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GENERATIVE AI SUPPORT IN MANAGERIAL LEARNING: AN INTEGRATIVE REVIEW OF COGNITIVE ENGAGEMENT AND INDEPENDENT PROBLEM-SOLVING

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ABSTRACT

Generative Artificial Intelligence (GenAI) is increasingly used to support learning and problem-solving, but its cognitive effects depend on how the support is designed. This integrative review examines how unrestricted, guided, scaffolded and collaborative forms of GenAI support influence cognitive engagement and independent problem-solving, with particular attention to managerial learning. A focused collection of 26 papers was screened, and 22 complete articles were retained for thematic synthesis. The evidence shows that unrestricted, complete-answer support can improve immediate task performance while increasing the risk of passive reliance, cognitive offloading and weaker retention. Guided, scaffolded and reflective forms of support are more likely to preserve active engagement because users must still interpret, question, verify and revise AI output. However, improved performance while AI is available does not necessarily show that the user can solve problems independently after the support is removed. Most available studies come from education and programming, while direct evidence from managerial and organizational settings remains limited. The review concludes that GenAI should support human reasoning rather than replace it, especially when the aim is to develop lasting judgement and independent problem-solving capability.

KEYWORDS: *Generative AI; Cognitive Engagement; Cognitive Offloading; Epistemic Agency; Scaffolding; Managerial Learning; Independent Problem-Solving*

1. INTRODUCTION

Generative Artificial Intelligence tools such as ChatGPT have quickly become common aids for learning, writing, programming and decision support. This convenience is useful, but it also raises a basic question: does GenAI help people develop stronger problem-solving ability, or does it mainly help them perform better while the tool is available? The answer may depend on the form of support. GenAI can provide unrestricted, complete answers, but it can also offer hints, guiding questions, staged feedback or reflective dialogue. Complete-answer support may reduce the effort required to understand and solve a problem. Guided or scaffolded support may preserve more active thinking because the user must still interpret the assistance, decide what to do next and evaluate whether the AI output is reliable. Lim et al. (2023) describe this tension as a capability–dependency paradox: GenAI can extend human performance while also creating dependence on the technology. A related issue is the difference between assisted performance and independent capability. A person may complete a task faster or obtain a higher score while using GenAI, yet still struggle to solve a similar problem later without assistance. Immediate task performance, learning, delayed retention and transfer to a new problem are therefore not interchangeable outcomes. The issue is especially relevant to managerial learning. Managers must recognize and frame problems, identify causes, compare alternatives, assess risks, consider stakeholders and justify decisions. These activities require contextual and ethical judgement, not merely a plausible answer. This review therefore asks:

How do different forms of Generative AI support influence cognitive engagement and independent problem-solving, and what do the findings imply for managerial learning?

Its central argument is that the influence of GenAI on independent problem-solving depends partly on how much reasoning responsibility remains with the user. Complete-answer support creates greater potential for cognitive substitution, while guided, scaffolded and reflective support is more likely to preserve epistemic agency. The most important test is whether the user can still perform independently after AI assistance is withdrawn.

2. OBJECTIVES

The objectives of the review are:

1. To classify the main forms of GenAI support as unrestricted, guided, scaffolded and collaborative-reflective support.
2. To examine how these forms of support relate to cognitive engagement, cognitive offloading and epistemic agency.

3. To distinguish AI-assisted task performance from independent performance, delayed retention and transfer.
4. To identify cautious implications for managerial learning and problem-solving while recognizing the limited amount of direct organizational evidence.

3. METHODOLOGY

This study adopted an integrative review approach to examine how different forms of Generative Artificial Intelligence support influence cognitive engagement and independent problem-solving. An integrative review was suitable because the available literature includes experimental, quasi-experimental, survey-based, qualitative, conceptual and review studies. These different forms of evidence were brought together through thematic analysis. A focused working collection of 26 papers was assembled around GenAI support, cognitive engagement, cognitive offloading, critical thinking, problem-solving, retention and transfer. The papers were checked for the availability of sufficient information on authorship, research design, sample or context, type of GenAI support, measures, findings and limitations. Twenty-two complete and verifiable papers were retained for the final review. Four papers were excluded because their complete original texts could not be adequately verified. The evidence was considered according to the strength of the research design. Greater emphasis was placed on randomized and controlled studies using objective performance, retention, transfer or behavioural measures. Survey and correlational findings were interpreted as relationships rather than causal effects. Qualitative and case-based studies were used to understand experiences and patterns of interaction, while conceptual papers and reviews supported theoretical explanation and broader interpretation. The findings were grouped under six themes: unrestricted and complete-answer support; hint-based and guided support; scaffolded support; collaborative and reflective human–AI support; cognitive offloading and epistemic agency; and independent performance, retention and transfer.

4. RESULTS

4.1 Unrestricted and Complete-Answer Support

Unrestricted GenAI allows users to ask questions and receive complete answers without limits on the amount or type of assistance. However, it may also reduce the effort users spend understanding, recalling and solving the problem themselves. Barcaui (2025) provides the clearest experimental evidence of this risk. In a randomized controlled trial, 120 undergraduate students studied artificial intelligence concepts either with unrestricted ChatGPT assistance or through traditional study methods. A surprise test was conducted 45 days later. The ChatGPT-assisted group obtained an average score of 57.5%, while the traditional-study group obtained 68.5%. This finding is limited to the tested study condition and should not be interpreted as evidence that every form of GenAI use harms learning. A similar concern appears in the study by Li et al. (2025). Students who actively questioned, checked and revised GenAI output showed more productive learning behaviour than students who mainly copied generated answers. More dependent use was associated with weaker knowledge acquisition and poorer long-term transfer. The outcome depends partly on whether the user treats the AI response as material to be examined or as a finished answer to be accepted. Salido et al. (2025) identified uncritical dependence, weak verification and reduced evaluative reasoning as recurring challenges in AI-supported higher education. Complete-answer support may be useful for routine work, rapid information gathering or tasks in which speed is more important than learning. The concern becomes greater when the purpose is to develop knowledge, judgement or a skill that the user is later expected to perform without AI.

4.2 Hint-Based and Guided Support

Hint-based support gives the user partial assistance instead of providing the entire solution. This allows the user to continue working while retaining responsibility for completing the task. Pardos and Bhandari (2024) tested this form of assistance in a randomized study involving 274 participants. They compared ChatGPT-generated hints, human-tutor hints and a no-help condition across mathematics problems. ChatGPT-generated help produced significant near-term learning gains compared with no help and was not significantly different from human-authored help. However, 32% of the original AI-generated hints failed quality checks. The Pardos and Bhandari study did not assess delayed retention or transfer to managerial problems. Therefore, it supports the value of guided assistance during learning, not the claim that such assistance necessarily develops lasting independent capability. Belkina et al. (2025), in a review of higher-education case studies, also identified stepwise guidance, structured feedback and reflective questioning as common ways of using GenAI. Nasr et al. (2025) examined passive AI-directed use and more collaborative human–AI interaction. Analysis of interaction scripts suggested that guided and collaborative use involved more iterative engagement than passive information retrieval. Since much of the evidence was self-reported and qualitative, the findings should not be treated as objective proof of improvement across all stages of critical thinking. Yavich (2025) reported a related pattern in a mixed-methods study involving 28 instructors and 28 students from three universities. Instructor involvement, formative feedback and reflective activities were associated with stronger critical-thinking outcomes and lower dependence on automatic answers. The Yavich study did not examine whether learners retained these abilities after AI assistance was removed. Overall, guided support appears more likely than complete-answer support to preserve active thinking. Its effectiveness, however, depends on the accuracy of the guidance and the user's willingness to evaluate it.

4.3 Scaffolded Support

Scaffolded support divides a task into stages, adjusts assistance according to the user's needs and may deliberately restrict access to complete solutions. Nathaniel et al. (2025) examined a scaffolded GenAI approach with prompt training among 25 programming students. The study reported significant pre-to-post gains in problem-solving, critical thinking, creativity and programming logic. Improvements in code optimization and the evaluation of solutions were smaller and not statistically significant. Because the study had no control group and involved a small sample, the changes cannot

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be attributed to GenAI alone. Liu et al. (2026) provide complementary qualitative evidence. Their grounded-theory study compared an AI-enabled programming group of 24 students with a human pair-programming group of 17 students. The study found that GenAI could function as a tool, a tutor or a cognitive substitute. Students sometimes used AI explanations to move forward while still remaining involved in the reasoning. At other times, they relied on generated code without fully understanding or verifying it. Vendrell and Johnston (2026) argue that effective scaffolding should preserve a degree of cognitive effort. Their conceptual framework proposes reflective prompts, limited access to final answers and periods in which learners work without AI. Adejumo et al. (2026), reviewing 64 empirical studies in computer science education, found that GenAI was more consistently associated with reflective problem-solving when it was placed within structured and pedagogically designed environments. Unguided or passive use was more often linked with surface-level engagement and over-reliance. Giannakos et al. (2025) similarly emphasize guided prompting, verification and metacognitive support as important conditions for productive GenAI use.

4.4 Collaborative and Reflective Human–AI Support

Collaborative support treats GenAI as a discussion partner rather than a source of final answers. Users may ask it to generate alternatives, challenge assumptions, compare options or critique a draft, while retaining responsibility for judgement. Wei et al. (2025) conducted a 20-week mixed-methods experiment with 60 university students. GenAI-supported teams showed stronger collaborative problem-solving and creativity, although the team-level outcomes did not establish improved independent capability for every member. Anwar (2025) used a reflective legal-education framework in which students compared AI-generated material with legal sources and justified whether outputs should be accepted or rejected. The findings suggested reduced passive acceptance, but the evidence came from one educational setting and does not establish a general causal effect. Daniels et al. (2025) studied AI-enhanced project-leadership education with 113 undergraduate and 47 postgraduate learners. AI-generated scenarios combined with discussion and reflection supported conceptual learning and ethical deliberation, but independent performance after AI withdrawal was not tested. Lee et al. (2023) propose using GenAI to sustain collaborative knowledge creation rather than close discussion with a final answer, while Lee and Low (2024) argue that AI output should be evaluated as a secondary source. Overall, collaborative support is most useful when AI expands possibilities but users continue to compare, question, revise and make the final judgement.

4.5 Cognitive Offloading and Epistemic Agency

Cognitive offloading occurs when mental work is transferred to an external tool. It can be helpful when GenAI reduces routine effort, but problematic when the tool performs reasoning that users need to learn or retain. Jose et al. (2025) organize cognitive offloading into three forms: assistive, substitutive and disruptive. In assistive use, technology handles limited demands while the individual continues to direct and assess the task. In substitutive use, a larger part of the thinking process is handed over to the system. Disruptive use represents the greatest concern because repeated dependence may interfere with memory, reflection and confidence in working without technological support. Since this classification is conceptual, it should be treated as a proposed framework rather than as a set of experimentally confirmed outcomes. Si et al. (2026), surveying 353 Chinese university students, found that learning motivation was associated with less relinquishment of cognitive autonomy, whereas deeper offloading was associated with greater relinquishment. Because the measures were self-reported, the findings indicate perceived relationships rather than objectively measured changes in critical thinking. Zhou et al. (2024), using structural equation modelling with 223 students, found that self-regulation was positively associated with perceived critical thinking and problem-solving. The correlational design does not establish causation. Together, these studies suggest that the central issue is not whether users offload work, but which work they transfer. Routine information search may be delegated, while problem framing, verification and judgement should remain with the user.

4.6 Independent Performance, Retention and Transfer

The most important limitation in the evidence is that few studies examine what happens after AI support is removed. Many studies measure performance during an AI-supported activity or immediately afterwards. These outcomes do not show whether the person can later perform independently. Barcaui (2025) directly tested delayed retention after 45 days and found weaker performance among students who had used unrestricted ChatGPT. Li et al. (2025) also reported weaker long-term transfer among users who relied more heavily on generated solutions. These studies provide some evidence that dependence during assisted work may affect later capability. Other studies, including Pardos and Bhandari (2024), Yilmaz and Karaoglan Yilmaz (2023), Wei et al. (2025) and Nathaniel et al. (2025), reported immediate or near-term outcomes but did not conduct delayed support-withdrawal tests. Yavich (2025) examined one semester of structured use but did not test long-term independent performance.

The evidence therefore supports a clear distinction between five outcomes:

1. task performance while AI is available;
2. immediate learning;
3. unaided performance after assistance is removed;
4. delayed retention; and
5. transfer to a different problem.

Most existing studies examine only the first two. Consequently, claims that GenAI develops independent problem-solving remain premature. The strongest test is not whether users can produce a good answer with AI, but whether they can still understand, explain and solve the problem when the tool is no longer available.

5. SUGGESTIONS

GenAI should support rather than replace human reasoning, especially in managerial learning, where users must explain decisions, consider consequences and remain accountable. First, managers and learners should define the problem in their own words before asking GenAI for assistance. This helps prevent the system from shaping the problem too early or narrowing attention to one interpretation. Second, GenAI should be used to generate questions, alternatives, assumptions and possible risks rather than only complete solutions. Guided prompts such as "What information may be missing?" or "What are the risks of this option?" are more likely to preserve active thinking. Third, users should verify important AI-generated information against reliable sources. Recording why an AI suggestion was accepted, revised or rejected makes the reasoning process visible and supports accountability. Fourth, management training should include tasks in which AI support is gradually reduced. Learners should sometimes complete a similar problem without assistance so that independent capability can be assessed. Finally, organizations should distinguish between routine and high-stakes tasks. Extensive automation may be suitable for repetitive work, but decisions involving employees, customers, ethics, finance or organizational risk should require human review and justification. Access to GenAI alone should not be treated as evidence of improved managerial capability.

6. CONCLUSION

The effect of Generative AI on problem-solving depends greatly on the form of support provided and the reasoning responsibility retained by the user. Unrestricted, complete-answer support may improve speed and immediate performance, but it also creates a greater risk of passive reliance and cognitive offloading. Guided, scaffolded and collaborative forms of support are more likely to preserve engagement because users must still interpret, question, verify and revise AI output. However, better performance while AI is available does not prove that independent capability has improved. Delayed retention, transfer and performance after AI removal are still rarely tested. Managerial evidence remains indirect because most studies concern education and programming. GenAI is therefore most useful when it acts as a support for judgement, not a substitute for it.

7. AREA FOR FURTHER RESEARCH

Future studies should compare complete-answer, guided, scaffolded and collaborative GenAI support in real managerial and organizational tasks. They should assess unaided performance after support withdrawal, delayed retention and transfer to unfamiliar situations to distinguish temporary improvement from lasting capability. Relevant outcomes include decision and explanation quality, stakeholder awareness, ethical judgement and the ability to identify misleading AI output. Research should also compare novice and experienced managers and examine through longitudinal studies whether repeated use strengthens reflective problem-solving, increases dependence or benefits from planned AI-free stages.

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TABLE 1. FORMS OF GenAI SUPPORT AND THEIR COGNITIVE IMPLICATIONS

Form of GenAI support	Nature of assistance	User's reasoning responsibility	Main possible benefit	Main possible risk
Unrestricted or complete-answer support	Provides a complete response or solution	Low	Speed, convenience and immediate task completion	Passive acceptance, cognitive offloading and dependence
Hint-based or guided support	Gives partial steps, explanations or guiding questions	Moderate	Helps the user continue while remaining involved	Incorrect or misleading hints
Scaffolded support	Provides staged, adaptive and gradually reduced assistance	High	Preserves productive effort, reflection and self-regulation	Poorly designed scaffolds may still encourage reliance
Collaborative-reflective support	Generates alternatives, critiques and questions for discussion	High	Supports comparison, revision, creativity and broader analysis	Users may still delegate final judgement to AI

Source: Developed by the authors from the reviewed literature.