LEARNING LETTERS

Year 2026
Volume 8
Article 60
https://doi.org/10.20851/ll.v8.60l

Efficiency vs. effectiveness: Self-regulated learning with LLM-mediated help-seeking

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AI tools powered by large language models (LLMs) are rapidly entering students' study practices, yet we know little about how they reshape self-regulated learning (SRL), particularly help-seeking and related task strategies. We report a qualitative study with 20 STEM students at a large Swedish university who were interviewed about their use of commercial LLM chatbots. Guided by Zimmerman's SRL model and the Online SRL subscales, we conducted a thematic analysis. Findings show that LLMs are integrated into a layered, context-dependent help-seeking ecosystem rather than replacing human support. Students described a four-stage process: (1) deciding whether help is needed, typically by attempting problems independently first; (2) choosing a source and using ChatGPT as a low-barrier first step, then peers for conceptual negotiation, and instructors for complex or high-stakes issues; (3) determining the type of help, from seeking hints and explanations to scaffolding problem-solving, streamlining routine work, and extending learning; and (4) judging the help by exercising selective trust, verifying AI outputs against coursework or with humans, and reserving human support for nuanced understanding and affective needs. Overall, students aligned LLM use with SRL goals and task demands, favouring instrumental over executive help-seeking to retain control of problem-solving. The findings suggest an adapted model of help-seeking for LLM-mediated learning practices and implications for promoting verification practices, instrumental help-seeking, and sustained learner agency.

Keywords: help-seeking, large language models, self-regulated learning, STEM higher education, task strategies

Recommended citation: Viberg, O., Feldman-Maggor, Y., & Wong, J. (2026). Efficiency vs. effectiveness: Self-regulated learning with LLM-mediated help-seeking. *Learning Letters*, 8, Article 60. https://doi.org/10.20851/ll.v8.60

Introduction and background

Generative artificial intelligence (GenAI) chatbots powered by large language models (LLMs) are rapidly becoming embedded in students' daily study routines, especially in STEM higher education (Handa et al., 2025). GenAI chatbots, such as ChatGPT, Claude, and GitHub Copilot, can draft essays, debug code, and create personalised study plans, promising to scaffold complex tasks while freeing time spent on simple tasks for higher-order thinking (Jin et al., 2025). However, our knowledge and understanding of how students use these tools to support them in their studies is limited (Viberg et al., 2025). Since current GenAI chatbots are

powered by LLMs, we use the term LLM throughout this paper to refer broadly to both chatbots and other GenAI applications.

While LLMs can enhance creative and analytical work by facilitating collaborative problem-solving, uncritical reliance on them (e.g., asking for direct solutions) may negatively impact critical thinking, mask misconceptions, and exacerbate equity gaps (e.g., Fan et al., 2025; Lee et al., 2025; Yan et al., 2024). A report by Anthropic, based on the analysis of one million university student interactions with Claude, found most use centred on creating (e.g., coding projects) and analysing (e.g., theoretical concepts) tasks, which align with higher-order cognitive processes in Bloom's taxonomy (Handa et al., 2025). This raises a critical concern: *How can students manage the potential drawbacks of LLM assistance, finding a balance between efficiency through cognitive offloading and maintaining effective control of their cognitive efforts?*

A critical factor in maintaining effective control of one's cognitive effort when using LLMs is self-regulated learning (SRL) (Lodge et al., 2023). SRL refers to the ability to plan, monitor, and evaluate one's learning, and has been consistently linked to academic success and lifelong learning (Barnard-Brak et al., 2010; Zimmerman, 2002). Self-regulated learners who set goals and plan their personal feedback needs may leverage LLMs to generate formative feedback by asking specific questions, judging the quality of feedback received, and refining their prompts to get more useful feedback (Zhan et al., 2025). In contrast, weaker SRL skills may lead to superficial "copy-and-paste" use that bypasses deep learning (Yan et al., 2025).

Academic help-seeking combines autonomous control with social interaction and is a unique SRL strategy involving engagement with external agents to support student learning and problem-solving (Karabenick & Berger, 2013; Karabenick & Knapp, 1988). Help-seeking may occur across all three phases of Zimmerman's (2002) SRL model: (1) forethought—deciding if, what, and from whom to seek help; (2) performance—obtaining help; and (3) self-reflection—evaluating its usefulness, which shapes future help-seeking behaviour (Karabenick & Gonida, 2017). Two forms of help-seeking have been proposed: *executive*, aimed at obtaining solutions, and *instrumental*, aimed at enhancing understanding (Nelson Le-Gall, 1981).

The introduction of LLMs extends the nature of external agents, moving from human-to-human only to human-AI interactions in the help-seeking process. Students' use of LLMs can vary by task and task strategies (Hou et al., 2024) and can reflect either *executive* help-seeking (e.g., asking ChatGPT to write a code for a programming task) or *instrumental* help-seeking (e.g., asking ChatGPT for a hint or an explanation). Unlike traditional online resources, such as discussion forums and search engines, LLM-mediated academic help-seeking enables immediate responses and enriched interactivity with audio and video beyond text-based interaction. Users often report reduced use of the Google search engine and increased reliance on LLMs (see e.g., Bearne, 2025; Fan et al., 2025; Kosmyna et al., 2025). This influences their SRL processes (e.g., Fan et al., 2025) as the effective use of search engines requires more evaluation and selection of information sources, whereas LLMs may bypass these steps by offering automatically generated fast responses.

Relationships between help-seeking and task strategies are often investigated (e.g., Karabenick, 2003; Karabenick & Knapp, 1991). Task strategies are methods students employ to complete learning tasks and include various cognitive and metacognitive strategies, such as organisation and elaboration. When faced with challenging tasks, students may experience difficulties in applying these strategies in a way that is conducive to their learning and may seek help as needed in order to cope and continue. Overall, despite rapid adoption, little is known about how students' help-seeking and interlinked task strategies manifest in LLM-

mediated learning practices in STEM higher education. Addressing this gap, this study asks:

RQ: *How do university students use help-seeking and task strategies as part of self-regulated learning when interacting with LLMs to support their learning?*

Method

Participants

The participants were 20 students (14 females, 6 males) enrolled in bachelor's or master's programs at a large STEM university. Most participants had completed at least one year of study and were in either the second or third year of their bachelor's program or the second year of their master's program. Given that data saturation is often reached after approximately 12 interviews (Guest et al., 2006), 20 participants were recruited to capture a diverse range of perspectives. The study follows the university's ethics protocol, and informed consent was obtained from the study participants.

Instruments

The data collection method was semi-structured interviews consisting of 20 questions designed to explore how students self-regulate their learning when interacting with LLMs. The questions were developed based on Zimmerman's three-phase cyclical SRL model (Zimmerman, 2002). In addition, the five subscales of the Online Self-Regulated Learning Questionnaire (OSLQ) (Barnard-Brak et al., 2010)—time management, goal setting, task strategies, help-seeking, and self-evaluation—were used to inform question development. This study is part of a larger project.

This paper reports only the data concerning students' help-seeking behaviour when interacting with commercial LLMs, with a particular focus on possible changes in help-seeking and task strategies. For *help-seeking*, three questions examined who students typically seek help from, and whether their approaches to seeking help from lecturers, teaching assistants (TAs), and peers had changed with the introduction of LLMs. For *task strategies*, two questions investigated whether students use LLMs to generate practice materials, and whether they use them to solve exercises provided in their courses. These questions were informed by the original OSLQ items (Barnard-Brak et al., 2010).

Procedure and data analysis

Participants were recruited by course announcements on the courses' online learning management system (Canvas). Informed written consent was obtained, and the interviews were scheduled at the participants' convenience between mid-May and July 2024. Each interview lasted 30 to 40 minutes and was conducted and recorded in English, either face-to-face (on campus) or via Zoom, an online meeting platform. The audio recordings were transcribed using the online transcription service otter.ai (https://otter.ai/). The transcripts were checked and coded by two authors using Atlas.ti (https://atlasti.com).

The analysis followed the six phases of thematic analysis (Braun & Clarke, 2006, 2013). First, two of the authors familiarised themselves with the data by reading the transcripts in full and noting initial analytic observations in relation to SRL. In the coding phase, a deductive approach was used initially, drawing on Zimmerman's SRL model and the relevant OSLQ subscales (help-seeking and task strategies mentioned previously) to guide coding. This was followed by an inductive approach to identify additional themes that emerged from the data without being constrained by the theoretical framework. In the third phase, the authors searched for themes by identifying similarities in the coded data and collating extracts relevant to each theme. In the fourth and fifth phases, the themes were reviewed and named

collaboratively. In the final phase, the results were written up and contextualised in relation to existing literature. To enhance trustworthiness, coding decisions were cross-checked by the first and the last author, and any discrepancies were resolved through consensus.

Results

Our findings show that students in STEM higher education increasingly incorporate LLMs into a *layered*, *context-dependent* help-seeking ecosystem that supports their SRL. Rather than replacing traditional sources of help, LLMs are used alongside peers, teaching assistants, and instructors in a tiered sequence. This approach revisits the help-seeking process by lowering barriers to asking for assistance, increasing efficiency, and allowing students to better align help-seeking with their task strategies. The LLM-mediated help-seeking process can be understood across four interconnected stages: (1) deciding whether help is needed, (2) choosing whom to ask, (3) determining the type of help, and (4) judging the help received.

Deciding whether help is needed

Students reported a *clear preference for attempting tasks independently before seeking* external assistance from LLMs. This approach is rooted in a desire to preserve the learning value of problem-solving and to avoid over-reliance on AI. For example, P1stressed: *"mostly when I get really stuck, I always try to do it myself first and then I always try to ask [ChatGPT] more for concepts instead of direct solutions because I feel like I learn more from that."*

LLMs are typically consulted when students reach a point where their own strategies could not resolve the problem, functioning as scaffolds to overcome specific obstacles or to check the validity of a solution. As P9 described, *"I have a solution I think is correct, then I usually check with it if I'm on the right path."* While some students acknowledged the temptation to let LLMs solve entire tasks, they expressed caution, seeing this as undermining learning goals: *"It just reduces the whole point of learning things"* (P13). Overall, students positioned LLMs as a targeted support mechanism used only after exhausting their own problem-solving efforts, reflecting a deliberate balance between leveraging AI assistance and maintaining the integrity of their learning process.

Choosing whom to ask for help

Once help was deemed necessary, students typically follow a *layered sequence of sources*, starting with ChatGPT for immediate, low-barrier queries, moving to peers for collaborative problem-solving, and consulting teacher assistants or instructors for complex, unresolved issues. As P2 explained, they would go "first [to] ChatGPT, then classmates, and lastly teachers."

Peers remain important for discussing theoretical concepts, negotiating understanding, offering diverse perspectives, and providing emotional support. For instance, one student reported going *"to classmates [for] theory, but for step-by-step coding help, ChatGPT is faster"* (P6). LLMs also help reduce emotional barriers to help-seeking, particularly for students who are hesitant to approach others due to fear of judgement or social discomfort, with one noting, *"It is easier to ask someone who is not a person"* (P14). Finally, the participants stress the *affective* support provided by the peers in the learning process: *"I get the most happiness out of talking to my peers"* (P10). However, in advanced courses or specialised tasks that exceed LLMs' capabilities, instructor support remains essential (P12, P19). In sum, students adopt a *layered help-seeking approach* in which LLMs serve as the first, low-barrier step, peers provide collaborative and conceptual support, and instructors are consulted for issues of high-complexity.

Determining the type of help sought

Students' LLMs-use clusters around three main purposes. First, they use them to overcome obstacles while maintaining independent problem-solving, often seeking step-by-step guidance or targeted hints that allow them to progress without bypassing the effort of solving the task themselves. As one student explained, ChatGPT is *"a hint, an assisting tool, but not the standalone solution"* (P7).

Second, LLMs are employed for efficiency by reducing time spent searching for information, debugging code, or switching between programming languages. One student likened this to *"a quick Google search"*, noting that it "*benefits me in terms of time"* (P4). Students also use LLMs to brainstorm for ideas that act as a starting point for them to refine: *"Maybe it's good to ask … can you give me a first draft … you tune it, but you already have, like, the skeleton"* (P15).

Third, some students use LLMs to help extend or augment learning, such as preparing for exams and generating additional exercises (P9, P11). Students also employ LLMs for explanations. In this regard, one student clarified: *"I created a mentor for each course … instructed it to act like a teacher, to explain and not solve"* (P2).

Across these uses, students differentiate between applying LLMs to small, well-defined tasks, such as syntax checks or debugging, and relying on human help for complex, ill-defined challenges requiring deeper conceptual understanding. This reflects a strategic alignment of LLM-use with task demands, where AI is valued for efficiency and targeted assistance, while *humans remain central for nuanced, high-level problem-solving,* and *affective learning* support.

Judging the help received

Students generally evaluate LLM-generated responses with a stance of selective trust, balancing appreciation for ChatGPT's speed and availability with an awareness of its limitations. Many described verifying AI outputs with peers, course materials, or instructors, especially when accuracy was uncertain. As one student explained, *"I only go to the TA if we can't tell whether ChatGPT is making things up"* (P8).

ChatGPT is widely regarded as effective for minor issues such as syntax checks, quick clarifications, or debugging, yet inadequate for tasks demanding deep conceptual understanding, emotional support, or the contextual expertise of human sources. As P2 put it, *"ChatGPT just helps me with small things".* This critical, discerning use meant that LLMs are positioned as complementary tools, highly useful for targeted, well-defined tasks but never a wholesale replacement for human guidance. Peers and instructors remain indispensable for complex, collaborative, and high-stakes learning situations, ensuring that the help-seeking process retains a human dimension.

In summary, the integration of LLMs into students' help-seeking reflects a reconfiguration rather than a displacement of traditional help-seeking pathways. By serving as a low-barrier entry point, ChatGPT supports greater independence and learner agency as well as reducing the social costs of asking for help, while the selective and layered approach allows students to align AI use with their SRL strategies and the specific demands of their learning context.

Discussion and conclusions

This study examined how students in STEM higher education employ SRL strategies using LLMs, particularly help-seeking and task strategies. Findings indicate that academic help-seeking is *layered* and *context-dependent*: LLMs were generally preferred for simple, well-defined tasks such as debugging or syntax checking, while peers and instructors were sought

for more complex conceptual challenges and affective support. This supports prior work on the contextual nature of SRL (e.g., Barnard-Brak et al., 2010; Krell et al., 2015) and help-seeking (Makara & Kuusinen, 2023) by highlighting the importance of task specificity even within a single discipline.

Our findings stand in contrast to recent studies demonstrating students' over-reliance on LLM-generated outputs (e.g., Fan et al., 2025; Kosmyna et al., 2025), and students exhibiting more executive help-seeking with AI than with human experts (Chen et al., 2025). Students in the current study expressed intentional efforts to prevent over-reliance on commercial LLMs, as they preferred to attempt solving tasks independently before turning to LLMs for assistance. This suggests students' decisions to use LLMs to overcome learning impasses is strategic and indicative of instrumental help-seeking. Chen et al. (2025) used a quantitative experimental approach to analyse student help-seeking process in AI-mediated writing in Chinese higher education, whereas our study undertook an exploratory qualitative approach to investigate students' self-initiated, authentic everyday interactions with commercial LLMs to support their study in STEM higher education. Differences in the nature of the tasks (writing vs programming), study settings (experimental vs non-experimental), and cultural contexts (China vs Sweden) may explain the variations in findings. Future research should pursue cross-cultural replication and mixed-method approaches to further deepen our understanding of academic help-seeking in human-AI interactions across tasks, disciplines, and research settings (e.g., lab experiments vs authentic learning contexts).

Our inductive analysis aligns with Karabenick and Berger's (2013) model of help-seeking processes. Accordingly, we suggest adapting this model for LLM-mediated academic help-seeking: (1) deciding whether help is needed, (2) selecting a source, (3) determining the type of help, and (4) judging the help received. LLMs' affordances, such as anonymity, immediacy, and adaptiveness, allow students to experiment, self-diagnose, and receive adaptive feedback without fear of judgement. While LLMs lower the cost of help-seeking (e.g., threat to self-esteem) (Karabenick & Knapp, 1991), they do not replace the relational and affective dimensions of learning; rather, they introduce new layers of strategic choice, reflecting whom to approach (i.e., the LLM or the instructor) for different types of assistance within the human-AI help-seeking process. That is, our results underscore the role of human social interaction in LLM-mediated help-seeking. Consistent with Zimmerman's (2002) emphasis on the affective dimension of SRL, human interactions with peers and instructors remain essential for building confidence, negotiating meaning, and supporting emotional needs.

A key implication of this study is the need to revise the existing psychometric measures to capture SRL in LLM-mediated learning contexts. While general instruments exist to measure SRL (e.g., Pintrich, 1993) and to target online learning in particular (e.g., Barnard-Brak et al., 2010), no adapted measures currently assess SRL in LLM-mediated learning contexts to our knowledge. Such measures are necessary for examining SRL to understand effective engagement and improved learning with LLMs. Ultimately, we aim for a more nuanced conceptual basis for developing an *SRL-for-LLM* measurement instrument. Starting with academic help-seeking, Table 1 proposes potential items to measure LLM-mediated help-seeking.

Table 1. Items to measure academic help-seeking in LLM-mediated learning

Help-seeking process	Potential items for SRL-for-LLMs
Whether help is needed	I try to solve tasks on my own first, and then turn to LLM if I still need help.
Whom to ask for help	When I need help with a simple task, I can use LLM before asking peers or instructors.
Type of help	I ask LLM for hints or step-by-step guidance rather than full solutions so that I can solve the problem myself.
Judging the help received	I usually verify LLMs' answers with course materials, peers, or instructors.

In this study, academic help-seeking was examined within the context of Swedish STEM higher education. To establish the further broader relevance of the findings, future research should pursue cross-cultural replication and mixed-method validation of the proposed items. Moreover, our findings raise a question about equitable learning opportunities for all, as students exhibiting executive over instrumental help-seeking with LLMs may be disadvantaged in their future studies and life. In this regard, Chen et al. (2025) argue that students' non-linear academic help-seeking processes (e.g., skipping evaluation of LLM-generated outputs), identified in their recent study, can be understood as offloading monitoring to and over-reliance on LLMs.

Our study similarly raises questions about cognitive offloading as opposed to efficiency. While students avoid using LLMs for direct answers, reliance on them for debugging or cross-language programming may risk bypassing opportunities for independent problem-solving and learning. Fan et al. (2025) warned of "metacognitive laziness" and reduced cognitive effort when using LLMs in learning practices. Recent research by Xu and colleagues (2025) has shown that metacognitive support improves students' SRL in LLM–mediated settings, but instructors need to be able to effectively integrate such support in their teaching; they need targeted training on SRL strategies in these settings. Although students, with their best intentions, may try to mitigate this risk through selective trust and verification practices, prolonged exposure to "good enough" AI outputs may normalise shortcuts at the expense of deeper learning (Zhai et al., 2024), especially in students with low SRL skills. Therefore, the challenge ahead is to not only support teachers but also support students in fostering the SRL-for-LLM strategies needed to effectively navigate increasingly AI-mediated higher education settings.

Acknowledgements

We thank Saga Lundborg for helping us in data collection and all the study participants for their engagement in this study.

Funding

Viberg's work has been supported by the STINT grant: "Capitalizing on the potentials of technology to promote self-regulation" (MG2018-7984). Viberg and Feldman-Maggor's work has also been supported, in part, by an unrestricted grant within the Google Academic Research (GARA) program. Wong's work is supported by the Dutch Research Council (NWO)

under the Talent programme with project number VI.Veni.221G.065 and the KTH Digital Futures Summer Early Career Programme.

Disclosure of conflicts of interest

The authors report no potential conflicts of interest.

Disclosure of the use of AI-assisted technologies during writing

The authors used ChatGPT 5.0 to support final language editing and stylistic refinement of the manuscript. The tool was applied critically, and all original writing, conceptual and analytical contributions are the sole responsibility of the authors.

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References

Barnard-Brak, L., Paton, V. O., & Lan, W. Y. (2010). Profiles in self-regulated learning in the online learning environment. *International Review of Research in Open and Distributed Learning*, *11*(1), 61–80. https://doi.org/10.19173/irrodl.v11i1.769

Bearne, S. (2025, 16 September). AI challenges the dominance of Google search. *BBC*. https://www.bbc.co.uk/news/articles/c1dx9qy1eeno

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Braun, V., & Clarke, V. (2013). *Successful qualitative research: A practical guide for beginners*. SAGE Publications.

Chen, A., Xiang, M., Zhou, J., Jia, J., Shang, J., Li, X., Gašević, D., & Fan, Y. (2025). Unpacking help-seeking process through multimodal learning analytics: A comparative study of ChatGPT vs human expert. *Computers & Education*, *226*, 105198. https://doi.org/10.1016/j.compedu.2024.105198

Fan, Y., Tang, L., Le, H., Shen, K., Tan, S., Zhao, Y., Shen, T., Li, X & Gašević, D. (2025). Beware of metacognitive laziness: Effects of generative artificial intelligence on learning motivation, processes, and performance. *British Journal of Educational Technology*, *56*(2), 489–530. https://doi.org/10.1111/bjet.13544

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, *18*(1), 59–82. https://doi.org/10.1177/1525822X05279903

Handa, K., Bent, D., Tamkin, A., McCain, M., Durmus, E., Stern, M., Schiraldi, M., Huang, S., Ritchie, S., Syverud, S., Jagadish, K., Vo, M., Bell, M., & Ganguli, D. (2025). *Anthropic education report: How university students use Claude*. https://www.anthropic.com/news/anthropic-education-report-how-university-students-use-claude

Hou, I., Mettille, S., Man, O., Li, Z., Zastudil, C., & MacNeil, S. (2024). The effects of generative AI on computing students' help-seeking preferences. In N. Herbert & C. Seton (Eds.). *Proceedings of the 26th Australasian Computing Education Conference* (pp. 39–48). ACM. https://doi.org/10.1145/3636243.3636248

Jin, Y., Yan, L., Echeverria, V., Gasevic, D., & Martinez-Maldonado, R. (2025). Generative AI in higher education: A global perspective of institutional adoption policies and guidelines. *Computers & Education, 6,* 100348. https://doi.org/10.1016/j.caeai.2024.100348

Karabenick, S. A. (2003). Seeking help in large college classes: A person-centered approach. *Contemporary Educational Psychology, 28(*1), 37–58. https://doi.org/10.1016/S0361-476X(02)00012-7

Karabenick, S. A., & Berger, J. L. (2013). Help seeking as a self-regulated learning strategy. In H. Bembenutty, T. J. Cleary, & A. Kitsantas (Eds.), *Applications of self-regulated learning across diverse disciplines: A tribute to Barry J. Zimmerman* (pp. 237–261). Information Age Publishing.

Karabenick, S. A., & Gonida, E. N. (2018). Academic help seeking as a self-regulated learning strategy: Current issues, future directions. In D. H. Schunk & J. A. Greene (Eds.), *Handbook of self-regulation of learning and performance* (2nd ed., pp. 421–433). Routledge. https://doi.org/10.4324/9781315697048-27

Karabenick, S. A., & Knapp, J. R. (1988). Help seeking and the need for academic assistance. *Journal of Educational Psychology, 80*(3), 406–408. https://doi.org/10.1037/0022-0663.80.3.406

Karabenick, S. A., & Knapp, J. R. (1991). Relationship of academic help seeking to the use of learning strategies and other instrumental achievement behavior in college students. *Journal of Educational Psychology, 83*(2), 221–230. https://doi.org/10.1037/0022-0663.83.2.221

Kosmyna, N., Hauptmann, E., Yuan, Y. T., Situ, J., Liao, X.-H., Beresnitzky, A. V., Braunstein, I., & Maes, P. (2025). Your brain on ChatGPT: Accumulation of cognitive debt when using an AI assistant for essay writing task [Preprint]. *arXiv*. https://arxiv.org/abs/2506.08872

Krell, M., Reinisch, B., & Krüger, D. (2015). Analyzing students' understanding of models and modeling referring to the disciplines biology, chemistry, and physics. *Research in Science Education*, *45*(3), 367–393. https://doi.org/10.1007/s11165-014-9427-9

Lee, H.-P., Sarkar, A., Tanklevith, L., Drosos, I., Rintal, S., Banks, R., & Wilson, N. (2025). The impact of generative AI on critical thinking: Self-reported reductions in cognitive effort and confidence effects from a survey of knowledge workers. In N. Yamashita, V. Evers, & K. Yatani (Eds.), *CHI'25; Conference on Human Factors in Computing Systems* (pp. 1–22). ACM. https://doi.org/10.1145/3706598.3713778

Lodge, J. M., de Barba, P., & Broadbent, J. (2023). Learning with generative artificial intelligence within a network of co-regulation. *Journal of University Teaching and Learning Practice, 20*(7), 1–10. https://doi.org/10.53761/1.20.7.02

Makara, K. A., & Kuusinen, C. M. (2023). Academic help seeking as a process of seeking formative feedback on learning. In T. Urdan & E. N. Gonida (Eds.), *Remembering the life, work, and influence of Stuart Karabenick: A legacy of research on self-regulation, help seeking, teacher motivation, and more* (pp. 69–90). Emerald Publishing. https://doi.org/10.1108/S0749-742320230000022006

Nelson-Le Gall, S. (1981). Help-seeking: An understudied problem-solving skill in children. *Developmental Review*, *1*(3), 224–246. https://doi.org/10.1016/0273-2297(81)90019-8

Pintrich, P. R., Smith, D. A., Garcia, T., & McKeachie, W. J. (1993). Reliability and predictive validity of the Motivated Strategies for Learning Questionnaire (MSLQ). *Educational and Psychological Measurement*, *53*(3), 801–813. https://doi.org/10.1177/0013164493053003024

Viberg, O., Wong, J., Feldman-Maggor, Y., Dunder, N., Epp, C.D. (2025). Chatting with code: Exploring LLMs as learning partners in programming education. In A. I. Cristea, E. Walker, Y. Lu, O. C. Santos, & S. Isotani (Eds.), *Artificial intelligence in education*. *AIED 2025. Lecture Notes in Computer Science* (Vol.16882, pp. 679–691). Springer. https://doi.org/10.1007/978-3-031-98465-5_57

Xu, X., Qiao, L., Cheng, N., Liu, H., & Zhao, W. (2025). Enhancing self-regulated learning and learning experience in generative AI environments: The critical role of metacognitive support. *British Journal of Educational Technology, 56*(5), 1842–1863. https://doi.org/10.1111/bjet.13599

Yan, L., Greiff, S., Teuber, Z., & Gašević, D. (2024). Promises and challenges of generative artificial intelligence for human learning. *Nature Human Behaviour*, *8*(10), 1839–1850. https://doi.org/10.1038/s41562-024-02004-5

Yan, L., Pammer-Schindler, V., Mills, C., Nguyen, A., & Gašević, D. (2025). Beyond efficiency: Empirical insights on generative AI's impact on cognition, metacognition and epistemic agency in learning. *British Journal of Educational Technology*. https://doi.org/10.1111/bjet.70000

Zhai, C., Wibowo, S., & Li, L. D. (2024). The effects of over-reliance on AI dialogue systems on students' cognitive abilities: A systematic review. *Smart Learning Environments*, *11*(1), 28. https://doi.org/10.1186/s40561-024-00316-7

Zhan, Y., Boud, D., Dawson, P., & Yan, Z. (2025). Generative artificial intelligence as an enabler of student feedback engagement: A framework. *Higher Education Research & Development*, *44*(5), 1289–1304. https://doi.org/10.1080/07294360.2025.2476513

Zimmerman, B. J. (2002). Becoming a self-regulated learner: An overview. *Theory Into Practice*, *41*(2), 64–70. https://doi.org/10.1207/s15430421tip4102_2