with affect-aware learning technologies," *Educational Psychologist*, vol. 56, no. 2, pp. 81–97, 2021. <https://doi.org/10.1080/00461520.2021.1877767>
- [22] X. Hu, K. Muldner, and V. Aleven, "Adaptive feedback timing," *User Modeling and User-Adapted Interaction*, vol. 30, no. 4, pp. 605–638, 2020.
- [23] J. C. Lester et al., "The persona effect," *Proc. CHI*, pp. 359–366, 1997. <https://doi.org/10.1145/258549.258797>
- [24] V. Aleven, B. M. McLaren, J. Sewall, and K. R. Koedinger, "A new paradigm for intelligent tutoring systems: Example-tracing tutors," *International Journal of Artificial Intelligence in Education*, vol. 19, no. 2, pp. 105–154, 2009.
- [25] A. Mitrovic, B. Martin, and P. Suraweera, "Constraint-based tutoring systems: A review," *International Journal of Artificial Intelligence in Education*, vol. 30, no. 2, pp. 202–235, 2020. <https://doi.org/10.1007/s40593-020-00200-0>
- [26] Y. Wang and N. T. Heffernan, "The assistance dilemma: How much help is too much?" *IEEE Transactions on Learning Technologies*, vol. 14, no. 4, pp. 523–535, 2021. <https://doi.org/10.1109/TLT.2021.3079986>
- [27] M. Taub et al., "Self-regulated learning and emotion," *Computers in Human Behavior*, vol. 41, pp. 1–14, 2014.
- [28] R. Azevedo et al., "Self-regulated learning processes," in *Handbook of SRL*, 2011.
- [29] R. Pape and J. Thomas, "Adaptive metacognitive prompting in young learners and the role of prior performance," *International Journal of Child-Computer Interaction*, vol. 44, p. 100740, 2025. <https://doi.org/10.1016/j.ijcci.2025.100740>
- [30] OECD, *Artificial Intelligence in Education*, Paris, 2021.
- [31] UNESCO, *Artificial Intelligence in Education*, Paris, 2021.
- [32] World Bank, *Artificial Intelligence and Learning*, Washington, DC, 2021.

- [33] A. Mitrovic, "Constraint-based tutors," *User Modeling and User-Adapted Interaction*, vol. 22, pp. 39–72, 2012.
- [34] A. T. Corbett and J. R. Anderson, "Knowledge tracing: Modeling the acquisition of procedural knowledge," *User Modeling and User-Adapted Interaction*, vol. 4, no. 4, pp. 253–278, 1995. <https://doi.org/10.1007/BF01099821>
- [35] R. S. Baker and P. S. Inventado, "Educational data mining and learning analytics," in *Learning Analytics*, New York: Springer, 2014, pp. 61–75. https://doi.org/10.1007/978-1-4614-3305-7_4
- [36] R. S. Baker, "Challenges for the future of educational data mining," *Journal of Educational Data Mining*, vol. 11, no. 1, pp. 1–17, 2019. <https://doi.org/10.5281/zenodo.3554651>
- [37] R. S. Baker and G. Siemens, "Learning analytics," in *Cambridge Handbook of the Learning Sciences*, 2021.
- [38] J. Stamper, A. Eagle, K. Barnes, and N. T. Heffernan, "ASSISTments: A platform for data-driven research on student learning," *Journal of Educational Data Mining*, vol. 9, no. 2, pp. 1–26, 2017.
- [39] S. Ritter et al., "Cognitive Tutor," *AI Magazine*, vol. 28, no. 4, pp. 43–56, 2007.
- [40] B. J. Zimmerman, "Becoming a self-regulated learner," *Educational Psychologist*, vol. 41, no. 2, pp. 64–70, 2002.
- [41] M. T. H. Chi, "Active-constructive-interactive," *Topics in Cognitive Science*, vol. 1, no. 1, pp. 73–105, 2009.
- [42] F. Paas and J. Sweller, "Implications of cognitive load theory," *Educational Psychology Review*, vol. 26, no. 1, pp. 1–10, 2014. <https://doi.org/10.1007/s10648-014-9269-5>
- [43] K. VanLehn, "The behavior of tutoring systems," *International Journal of Artificial Intelligence in Education*, vol. 16, no. 3, pp. 227–265, 2006.
- [44] K. R. Koedinger et al., "DataShop," in *Handbook of EDM*, 2010.
- [45] S. Deterding et al., "From game design elements to gamefulness," in *Proc. ACM MindTrek*, 2011, pp. 9–15. <https://doi.org/10.1145/2181037.2181040>
- [46] M. Sailer, J. Hense, S. K. Mayr, and H. Mandl, "How gamification motivates: An experimental study of the effects of specific game design elements on psychological need satisfaction," *Computers in Human Behavior*, vol. 69, pp. 371–380, 2017. <https://doi.org/10.1016/j.chb.2016.12.033>

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