



Journal of Educational Technology and E-Learning Innovations (JETELI)

ISSN: 3069-3824 (ONLINE)

VOLUME 2 ISSUE 2 (2026)



PUBLISHED BY
E-PALLI PUBLISHERS, DELAWARE, USA

Artificial Intelligence as Cognitive Scaffolding for Executive Functioning in Students with Special Educational Needs

Ilias Vasileiou^{1*}, Evangelos Mantsos², Zoe Krokou³, Olga Kofa³, Georgios Polydoros⁴

Article Information

Received: July 11, 2026

Accepted: September 23, 2026

Published: October 06, 2026

Keywords

Artificial Intelligence, Cognitive Scaffolding, Executive Functioning, Inclusive Education, Self-Regulated Learning, Special Educational Needs

ABSTRACT

Executive functioning enables learners to organize work, monitor progress, and decide when a response needs revision. For some students with special educational needs, difficulties in these areas can restrict participation even when they understand the subject matter. This critical narrative review considers whether artificial intelligence can reduce such barriers and, more importantly, what kind of support it actually provides. Research on executive functions, self-regulated learning, artificial intelligence in education, and special education was brought together to examine intelligent tutoring systems, adaptive platforms, planning tools, learning analytics, conversational agents, and generative AI. Across this literature, a recurring distinction emerges. Some applications compensate for an executive demand, others scaffold performance while a task is being completed, and a smaller group are designed to foster strategies that learners can later use without the tool. These outcomes should not be treated as equivalent. Completing a task successfully with automated prompts does not, by itself, demonstrate lasting improvement in executive functioning. AI may nevertheless be useful when support is tied to a clearly defined learning goal, interpreted by a teacher, and adjusted or faded in response to the learner's progress. Its use also raises practical concerns about cognitive offloading, inaccurate feedback, privacy, bias, and unequal access. The review proposes a three-function framework - compensation, scaffolding, and development - for planning and evaluating AI-supported practice.

INTRODUCTION

Executive functions are higher-order regulatory processes that enable people to maintain goals, inhibit unhelpful responses, update information in working memory, shift between strategies, plan actions, and monitor performance (Diamond, 2013; Miyake & Friedman, 2012). These processes are central to classroom learning. Following multistep instructions, beginning an assignment, selecting relevant information, revising an unsuccessful approach, and checking completed work all place demands on executive control. Executive functioning is consequently associated with academic performance and with students' ability to participate independently in everyday educational routines (Best & Miller, 2010; Meltzer, 2018). Students identified with attention-deficit/hyperactivity disorder, autism, or specific learning disabilities may experience difficulties in one or more executive domains. These groups are heterogeneous, and neither a diagnosis nor the label of special educational needs implies a uniform cognitive profile. Nevertheless, difficulties with attention regulation, working-memory management, cognitive flexibility, planning, or self-monitoring can create barriers when instruction assumes that learners can independently organize materials, manage time, and coordinate several mental operations at once. Effective support therefore requires attention to both the learner and the demands created by the educational environment. Established educational approaches include explicit strategy instruction, task decomposition, visual

schedules, guided practice, environmental modification, and metacognitive prompts (Meltzer, 2018). These approaches can improve access and performance, but sustained individualization is difficult in classrooms containing learners with varied strengths, needs, and rates of progress. Artificial intelligence in education has attracted interest partly because it can use learner responses and interaction data to adapt content, generate feedback, recommend next steps, and provide support at the point of need (Chen *et al.*, 2020; Holmes *et al.*, 2019; Zhai *et al.*, 2021).

The educational relevance of artificial intelligence should not, however, be inferred directly from its technical capacity. A reminder may help a student complete an assignment without strengthening independent planning. Automated summarization may reduce working-memory demands while also reducing productive engagement with a text. Adaptive feedback may promote reflection, or it may encourage trial-and-error responding if poorly designed. The distinction between improved performance with a tool and development of an underlying capacity is therefore essential.

This review examines how artificial-intelligence-supported educational tools may support executive functioning among students with special educational needs. It addresses three questions: (a) which artificial-intelligence applications plausibly support executive-function-related learning processes; (b) under what conditions might such support contribute to independent

¹ College for Humanistic Sciences-ICPS, University of Lancashire, Greece

² University of Western Macedonia, Greece

³ National and Kapodistrian University of Athens, Greece

⁴ University of Crete, Greece

* Corresponding author's e-mail: ivasileiou@lancashire.ac.uk

self-regulation rather than dependency; and (c) what pedagogical, ethical, and research considerations should guide implementation? The article's principal contribution is a framework distinguishing compensatory, scaffolding, and developmental functions of artificial intelligence

LITERATURE REVIEW

This section brings together three bodies of scholarship: research on executive functioning and self-regulated learning, inclusive approaches to educational support, and evidence on artificial intelligence in education. Their intersection matters because an improvement in task performance while a tool is available may reflect external support rather than a change in the learner's executive skills. The literature therefore needs to be read in terms of what a system does, the demands it removes or makes visible, and the independence of the outcome measured.

Executive Functioning and Learning.

Executive functioning is multidimensional. Influential accounts identify inhibition, working-memory updating, and cognitive flexibility as distinguishable but related processes that support more complex activities such as planning and problem solving (Diamond, 2013; Miyake & Friedman, 2012). In educational settings, these processes interact with prior knowledge, language, motivation, emotion, and the structure of the task. A student's difficulty completing work cannot therefore be attributed automatically to an internal executive deficit. Instructions may be ambiguous, materials may impose unnecessary cognitive load, or the classroom may provide insufficient cues and opportunities for guided practice.

This contextual perspective is particularly important in inclusive education. Support should not be limited to remediating presumed deficits within individual learners. Inclusive pedagogy seeks to extend opportunities available to everybody while responding flexibly to individual differences (Florian & Black-Hawkins, 2011). Universal Design for Learning similarly encourages multiple means of engagement, representation, and action so that barriers are anticipated rather than addressed only after failure (Meyer *et al.*, 2014). Artificial intelligence is educationally valuable only when it advances these aims rather than creating new forms of exclusion.

Executive Functioning and Self-regulated Learning.

Self-regulated learning describes the cyclical processes through which learners set goals, select strategies, monitor progress, and evaluate outcomes (Zimmerman, 2008). It overlaps with executive functioning but is not identical to it. Executive processes contribute to regulation, whereas self-regulated learning also includes motivational beliefs, metacognitive knowledge, and context-sensitive strategy use. This distinction prevents an overly cognitive interpretation of educational difficulty and clarifies possible mechanisms of support.

Artificial-intelligence systems can intervene at several points in the self-regulation cycle. Before a task, a system may help clarify a goal or generate a plan.

During performance, it may provide prompts, visual progress indicators, or feedback. After performance, it may support reflection by comparing an outcome with criteria. Such features are most educationally useful when they make regulatory processes visible and invite learner decisions rather than silently making decisions on the learner's behalf.

Artificial Intelligence in Education and Special Education

Artificial intelligence in education includes intelligent tutoring systems, adaptive learning platforms, automated feedback, learning analytics, conversational agents, and generative systems. Reviews show rapid growth in these applications, although much research has focused on higher education, technical performance, or general attainment rather than special education and executive-function outcomes (Zawacki-Richter *et al.*, 2019; Zhai *et al.*, 2021). A systematic review of artificial intelligence in special education similarly identified potential benefits alongside substantial heterogeneity in technologies, populations, and outcome measures (Hopcan *et al.*, 2023). The strongest evidence in adjacent literature concerns learning outcomes from intelligent tutoring systems rather than direct change in executive functioning. A meta-analysis found that intelligent tutoring systems can improve learning relative to several comparison conditions (Ma *et al.*, 2014). Recent syntheses also describe wide variation in educational purposes, technologies, and outcome measures, with persistent gaps in theory, ethics, and stakeholder involvement (Bond *et al.*, 2024; Chiu *et al.*, 2023). Ouyang and Jiao's (2021) distinction among AI-directed, AI-supported, and AI-empowered paradigms is especially relevant because it places learner agency at the center of system design. Such findings establish that adaptive guidance may assist learning, but they do not demonstrate that artificial intelligence trains working memory, inhibition, or flexibility. This review consequently treats many links between specific technologies and executive processes as theoretically plausible mechanisms that require direct testing.

Taken together, the reviews establish a useful but incomplete evidence base. Studies of intelligent tutoring systems support claims about academic learning under particular instructional conditions (Ma *et al.*, 2014), whereas the special education literature spans different learner groups, tools, and outcomes (Hopcan *et al.*, 2023). Broad AI-in-education reviews document expansion of the field and recurring methodological concerns (Chiu *et al.*, 2023; Zhai *et al.*, 2021), but they do not isolate executive-function development among students with special educational needs. Evidence of better achievement or engagement therefore cannot be used as a proxy for gains in inhibition, working-memory updating, or cognitive flexibility.

A further tension concerns learner agency. Self-regulated learning theory treats goal setting, strategy selection, monitoring, and evaluation as activities the learner gradually controls (Zimmerman, 2008). Adaptive

systems can make these activities more manageable, yet automation may also carry out the decisions that instruction aims to teach. Inclusive pedagogy and Universal Design for Learning favor flexible access to participation (Florian & Black-Hawkins, 2011; Meyer *et al.*, 2014); they do not require every support to be withdrawn. Accordingly, the key question is whether a particular use is intended to provide continuing access, temporary guidance, or transferable strategy learning. This unresolved distinction motivates the three-function framework developed below.

MATERIALS AND METHODS

Review Design and Scope

This study used a critical narrative review. This design was selected because the relevant evidence spans cognitive psychology, self-regulated learning, educational technology, and special education and includes theoretical papers, reviews, meta-analyses, empirical studies, and scholarly books. Narrative synthesis is suitable for integrating conceptually diverse evidence, provided that its interpretive character and limitations are made explicit (Baumeister & Leary, 1997; Ferrari, 2015).

The review was organized around three intersecting concepts: artificial intelligence in education, executive functioning or self-regulated learning, and special or inclusive education. Literature was identified through combinations of terms such as artificial intelligence in education, intelligent tutoring system, adaptive learning, generative artificial intelligence, executive function, self-regulated learning, special educational needs, learning disabilities, ADHD, and autism. Priority was given to peer-reviewed syntheses, influential conceptual works, and empirical research that clarified mechanisms relevant to planning, monitoring, attention regulation, information organization, and strategy use.

Inclusion principles and synthesis

Sources were included when they addressed at least two of the following: artificial-intelligence-supported educational practice; executive-function-related learning processes; self-regulation; disability, special educational needs, or inclusive education. Purely technical studies without an educational interpretation and clinical diagnostic applications without a learning context were outside the scope. Because the purpose was conceptual integration rather than exhaustive identification of every eligible study, the review does not report a PRISMA flow diagram or claim systematic-review completeness. Analysis proceeded through comparative reading and concept mapping. Claims were grouped by the function performed by the technology, the executive or self-regulatory demand addressed, the degree of learner agency retained, and whether outcomes represented supported performance or

independent development. This process produced three analytic categories: compensation, scaffolding, and development. The categories are interpretive and are proposed as a framework for research and practice rather than as the result of a quantitative effectiveness analysis.

Limitations

The narrative design does not permit an estimate of pooled effectiveness and remains more susceptible to selection and interpretive bias than a systematic review. The evidence base is also developing rapidly, and terminology varies across disciplines. Most importantly, many educational artificial-intelligence studies measure achievement, engagement, usability, or task completion rather than executive functions with validated instruments. Conclusions about executive-function development must therefore remain cautious.

Synthesis of Educational Applications

Intelligent tutoring and adaptive learning systems. Intelligent tutoring systems provide hints, feedback, sequencing, and practice adapted to learner performance. Their relevance to executive functioning lies principally in structuring problem solving. They can reduce the need to hold an entire procedure in working memory, direct attention to a relevant step, and prompt a learner to monitor an error. Adaptive platforms may also adjust difficulty to maintain an attainable level of challenge, which can support persistence and reduce frustration (Chen *et al.*, 2020; Ma *et al.*, 2014).

These functions should be interpreted as support for executive demands, not evidence of direct cognitive training. If a platform supplies every next step, the learner may complete more problems without developing an independent planning routine. Systems should therefore use graduated prompts, provide opportunities for the learner to select a strategy, and reduce assistance as competence increases.

Planning Assistants and Organizational Tools

Digital assistants can break an assignment into subtasks, estimate time, schedule reminders, and display progress. Such features directly address common barriers involving task initiation, prospective memory, sequencing, and time management. For a learner who repeatedly fails to begin work because the task is experienced as undifferentiated and overwhelming, an interactive plan can make the task actionable.

The educational objective determines whether this is compensation or instruction. Persistent reminders may be an appropriate accessibility accommodation. If the objective is independent planning, the system should progressively transfer responsibility by asking the learner to propose steps, justify priorities, and

review the accuracy of time estimates. The teacher must decide which supports should remain available and which should be faded.

Learning Analytics And Automated Feedback.

Learning analytics can summarize patterns such as time on task, repeated errors, help-seeking, incomplete activities, or irregular progress. When interpreted cautiously, these data may help teachers identify where a learner requires additional instruction or environmental support. Dashboards can also make progress visible to students and support self-monitoring.

Interaction traces are not transparent measures of internal cognitive states. Slow responding may reflect careful thought, language processing, distraction, inaccessible design, or technical difficulty. Algorithms should not infer an executive deficit or diagnostic status from behavioral data alone. Analytics are most defensible when used as one source of information within professional assessment and dialogue with the learner.

Conversational agents and generative artificial intelligence.

Conversational agents can answer questions, model self-questioning, and guide a learner through a task. Generative artificial intelligence adds the capacity to produce outlines, explanations, examples, summaries, and alternative representations. Reviews of the early ChatGPT literature describe potential roles in tutoring and content support but also inconsistent performance and confidently presented inaccuracies (Lo, 2023; Tlili *et al.*, 2023). These functions may reduce barriers for students who struggle to organize ideas or transform an intention into a sequence of written actions. Large language models may also support cognitive flexibility by generating contrasting explanations or inviting comparison of strategies (Grassini, 2023; Kasneci *et al.*, 2023).

The same affordances create significant risks. Generated content may be inaccurate, culturally narrow, developmentally inappropriate, or inconsistent across prompts. A systematic scoping review found limited transparency, replicability, privacy protection, and stakeholder involvement across educational applications of large language models (Yan *et al.*, 2024). Ready-made plans and prose may replace the very planning and monitoring processes education seeks to develop. Effective use should require students to inspect, verify, revise, and explain outputs. For example, a learner may compare an artificial-intelligence-generated outline with task criteria, identify missing elements, and construct a final plan rather than simply accept the proposed structure.

Reading And Writing Support.

Text-to-speech, adaptive text presentation, predictive writing, and structured writing prompts can improve access for some learners with reading or writing difficulties. Evidence concerning text-to-speech suggests that effects vary across learners and implementations, underlining the need for individualized evaluation (Wood *et al.*, 2018). Artificial intelligence can extend these tools through contextual explanations, adjustable language complexity, and feedback linked to criteria.

Accessibility support must not be confused with remediation. Reducing decoding or transcription demands may appropriately allow a learner to demonstrate comprehension or disciplinary knowledge. Whether a tool is used as an accommodation, as part of explicit strategy instruction, or as temporary practice support should be stated in the learning plan.

A three-function framework

Table 1 summarizes the proposed distinction between compensatory, scaffolding, and developmental uses. The same tool may serve different functions depending

Table 1: Functions of artificial intelligence support for executive-function-related learning

Function	Primary purpose	Example	Indicator of appropriate use	Main risk
Compensation	Reduce or externalize an executive demand	Persistent reminders or automated task sequencing	Improved access and participation while support remains available	Support is mistaken for improvement in the underlying capacity
Scaffolding	Help the learner perform a task just beyond current independent capability	Graduated hints, planning prompts, or feedback questions	The learner makes decisions with targeted assistance	Excessive prompting reduces agency and productive struggle
Development	Promote independent strategy use and transfer	Learner generates a plan, compares it with AI suggestions, reflects, and repeats with less help	Strategy use persists when support is faded or transferred to a new task	Short-term performance is reported as durable development

on its design, the learner's goal, and how responsibility is distributed.

The framework suggests a progression rather than a hierarchy. Compensation is not an inferior outcome: some learners require continuing supports to participate equitably. Problems arise when the purpose is unclear. A tool intended as an accommodation should be evaluated by accessibility and participation. A developmental intervention should be evaluated through retention, transfer, and performance after support has been reduced. A teacher-mediated cycle can guide implementation. First, the educator and learner identify the functional barrier and define an observable goal. Second, they select the least intrusive support likely to help. Third, the system provides support while the learner remains actively involved in decisions. Fourth, the educator and learner review both performance and the process used. Finally, assistance is maintained, adjusted, or faded according to the original purpose. This cycle places educational judgment, learner voice, and ongoing assessment above technological novelty.

RESULTS AND DISCUSSION

The reviewed literature supports a cautious interpretation of artificial intelligence as external cognitive scaffolding. Intelligent systems can structure tasks, make progress visible, provide immediate prompts, and adapt representations. These capabilities align with executive demands encountered by many students with special educational needs. They may also help teachers deliver timely differentiation that would otherwise be difficult to sustain.

The available evidence does not justify broad claims that artificial intelligence improves executive functioning. Most relevant studies examine general learning outcomes, engagement, or platform use. Even when attention or planning appears to improve during tool use, three alternative explanations remain: the system may have reduced task difficulty, externally performed part of the executive work, or temporarily increased motivation. Direct executive-function measures, withdrawal phases, transfer tasks, and longer follow-up periods are needed to distinguish these possibilities.

Cognitive Offloading And Productive Struggle

Cognitive offloading occurs when information or operations are transferred to an external aid. Offloading is not inherently harmful; notes, calendars, and calculators are ordinary tools of competent activity. For learners with disabilities, external support may be essential for equitable participation. The pedagogical question is whether the offloaded process is necessary for the intended learning outcome. If the goal is to construct an argument, generating the complete structure may remove important planning practice. If the goal is to demonstrate scientific understanding, reducing transcription or organizational load may enable a more valid demonstration of knowledge. Artificial-intelligence support should therefore be calibrated rather than categorically accepted or prohibited.

Useful designs preserve decision points, ask learners to justify choices, and incorporate deliberate fading. Molenaar (2022) describes this broader direction as hybrid human-AI learning, in which human and artificial capacities are deliberately combined rather than treated as substitutes. Such designs also allow educators to inspect the support provided and to override it when it conflicts with instructional aims.

Inclusion, Agency, And The Role Of The Teacher.

Artificial intelligence cannot determine the educational meaning of a student's behavior without contextual knowledge. Teachers understand classroom relationships, curriculum aims, prior instruction, emotional state, and the significance of a task within a longer learning trajectory. Their role is therefore not reduced to supervising technology. It expands to include selecting appropriate functions, teaching critical use, interpreting data, and protecting learner agency.

Students should participate in decisions about how support is used, especially when systems collect behavioral data or make recommendations about them. Learner voice can reveal whether prompts are supportive or distracting, whether feedback is understandable, and whether a tool increases confidence or dependence. Inclusive implementation also requires non-digital alternatives and attention to unequal access, language coverage, accessibility, and digital literacy.

Ethics And Data Governance

Artificial-intelligence systems may process sensitive information about disability, performance, behavior, and help-seeking. Educational institutions should minimize data collection, define retention and access, evaluate vendors, and communicate clearly with learners and families. Recent guidance emphasizes human oversight, age-appropriate use, data protection, transparency, and critical AI literacy (European Commission, 2022; UNESCO, 2023). Data used for one educational purpose should not silently be repurposed for diagnosis, discipline, or high-stakes prediction. Transparency is particularly important when automated recommendations influence expectations or opportunities.

Algorithmic bias can emerge from unrepresentative training data, inaccessible design assumptions, or outcome definitions that treat conformity as success. A system may interpret atypical communication, longer response times, or frequent help-seeking as low ability rather than as evidence of a mismatch between the learner and the environment. Human review is therefore necessary but not sufficient; institutions also require procedures for contesting automated outputs and documenting consequential decisions (Dignum, 2019; Williamson & Eynon, 2020).

Research priorities

Future research should report the precise function of the technology, the support provided, the target executive

process, and whether the outcome was measured during or after tool use. Studies need validated executive-function or self-regulation measures alongside academic outcomes. Designs should include comparison conditions that distinguish artificial intelligence from equivalent non-AI scaffolding, because benefits may arise from feedback or structure rather than from artificial intelligence itself. Longitudinal and single-case experimental designs could examine maintenance and individual variability. Research should also evaluate transfer to unfamiliar tasks, learner agency, teacher workload, accessibility, and unintended effects. Participants with disabilities should contribute to design and evaluation rather than appear only as recipients of a finished system. Finally, transparent reporting of privacy arrangements, model limitations, and human oversight should become standard.

Educational Implications

Educational use can be guided by six principles. First, begin with a clearly defined learner barrier and educational objective rather than with an available tool. Second, specify whether the intended function is compensation, scaffolding, or development. Third, preserve learner agency by requiring meaningful choices, verification, and reflection. Fourth, use graduated assistance and assess performance when support is reduced whenever independent development is the goal. Fifth, retain teacher oversight and provide a non-digital alternative. Sixth, apply data minimization, transparency, accessibility, and procedures for challenging automated outputs.

These principles support a balanced approach. Artificial intelligence may extend inclusive practice by making individualized prompts and representations more available, but it should operate within established pedagogical relationships. The quality of implementation depends less on the sophistication of an algorithm than on alignment among learner needs, instructional aims, assessment, and ethical safeguards.

CONCLUSION

Artificial-intelligence-supported tools can help students manage planning, monitoring, information organization, and other demands associated with executive functioning. Their most defensible role is as teacher-mediated cognitive support within inclusive educational environments. Improved task completion while a system is available should not be described as executive-function development unless independent performance, retention, or transfer has been demonstrated.

The proposed three-function framework clarifies whether artificial intelligence is being used to compensate for a continuing barrier, scaffold current performance, or promote independent strategy use. This distinction can improve research design, educational decision-making, and the interpretation of outcomes. Artificial intelligence may contribute meaningfully to inclusive education when it strengthens access and agency, remains subject to

human judgment, and is evaluated against clearly stated educational purposes.

REFERENCES

- Baumeister, R. F., & Leary, M. R. (1997). Writing narrative literature reviews. *Review of General Psychology*, 1(3), 311-320. <https://doi.org/10.1037/1089-2680.1.3.311>
- Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education*, 21, 4. <https://doi.org/10.1186/s41239-023-00436-z>
- Best, J. R., & Miller, P. H. (2010). *A developmental perspective on executive function*. *Child Development*, 81(6), 1641-1660. <https://doi.org/10.1111/j.1467-8624.2010.01499.x>
- Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, 8, 75264-75278. <https://doi.org/10.1109/ACCESS.2020.2988510>
- Chiu, T. K. F., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, 4, 100118. <https://doi.org/10.1016/j.caeai.2022.100118>
- Diamond, A. (2013). Executive functions. *Annual Review of Psychology*, 64, 135-168. <https://doi.org/10.1146/annurev-psych-113011-143750>
- Dignum, V. (2019). Responsible artificial intelligence: How to develop and use AI in a responsible way. *Springer*. <https://doi.org/10.1007/978-3-030-30371-6>
- European Commission. (2022). Ethical guidelines on the use of artificial intelligence and data in teaching and learning for educators. *Publications Office of the European Union*. <https://doi.org/10.2766/153756>
- Ferrari, R. (2015). Writing narrative style literature reviews. *Medical Writing*, 24(4), 230-235. <https://doi.org/10.1179/2047480615Z.000000000329>
- Florian, L., & Black-Hawkins, K. (2011). Exploring inclusive pedagogy. *British Educational Research Journal*, 37(5), 813-828. <https://doi.org/10.1080/01411926.2010.501096>
- Grassini, S. (2023). Shaping the future of education: Exploring the potential and consequences of AI and ChatGPT in educational settings. *Education Sciences*, 13(7), 692. <https://doi.org/10.3390/educsci13070692>
- Holmes, W., Bialik, M., & Fadel, C. (2019). *Artificial intelligence in education: Promises and implications for teaching and learning*. Center for Curriculum Redesign.
- Holmes, W., & Tuomi, I. (2022). State of the art and practice in AI in education. *European Journal of Education*, 57(4), 542-570. <https://doi.org/10.1111/ejed.12533>
- Hopcan, S., Polat, E., Ozturk, M. E., & Ozturk, G. (2023). Artificial intelligence in special education: A systematic review. *Interactive Learning Environments*,

- 31(8), 4571-4589. <https://doi.org/10.1080/10494820.2022.2067186>
- Kasneci, E., Sessler, K., Kuchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Gunnemann, S., Hullermeier, E., Krusche, S., Kutyniok, G., Michaeli, T., Nerdel, C., Pfeffer, J., Poquet, O., Sailer, M., Schmidt, A., Seidel, T., Stadler, M., Weller, J., Kuhn, J., & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. <https://doi.org/10.1016/j.lindif.2023.102274>
- Lo, C. K. (2023). What is the impact of ChatGPT on education? A rapid review of the literature. *Education Sciences, 13*(4), 410. <https://doi.org/10.3390/educsci13040410>
- Ma, W., Adesope, O. O., Nesbit, J. C., & Liu, Q. (2014). Intelligent tutoring systems and learning outcomes: A meta-analysis. *Journal of Educational Psychology, 106*(4), 901-918. <https://doi.org/10.1037/a0037123>
- Meltzer, L. (Ed.). (2018). *Executive function in education: From theory to practice* (2nd ed.). Guilford Press.
- Meyer, A., Rose, D. H., & Gordon, D. (2014). *Universal design for learning: Theory and practice*. CAST.
- Molenaar, I. (2022). Towards hybrid human-AI learning technologies. *European Journal of Education, 57*(4), 632-645. <https://doi.org/10.1111/ejed.12527>
- Miyake, A., & Friedman, N. P. (2012). The nature and organization of individual differences in executive functions: Four general conclusions. *Current Directions in Psychological Science, 21*(1), 8-14. <https://doi.org/10.1177/0963721411429458>
- Ouyang, F., & Jiao, P. (2021). Artificial intelligence in education: The three paradigms. *Computers and Education: Artificial Intelligence, 2*, 100020. <https://doi.org/10.1016/j.caeai.2021.100020>
- Tlili, A., Shehata, B., Adarkwah, M. A., Bozkurt, A., Hickey, D. T., Huang, R., & Agyemang, B. (2023). What if the devil is my guardian angel: ChatGPT as a case study of using chatbots in education. *Smart Learning Environments, 10*, 15. <https://doi.org/10.1186/s40561-023-00237-x>
- UNESCO. (2023). *Guidance for generative AI in education and research*. UNESCO. <https://doi.org/10.54675/EWZM9535>
- Williamson, B., & Eynon, R. (2020). Historical threads, missing links, and future directions in AI in education. *Learning, Media and Technology, 45*(3), 223-235. <https://doi.org/10.1080/17439884.2020.1798995>
- Wood, S. G., Moxley, J. H., Tighe, E. L., & Wagner, R. K. (2018). Does use of text-to-speech and related read-aloud tools improve reading comprehension for students with reading disabilities? A meta-analysis. *Journal of Learning Disabilities, 51*(1), 73-84. <https://doi.org/10.1177/0022219416688170>
- Yan, L., Sha, L., Zhao, L., Li, Y., Martinez-Maldonado, R., Chen, G., Li, X., Jin, Y., & Gasevic, D. (2024). Practical and ethical challenges of large language models in education: A systematic scoping review. *British Journal of Educational Technology, 55*(1), 90-112. <https://doi.org/10.1111/bjet.13370>
- Zhai, X., Chu, X., Chai, C. S., Jong, M. S.-Y., Istenic, A., Spector, M., Liu, J.-B., Yuan, J., & Li, Y. (2021). A review of artificial intelligence in education from 2010 to 2020. *Computers and Education: Artificial Intelligence, 2*, 100019. <https://doi.org/10.1016/j.caeai.2021.100019>
- Zawacki-Richter, O., Marin, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education: Where are the educators? *International Journal of Educational Technology in Higher Education, 16*, 39. <https://doi.org/10.1186/s41239-019-0171-0>
- Zimmerman, B. J. (2008). Investigating self-regulation and motivation: Historical background, methodological developments, and future prospects. *American Educational Research Journal, 45*(1), 166-183. <https://doi.org/10.3102/0002831207312909>