Prisma Sains: Jurnal Pengkajian Ilmu dan Pembelajaran Matematika dan IPA IKIP Mataram
https://e-journal.undikma.ac.id/index.php/prismasains/index
e-mail: prismasains.pkpsm@gmail.com

July 2026. Vol. 14, No. 3
p-ISSN: 2338-4530
e-ISSN: 2540-7899
pp. 1496-1515

Generative AI as a Metacognitive Co-Regulator in Training and Development: An Integrated Bibliometric and Systematic Review

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Received: June 2026; Revised: June 2026; Published: July 2026

Abstract

The rapid integration of Generative Artificial Intelligence (GenAI) into organisational learning environments has reshaped how employees plan, monitor, and evaluate their learning. However, the role of GenAI as a metacognitive co-regulator in Training and Development (T&D) remains conceptually fragmented across research on metacognition, AI-supported learning, and global talent development. Drawing on an integrated bibliometric analysis and systematic review approach, this study examines the intellectual structure, thematic evolution, and conceptual intersections of these three domains. A structured search of Scopus and Web of Science, supplemented by Google Scholar, identified 196 records published between 2000 and 2025. After duplicate removal and screening following an adapted PRISMA protocol, 139 records were retained for bibliometric mapping using Biblioshiny, and 139 full-text studies were included in the qualitative synthesis. Using bibliometric mapping techniques, the study identifies dominant research trends, functional roles of GenAI, and underexplored thematic gaps. The analysis reveals three dominant thematic clusters, with metacognition and self-regulated learning occupying the motor-theme quadrant and GenAI-related themes moving rapidly toward conceptual centrality, while global talent development remains peripheral. A complementary systematic qualitative synthesis further clarifies how GenAI supports metacognitive regulation across planning, monitoring, and evaluation phases. The integrated evidence reveals a conceptual shift from automation-oriented AI applications toward learner-centred metacognitive scaffolding, while highlighting the limited integration of AI-supported metacognition within global talent development frameworks. Based on these findings, the study proposes the GenAI–Metacognitive Workforce Development (GMWD) model, which conceptualises GenAI as a phase-sensitive metacognitive co-regulator that preserves learner agency while fostering adaptive performance, self-regulated professional learning, and global competence. The model provides a theoretically grounded framework for advancing research and practice in AI-enhanced training and development (T&D), offering practical implications for designing reflective, adaptive, and globally oriented learning environments for the workforce.

Keywords: Generative artificial intelligence; Metacognition; Self-regulated learning; Training and development; Global talent development; Human–AI collaboration

How to Cite: Yulandari, S. N., Rachmadiarti, F., Anggaryani, M., & Adam, A. S. (2026). Generative AI as a Metacognitive Co-Regulator in Training and Development: An Integrated Bibliometric and Systematic Review. *Prisma Sains : Jurnal Pengkajian Ilmu Dan Pembelajaran Matematika Dan IPA IKIP Mataram*, *14*(3), 1496–1515. https://doi.org/10.33394/j-ps.v14i3.21258

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INTRODUCTION

Digital transformation has contributed to a significant reconfiguration of organisational skill demands. Employees are now expected to navigate ill-structured problems, adapt to rapidly evolving technological environments, and demonstrate globally oriented competencies (Cascio & Montealegre, 2016). Within this context, Training and Development (T&D) has become a strategic function for enhancing organisational competitiveness and individual adaptability (Aguinis & Kraiger, 2009; Noe, 2020). However, many T&D practices remain content-centric and procedural, with limited attention to the metacognitive processes that underlie deep, transferable learning (Salas et al., 2012).

Metacognition is defined as the ability to plan, monitor, and evaluate one's cognitive processes (Flavell, 1979). It is a critical foundation for lifelong learning and adaptability. Research on self-regulated learning (SRL) has established that learners who engage in strategic metacognitive regulation demonstrate improved performance, greater transfer of skills, and more effective problem solving (Zimmerman, 2000; Panadero, 2017). These capabilities are essential for employees engaged in global assignments where cultural complexity, novelty, and uncertainty are pervasive (Deardorff, 2006; Caligiuri & Bonache, 2016). However, workplace learning models rarely foreground metacognition or provide structured means to cultivate it in professional settings.

Meanwhile, recent advances in Generative AI provide new opportunities for personalised coaching, reflective dialogue, and adaptive metacognitive scaffolding. GenAI systems are capable of eliciting reflective explanations, tracking learner progress, and generating prompts that guide strategic planning or performance monitoring (Kasneci et al., 2023; Holmes et al., 2020). Despite this potential, research on AI in workplace learning tends to focus on automation, assessment, or content generation rather than on metacognitive support. As a result, academic discourse lacks a coherent theoretical foundation for understanding how GenAI may function as a metacognitive co-regulator for adult learners.

The global talent development literature similarly emphasises adaptability, reflective judgment, and intercultural competence (OECD, 2018; Sparrow et al., 2015). However, these frameworks seldom consider how AI-mediated learning environments may enhance such competencies through metacognitive scaffolding. This lack of integration results in conceptual fragmentation across three essential domains: metacognition/SRL, AI-supported learning, and global talent development. To address this fragmentation, this study conducts an integrated bibliometric analysis and systematic review to map research patterns and synthesise theoretical insights (Liang et al., 2023). The result is the development of a conceptual model, the GenAI–Metacognitive Workforce Development (GMWD) model, which positions GenAI as a metacognitive co-regulator in talent development (T&D) for global talents.

Literature Review

Metacognition and Self-Regulated Learning in Adult and Professional Contexts

Metacognition, defined as the ability to monitor and regulate one's cognitive processes, remains a central determinant of effective learning across educational and professional settings (Flavell, 1979; Winne & Hadwin, 1998). Research consistently demonstrates that individuals who engage strategically in planning, monitoring, and self-evaluation achieve higher performance and transfer their skills more effectively to novel contexts (Efklides, 2009; Panadero, 2017). In adult training and workplace learning, these regulatory abilities are even more vital as employees are required to adapt rapidly to changing tasks, solve ill-structured problems, and learn autonomously in digitally mediated environments. Despite this importance, metacognitive development has been insufficiently integrated into many training and development (T&D) models, which often assume that adults will self-regulate spontaneously without structured support, even though evidence shows that many learners struggle to activate metacognitive strategies without explicit prompts or guidance (Wong & Viberg, 2024).

Empirical studies further highlight that metacognitive support significantly enhances strategic learning behaviours. For example, metacognitive cues and reflective prompts have been found to strengthen individuals' task strategies, self-assessment accuracy, goal setting, time management, and help-seeking behaviours (Daumiller & Dresel, 2019; van der Graaf et al., 2023). These findings confirm the crucial role of structured metacognitive scaffolding in enabling learners to manage complex learning environments, especially where direct instructor oversight is limited.

Generative AI as a Catalyst for Metacognitive Regulation

The emergence of Generative AI (GenAI) has transformed the landscape of technology-enhanced learning by enabling adaptive explanations, dialogic reasoning, and the generation of reflective feedback (Kasneci et al., 2023). Unlike earlier rule-based systems, GenAI's multimodal, context-sensitive outputs position it not merely as a tool, but as a potential cognitive partner capable of participating in learners' metacognitive processes. Recent systematic evidence indicates that structured metacognitive support in GenAI environments substantially improves self-regulated learning performance, including enhanced strategic planning, improved self-evaluation, and more efficient monitoring of learning progress (Xu et al., 2025b).

At the same time, studies warn that learners often become overly reliant on GenAI, leading to decreased self-regulation and reduced critical engagement unless deliberate metacognitive support is provided (Fan et al., 2024; Urban et al., 2024; Chang & Sun, 2024). These concerns have led scholars to argue for the development of "meta-AI skills," a specialised subset of metacognitive competencies required to critically evaluate AI outputs, interrogate ambiguities, and strategically orchestrate human–AI interaction (Kojukhov et al., 2025). Meta-AI literacy thus extends beyond traditional metacognition by focusing on the dynamic, non-deterministic nature of AI systems and preparing learners to collaborate with AI as an adaptive and generative partner rather than a static source of information.

Complementary frameworks, such as the Human–Human–AI Regulation (HHAIR) model, emphasise the need to balance autonomy with AI-driven support, so that learners retain agency while benefiting from personalised AI-mediated reflection and feedback (Hong & Guo, 2025). Together, this emerging body of work positions GenAI as a transformative mediator of metacognition, capable of reshaping how individuals plan, monitor, and evaluate their learning activities.

AI-Supported Learning and Its Implications for Training and Development

AI-enhanced learning environments have been shown to improve learning experience, reduce cognitive load, and increase perceived usefulness of digital tools when paired with appropriate metacognitive scaffolding (Xu et al., 2025b). These findings are directly relevant to T&D contexts where employees must navigate complex information environments, learn new procedures, and engage in continual skill renewal.

Research indicates that in AI-mediated environments, metacognitive interventions, such as planning prompts, reflective questioning, and self-evaluation guidance, substantially enhance learners' ability to manage ambiguity and regulate their performance (Wang et al., 2025). This aligns with broader arguments that AI can serve as a metacognitive co-regulator, supporting the formative phases of learning while preventing overdependence on automated feedback (Holmes et al., 2020).

Within workplace learning, these insights highlight the need to reconceptualize T&D not as a process of transmitting content, but as a structured developmental experience in which learners build adaptive regulatory capabilities supported by AI. As workplaces become more global and technologically mediated, the ability to engage in reflective judgment, adaptive learning, and cross-cultural sense-making becomes essential (Caligiuri & Bonache, 2016; Deardorff, 2006). However, current global talent frameworks rarely integrate metacognitive development or AI-supported self-regulation, revealing a conceptual gap at the intersection of HRD, cognitive science, and AI research.

Human–AI Collaboration, Meta-AI Skills, and Global Talent Competence

The integration of AI into learning and professional development contexts has prompted a re-evaluation of how human–AI collaboration shapes knowledge construction, decision-making, and problem-solving. Scholars argue that collaboration with AI requires new competencies that enable individuals to critique AI outputs, manage uncertainty, calibrate trust, and engage in reflective dialogue with automated agents (Edwards et al., 2025). These competencies contribute not only to deeper cognitive engagement but also to broader global talent skills such as adaptability, perspective-taking, and intercultural problem-solving.

Recent work positions GenAI as a catalyst for transformative learning, capable of reshaping how individuals think, reason, and regulate their learning trajectories (Kojukhov et al., 2025). For global talent development, AI-mediated metacognitive scaffolding may support employees as they navigate unfamiliar cultural environments, work across diverse teams, and interpret complex information landscapes. However, this potential remains largely untapped in existing T&D models, which seldom integrate AI-supported metacognition or examine its role in developing global competence.

The purpose of this study is to integrate and synthesise literature from metacognition and self-regulated learning, AI-supported learning, and global talent development in order to theorise the role of GenAI as a metacognitive co-regulator in T&D. The study seeks to move beyond fragmented conceptual discussions and establish a coherent framework grounded in rigorous bibliometric and systematic analyses. The following research questions guide the study:

- RQ1. How have metacognition and self-regulated learning been conceptualised and applied in workplace learning and T&D contexts?
- RQ2. How has Generative AI been employed to support learning, feedback, and coaching in professional or adult learning settings, and how do these uses relate to metacognitive regulation?
- RQ3. How do global talent development frameworks conceptualise the learning needs of employees operating in cross-cultural and international environments?
- RQ4. What conceptual gaps and underexplored intersections exist between metacognition/SRL, GenAI-supported learning, and global talent development?
- RQ5. Based on integrated bibliometric and systematic evidence, what core components should underpin a theoretical model in which GenAI functions as a metacognitive co-regulator in T&D?

This study makes several theoretical contributions. First, it advances the conceptualisation of GenAI by framing it as an active metacognitive co-regulator that interacts with learners during the planning, monitoring, and evaluation phases. This extends prior understandings of AI in education (Holmes et al., 2020) into the domain of adult workplace learning. Second, by integrating disparate bodies of literature (metacognition/SRL, AI-supported learning, and global talent development), the study addresses long-standing conceptual fragmentation. Third, the hybrid methodological approach enriches theoretical model building by leveraging the strengths of both bibliometric mapping and systematic synthesis (Aria & Cuccurullo, 2017; Snyder, 2019).

Practically, the proposed GMWD model provides insights for designing T&D interventions that use GenAI to deliver scalable, personalised metacognitive support. This has implications for enhancing employees' strategic learning capabilities, adaptability, and global competence (OECD, 2018). Organisations may leverage GenAI-supported metacognitive coaching to promote reflective learners who can thrive in culturally and operationally complex environments.

METHOD

The methodological framework adopted in this review follows the integrated bibliometric analysis and systematic review approach used by Liang et al. (2023), who demonstrated that combining science mapping with full-text synthesis yields a comprehensive understanding of how research domains evolve conceptually and structurally. This approach is appropriate for the present study because scholarship related to metacognition, Generative AI-supported learning, and global talent development has expanded in separate literatures, necessitating a methodology that captures both the macro-level distribution of knowledge and the micro-level interpretive insights that define conceptual evolution within these fields. The dual-layer design employed here is therefore essential for developing the GenAI Metacognitive Workforce Development model, which requires both structural and conceptual evidence.

Review Design

The review design integrates bibliometric analysis and systematic qualitative synthesis into a single coherent framework. The bibliographic component utilises science mapping techniques to visualise intellectual structures, thematic clusters, and keyword co-occurrence patterns across relevant publications, as recommended by Aria and Cuccurullo (2017) and van Eck and Waltman (2010). This component offers a macro perspective on the development of research related to metacognition, AI-mediated learning, and global competence over time. In parallel, the systematic qualitative synthesis involves close reading and interpretive analysis of full-text articles to identify conceptual frameworks, theoretical assumptions, methodological tendencies, and empirical evidence. The combination of both strands follows the logic articulated by Snyder (2019), who emphasises that literature reviews aiming at theory development must integrate breadth and depth in equal measure.

Data Sources and Search Strategy

Data collection was conducted across Scopus, Web of Science, and Google Scholar because these databases provide comprehensive coverage of international scholarly output in education, organisational psychology, learning sciences, and artificial intelligence research (Noe, 2020; Holmes et al., 2020). Scopus and Web of Science served as the primary databases for both the bibliometric mapping and the systematic synthesis because they provide structured and standardised metadata suitable for science mapping. Google Scholar was used only as a supplementary source to identify additional relevant records that might not be indexed in the two primary databases. Because Google Scholar metadata are frequently inconsistent and may compromise the reproducibility of bibliometric procedures, Google Scholar records were not included in the bibliometric mapping and were used solely during the supplementary screening stage of the qualitative synthesis. The full search was executed on 8-9 December 2025, and all queries were run on the same day to ensure consistency of the retrieved records. The search procedure employed an iterative strategy similar to the process described by Liang et al. (2023). Initial exploratory queries helped identify common terminology used across the three research domains. These queries informed the refinement of search strings, which included terms related to metacognition, self-regulated learning, reflective judgment, Generative AI, large language models, adaptive coaching systems, workplace learning, Training and Development, global talent, and cultural intelligence. Boolean operators were used to improve accuracy and sensitivity. The search was restricted to publications between 2000 and 2025 to capture contemporary developments in AI-supported learning while incorporating foundational work on metacognition, such as that of Flavell (1979) and Zimmerman (2000). All retrieved items were exported in bibliographic format for subsequent screening. The complete Boolean search strings used for each database are presented in Table 1, ensuring that the search procedure is fully transparent and reproducible.

Table 1. Search Strategy and Boolean Search Strings for Each Database

Database	Boolean Search String and Field
Scopus	TITLE-ABS-KEY ((“metacognition” OR “self-regulated learning” OR “reflective judgment” OR “metacognitive regulation”) AND (“generative AI” OR “generative artificial intelligence” OR “large language model*” OR “ChatGPT” OR “AI-supported learning”) AND (“training and development” OR “workplace learning” OR “professional learning” OR “global talent” OR

Database	Boolean Search String and Field
	“adult learning”)) AND PUBYEAR > 1999 AND PUBYEAR < 2026 AND (LIMIT-TO (LANGUAGE , “English”))
Web of Science	TS = ((“metacognition” OR “self-regulated learning” OR “reflective judgment” OR “metacognitive regulation”) AND (“generative AI” OR “generative artificial intelligence” OR “large language model*” OR “ChatGPT” OR “AI-supported learning”) AND (“training and development” OR “workplace learning” OR “professional learning” OR “global talent” OR “adult learning”)) ; Timespan = 2000–2025 ; Language = English ; Document types = Article, Review
Google Scholar (supplementary)	“metacognition” AND “generative AI” AND (“training and development” OR “workplace learning”) ; first 100 most relevant results screened ; used only to identify additional records, not included in bibliometric mapping

Inclusion and Exclusion Criteria

The inclusion and exclusion criteria were applied consistently to maintain methodological rigour and transparency, in line with guidelines for integrative systematic reviews (Snyder, 2019). Studies were included if they appeared in peer-reviewed journals, were written in English, and examined phenomena related to metacognition, AI-supported learning, or global competence in adult or professional learning contexts. Conceptual papers, empirical research, and review studies were included in order to reflect methodological diversity within the fields. Exclusion criteria were applied to studies focusing exclusively on primary or secondary education without relevance to adult learning, studies addressing artificial intelligence solely as automation with no educational component, and studies without accessible full texts. This process ensured that the selected literature was substantively aligned with the objectives of the review. The complete set of inclusion and exclusion criteria is summarised in Table 2.

Table 2. Inclusion and Exclusion Criteria

Dimension	Inclusion Criteria	Exclusion Criteria
Publication type	- Peer-reviewed journal articles, including empirical, conceptual, and review studies	Editorials, blog posts, and grey literature without peer review
Language	- Written in English	- Non-English publications
Time span	- Published between 2000 and 2025	- Published before 2000
Topic relevance	- Addresses metacognition or self-regulated learning, AI-supported learning, or global competence in adult or professional learning contexts	- Focuses exclusively on primary or secondary education with no relevance to adult learning, or treats AI solely as automation with no educational component
Accessibility	- Full text accessible	- Full text not accessible

Screening and Eligibility Procedure

The screening and eligibility procedure followed an adapted PRISMA framework, mirroring the review logic used by Liang et al. (2023). All retrieved records were first subjected to duplicate removal. Titles and abstracts were screened to evaluate conceptual alignment with the review scope. Articles that met the initial criteria proceeded to full-text eligibility assessment. During this stage, studies were examined for methodological soundness, theoretical relevance, and substantive contribution in relation to metacognition, Generative AI-supported learning, and global talent development. The final selection yielded two sets of studies: one for bibliometric analysis and one for qualitative synthesis. Several studies contributed to both datasets, as they included rich metadata for science mapping and conceptual content for thematic analysis. The flow of these procedures is illustrated in the following diagram. Specifically, the initial search identified 196 records (122 from Scopus and 74 from Web of Science). Consistent with the protocol, Google Scholar was screened only as a supplementary source and did not contribute additional records that were retained in the final corpus. After 16 duplicate records were removed, 180 records remained for title and abstract screening. Of these, 17 records were excluded for not meeting the eligibility criteria, leaving 163 records for full-text assessment. Following the full-text eligibility assessment, 24 records were excluded (mainly because they focused exclusively on primary or secondary education without relevance to adult learning, treated artificial intelligence solely as automation with no educational component, or did not provide accessible full texts). The final corpus comprised 139 records for the bibliometric analysis and 139 full-text studies for the qualitative synthesis, with all 139 studies contributing to both datasets. The exact numbers at each stage are presented in the PRISMA flow diagram in Figure 1.

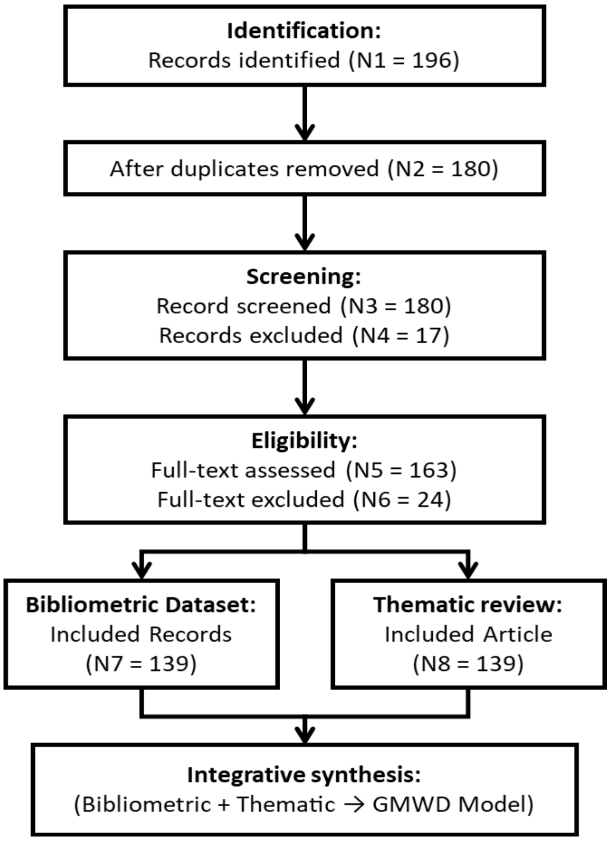

Figure 1. PRISMA Adapted Review Flow

The PRISMA adapted diagram provides a clear illustration of how studies progress through the identification, screening, eligibility, and inclusion stages. This documentation enhances procedural transparency and aligns the study with recommended standards for scholarly reviewing.

Bibliographic data, including titles, abstracts, keywords, author information, citation counts, and journal sources, were analysed using Biblioshiny (the web interface of the Bibliometrix R package version 5.1.1, running on R version 4.5.2) (Aria & Cuccurullo, 2017). Only records from Scopus and Web of Science were used for the bibliometric mapping, because these databases provide standardised metadata compatible with science mapping procedures. Keyword co-occurrence networks were generated to detect conceptual clusters and thematic proximities. Author co-citation patterns revealed the intellectual structure of the fields and highlighted influential theoretical traditions, including the metacognition literature (Flavell, 1979; Efklides, 2009), the self-regulation literature (Zimmerman, 2000; Panadero, 2017), and the AI in education literature (Holmes et al., 2020; Kasneci et al., 2023). The mapping outputs also revealed evolving trends related to global competence and international talent development (OECD, 2018; Sparrow et al., 2015). These structural insights provided the macro-level basis for identifying underexplored intersections across the three research domains.

Thematic Synthesis

The systematic qualitative synthesis is adapted from Liang et al. (2023). The dimensions included research methods, professional learning contexts, targeted metacognitive constructs, types of AI systems employed, functional roles of AI such as tutoring, assessment, coaching, or co-regulation, learning outcomes such as cognitive, metacognitive, behavioural, and global competence outcomes, learner characteristics, intervention features, and the specific Training and Development domain addressed. These dimensions provided a structured means of capturing conceptual richness across studies.

Through iterative reading and the constant comparative method described by Braun and Clarke (2006), recurring themes emerged. These included the role of Generative AI as a reflective dialogue partner that stimulates metacognitive awareness, the influence of AI-generated prompts on learners' planning and monitoring behaviours, the articulation of reasoning processes through conversational interaction with AI, and the alignment between metacognitive development and competencies required for global mobility and international work settings. These themes reflect conceptual integration that was not detectable through bibliometric mapping alone.

Coding Procedure and Trustworthiness

To ensure the trustworthiness of the qualitative synthesis, the coding process was conducted independently by the first author, a master's student in science education, and the fourth author, a doctoral candidate with expertise in systematic review methodology. This dual-coder arrangement was adopted to strengthen inter-rater reliability and minimise interpretive bias, consistent with established practices in systematic and integrative reviews (Braun & Clarke, 2006; Nowell et al., 2017). The coding unit was the individual study, and each study was coded according to the analytical dimensions described above, namely study type, methodology, professional learning context, targeted metacognitive construct, type of AI system, functional role of AI, intervention features, learning outcomes, and the Training and Development domain addressed. A preliminary coding scheme was developed deductively from these dimensions and then refined inductively as new patterns emerged during the constant comparative process (Braun & Clarke, 2006).

Both raters coded each of the 30 included articles independently before comparing their results. Any disagreements between raters were resolved through discussion and consensus. During this process, the raters revisited the coding scheme, operational definitions, and original data to reach a mutually agreed decision. Inter-rater reliability was assessed using Cohen's Kappa coefficient (κ), a widely accepted statistical measure of agreement between two independent coders that accounts for agreement occurring by chance (Cohen, 1960; McHugh, 2012), with interpretive benchmarks following Landis and Koch (1977). The results demonstrated acceptable to strong levels of agreement across all five coding dimensions. Specifically, the κ value for Study Type was 0.84 (Almost Perfect), Methodology was 0.73 (Substantial), Domain Category was 0.55 (Moderate), AI Functional Role was 0.54 (Moderate), and Regulation Type was 0.36 (Fair). Dimensions yielding moderate or fair agreement, namely Domain Category, AI Functional Role, and Regulation Type, were subjected to further discussion between the two coders to reconcile divergent interpretations and refine operational definitions prior to finalising the coding scheme.

To further enhance dependability, an audit trail was maintained throughout the coding process, documenting every coding decision, scheme revision, and analytical memo so that the procedure could be traced and reconstructed by other researchers. Reflexive notes were written at each phase of analysis to surface potential interpretive bias and make analytical choices explicit. To strengthen credibility, the emerging codes and thematic interpretations were reviewed periodically by the supervisory team, whose feedback informed iterative refinement of the coding scheme. Finally, the interpretive findings of the qualitative synthesis were triangulated against the structural patterns identified through the bibliometric mapping, providing convergent evidence that supports the thematic claims advanced in the Results and Discussion section.

Quality Appraisal

The methodological quality of the studies included in the qualitative synthesis was appraised to ensure that the interpretive findings rested on a sound evidence base. Because the included studies represented diverse designs, including empirical, conceptual, and review work, the appraisal applied four general criteria suited to a mixed-evidence corpus: (1) clarity of research aims and theoretical framing, (2) appropriateness and transparency of the method in relation to the stated aims, (3) clarity and traceability of findings, and (4) relevance of the contribution to metacognition, GenAI-supported learning, or global talent development. Each study was rated as high, moderate, or low on these criteria. Studies rated low across multiple criteria were either excluded or, where retained for conceptual value, were given correspondingly lower interpretive weight in the synthesis. This appraisal step enhanced the rigour and credibility of the integrated findings.

Integration of Bibliographic and Systematic Evidence

The final phase involved integrating insights from both analytical strands following the logic of integrative synthesis recommended for theory-building reviews (Snyder, 2019). Bibliometric analysis provided a structural map of the intellectual landscape, revealing key thematic clusters across metacognition, AI-supported learning, and global competence research. The qualitative synthesis clarified the conceptual relationships between these clusters and how theoretical mechanisms operate within and across studies. The combined evidence reveals a convergent pattern indicating that Generative AI possesses substantial potential to function as a metacognitive co-regulator in Training and Development. These insights form the conceptual foundation for the GenAI Metacognitive Workforce Development model, which is proposed in the next section.

RESULTS AND DISCUSSION

Descriptive Overview of the Research Landscape

Figure 2 presents the annual distribution of publications related to metacognition, Generative AI, and professional learning from 2004 to 2025. The results reveal a clear evolutionary trajectory comprising three phases. During the early phase (2004–2014), research output remained limited and was largely grounded in traditional self-regulated learning and workplace training theories, with minimal engagement with artificial intelligence. This pattern reflects an early emphasis on human cognitive regulation without substantial technological mediation, consistent with foundational work on metacognition and adult learning (Panadero, 2017).

The intermediate phase (2015–2019) shows a gradual increase in publications, coinciding with the emergence of adaptive learning systems, learning analytics, and early AI-supported instructional tools. Studies during this period increasingly examined automated feedback and intelligent tutoring systems in professional contexts; however, metacognitive regulation was often treated implicitly rather than as a focal construct (Holmes et al., 2020).

A pronounced shift is observed in the most recent phase (2020–2025), where publication output increases sharply. This surge aligns with the rapid diffusion of Generative AI and large language models, alongside heightened scholarly attention to AI-supported reflection, self-regulation, and adaptive competence in Training and Development (T&D) contexts. Similar acceleration patterns have been reported in recent integrated bibliographic reviews of AI in education, suggesting a broader transformation in how AI is conceptualised across learning domains (Liang et al., 2023).

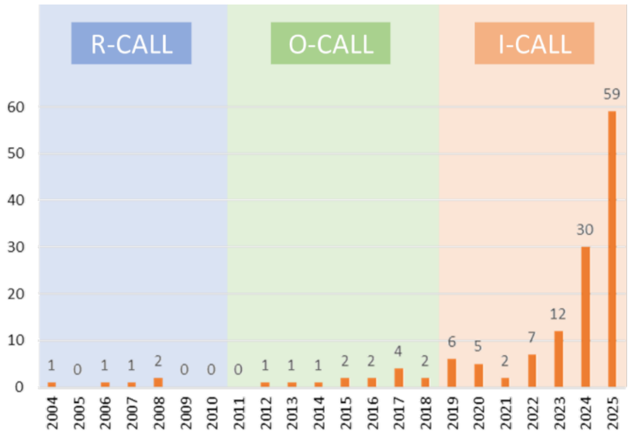

Figure 2. Published literature on metacognition, GenAI, and workplace learning from 2004 to 2025

Figure 3 further reveals a methodological transformation across phases. While conceptual and descriptive studies dominated early research, empirical investigations, particularly quantitative and mixed-methods designs, have become increasingly prevalent since 2020. This methodological shift signifies the maturation of the field, transitioning from exploratory discussions to an evidence-based examination of how AI interacts with learners' cognitive and metacognitive processes in authentic professional learning environments.

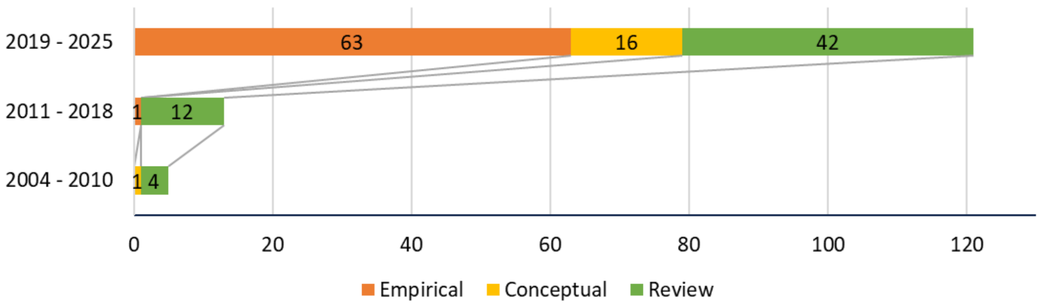

Figure 3. Published literature on metacognition, GenAI, and workplace learning from 2004 to 2025 based on the study type

Figure 4 presents the geographical distribution of publications, ranking the top eight countries by single-country and multiple-country publications. The results indicate that research output is concentrated in a limited number of countries, with international collaboration increasing over time. This pattern suggests that although interest in GenAI-supported learning is global, the conceptualisation of metacognition and AI in T&D may still reflect context-specific training cultures, highlighting the importance of developing globally relevant frameworks.

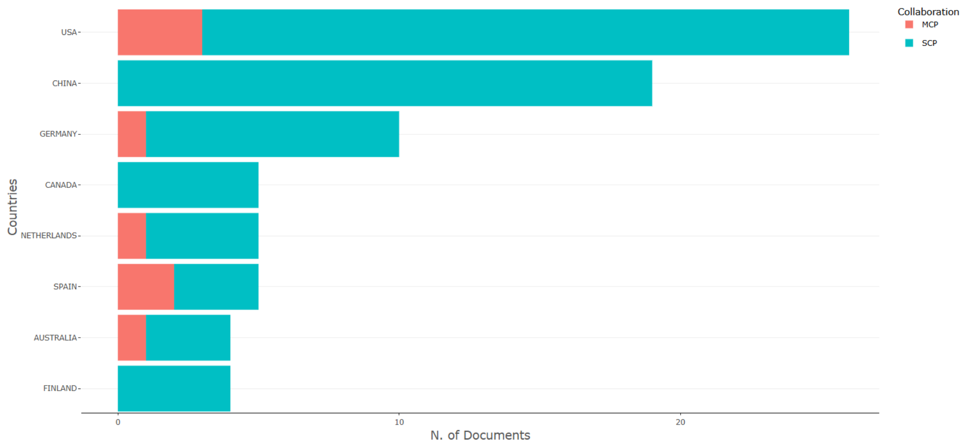

Figure 4. Top 8 countries ranked by the single and multiple country publications on metacognition, GenAI, and workplace learning from 2004 to 2025

Intellectual Structure of the Field

Figure 5 displays the author co-citation network for research on metacognition, GenAI, and workplace learning. The network reveals a well-defined intellectual structure centred on foundational scholars in metacognition and self-regulated learning. The prominence of these authors indicates that contemporary research on AI-supported professional learning remains theoretically anchored in established cognitive and educational psychology traditions, rather than emerging as a purely technology-driven discourse.

Surrounding this theoretical core are clusters related to AI-supported feedback, adaptive systems, and dialogic interaction. The increasing density of links between these clusters suggests a growing convergence between metacognitive theory and AI-mediated learning practices. This convergence supports arguments that AI systems are increasingly conceptualised not merely as instructional tools, but as interactive agents capable of supporting learners' regulatory processes (Kasneci et al., 2023). The author's co-citation structure thus provides bibliometric evidence for reframing GenAI as a metacognitive co-regulator rather than a content delivery mechanism.

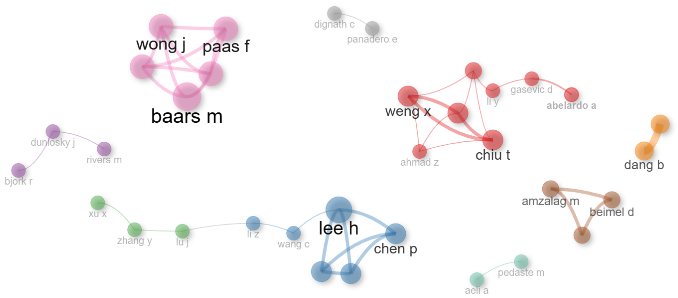

Figure 5. Author Co-Citation Network on metacognition, GenAI, and workplace learning from 2004 to 2025

Thematic Clusters Across Metacognition, GenAI, and Global Talent

Figure 6 presents the keyword co-occurrence network, revealing several dominant thematic clusters. One major cluster is centred on metacognition and self-regulated learning, emphasising planning, monitoring, and evaluation processes. A second cluster focuses on Generative AI, chatbots, and adaptive learning technologies. A third cluster relates to professional learning, workforce development, and global competence.

The spatial proximity between the metacognition and GenAI clusters indicates increasing conceptual integration. Keywords associated with reflective dialogue, feedback, and learning regulation frequently co-occur with GenAI-related terms, suggesting that a growing body of research explicitly examines how AI can scaffold metacognitive processes. This pattern is consistent with empirical studies showing that AI-mediated interaction can enhance learners' strategic planning and monitoring in complex learning environments (Wang et al., 2025; Xu et al., 2025b).

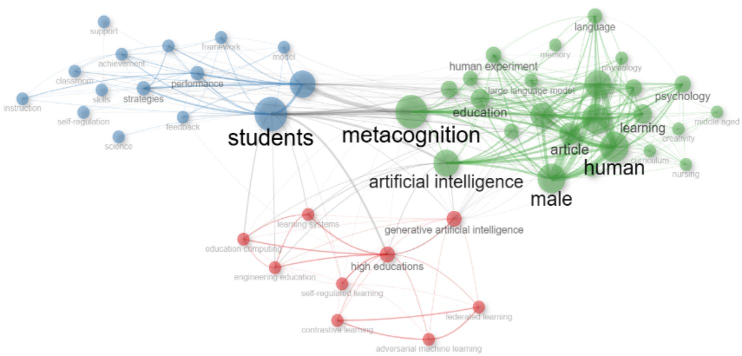

Figure 6. Keyword Co-occurrence Network on metacognition, GenAI, and workplace learning from 2004 to 2025

Figure 7 further illustrates trend topics over time. Earlier research primarily focused on intelligent tutoring systems and automated assessment, whereas more recent studies increasingly foreground reflective learning, self-regulation, and learner agency. This temporal evolution reflects a conceptual shift from technology-centred innovation to learner-centred regulatory support, reinforcing the relevance of metacognition as a unifying framework for AI-supported T&D.

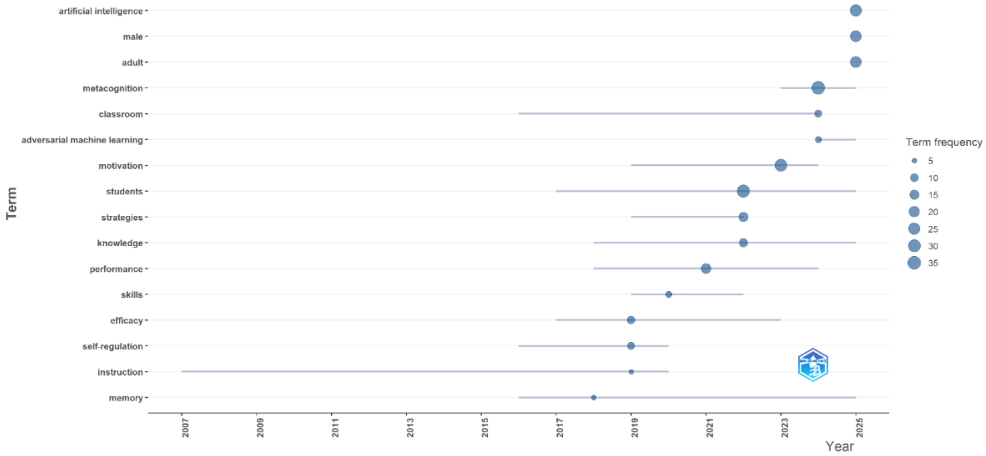

Figure 7. Trends in metacognition, GenAI, and workplace learning from 2004 to 2025

Functional Roles of Generative AI in Professional Learning

Figure 8 summarises the distribution of functional roles attributed to Generative AI across the reviewed studies. Early research predominantly conceptualised AI as an intelligent tutor or assessment facilitator, focusing on efficiency and automated feedback. This orientation aligns with early AI-in-education paradigms that prioritised system performance over learner regulation (Holmes et al., 2020).

More recent studies, however, demonstrate a clear diversification of AI roles. Generative AI is increasingly framed as a reflective dialogue partner, adaptive learning advisor, and metacognitive prompting agent. Empirical evidence within the dataset indicates that dialogic interaction with GenAI supports learners' articulation of reasoning, enhances monitoring accuracy, and facilitates strategic adjustment during task execution (Kasneci et al., 2023; Xu et al., 2025b). These findings suggest a transition toward learner-centred regulatory support rather than automation-driven instruction.

Notably, several studies explicitly conceptualise GenAI as a metacognitive co-regulator, emphasising its role in scaffolding planning, monitoring, and evaluation without replacing learner agency. This role diversification forms a critical empirical foundation for the proposed GMWD model.

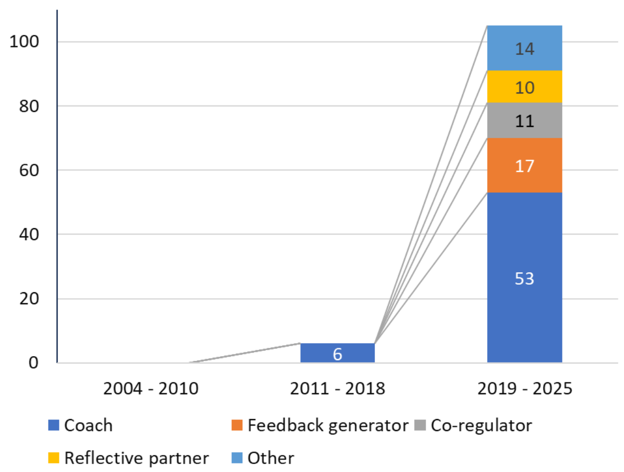

Figure 8. Distribution of GenAI Role from 2004 to 2025

Fragmentation and Underexplored Intersections Between Domains

Figure 9 presents an overlay keyword network highlighting convergence and fragmentation across metacognition, GenAI-supported learning, and global talent development. While metacognition and GenAI-related terms show increasing overlap, global talent and intercultural competence remain positioned at the periphery of the network.

This structural separation provides bibliometric evidence that, despite shared emphasis on adaptability and reflective judgment, global workforce development literature has not yet systematically integrated AI-supported metacognitive mechanisms. This fragmentation mirrors prior observations in global talent research, where learning technologies and cognitive regulation frameworks are often discussed independently (Caligiuri & Bonache, 2016; OECD, 2018). The findings underscore the need for an integrative framework bridging these domains.

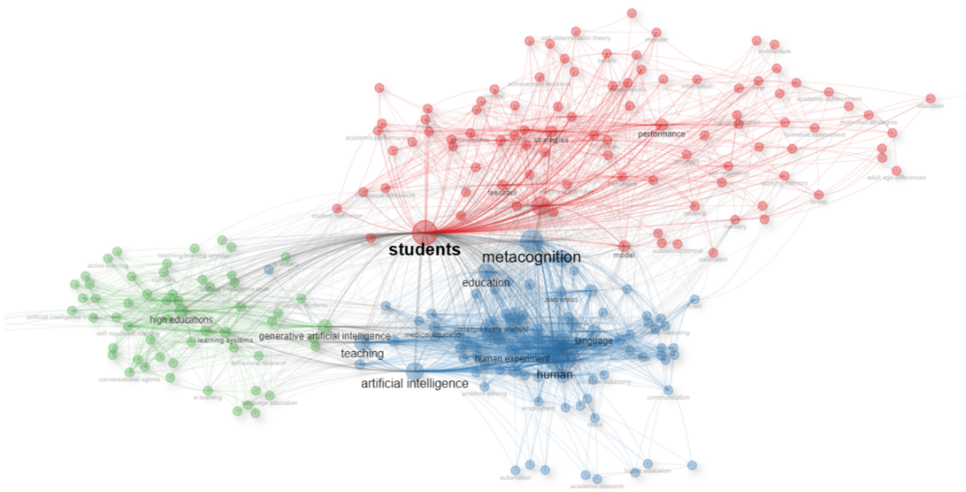

Figure 9. Overlay Keyword Network on metacognition, GenAI, and workplace learning from 2004 to 2025

Thematic Plot Over Time

Figure 10 presents the factorial analysis of thematic evolution from 2004 to 2025. Metacognition and self-regulated learning occupy the motor-theme quadrant, indicating both high centrality and density. This positioning confirms their role as the conceptual backbone of research on professional learning.

Generative AI-related themes demonstrate rapid movement toward this quadrant, reflecting their increasing theoretical and practical importance. In contrast, global talent development themes appear as emerging or transversal, suggesting conceptual relevance but limited consolidation. This factorial structure provides strong empirical justification for developing a model that integrates metacognition, GenAI, and global workforce competence.

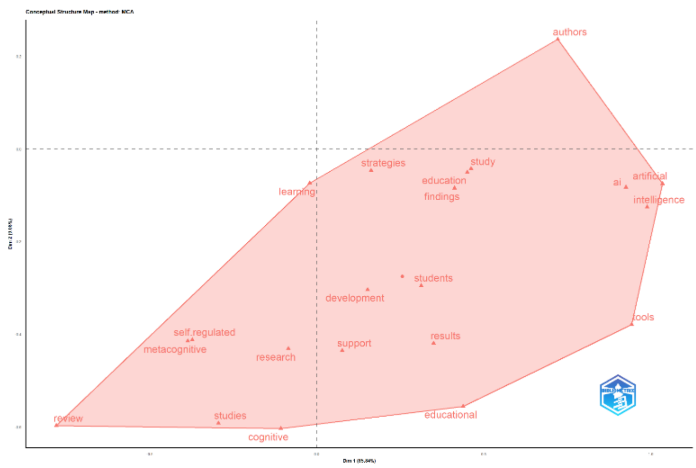

Figure 10. Factorial analysis on thematic plot from 2004 to 2025

Synthesis of Systematic Evidence on Metacognitive Mechanisms

Table 3 synthesises systematic evidence on how Generative AI supports metacognitive mechanisms across planning, monitoring, and evaluation phases. Across the reviewed studies, GenAI consistently functions as a phase-sensitive scaffold that supports goal clarification, reflective monitoring, and evaluative judgment. These mechanisms are associated with improved strategic planning, enhanced self-monitoring accuracy, deeper reflection, and increased learning transfer in training and development (T&D) contexts (Kasneci et al., 2023; Wang et al., 2025).

Importantly, the synthesis reveals that effective GenAI support preserves learner agency while enhancing regulatory processes, thereby mitigating risks associated with overdependence on AI. This balance is particularly critical in complex, ill-structured, and globally situated professional learning environments.

Table 3. Summary of Systematic Evidence on Metacognitive Mechanisms Supported by GenAI

Metacognitive Phase	Role of Generative AI	Key AI-Supported Mechanisms	Learning Outcomes in T&D Contexts
Planning	Metacognitive Prompting Agent	- Goal clarification through reflective questioning. - Task analysis support in ill-structured problems. - Activation of prior knowledge and strategy selection	- Improved goal-setting accuracy. - Enhanced strategic planning skills. - Greater learner autonomy at task initiation
	Adaptive Learning Advisor	- Personalised recommendations based on learner needs - Anticipatory guidance for complex or novel tasks	- Reduced uncertainty at early learning stages. - Increased confidence in task engagement.
Monitoring	Reflective Dialogue Partner	- Ongoing dialogic interaction to articulate reasoning - Prompting learners to check understanding and progress	- Improved self-monitoring accuracy. - Heightened metacognitive awareness during task execution.
	Performance Feedback Mediator	- Immediate formative feedback. - Comparative feedback between expected and actual performance.	- More efficient regulation of learning strategies. - Reduced cognitive overload in complex environments.
Evaluation	Metacognitive Coach	- Guided self-evaluation through evaluative prompts. - Encouragement of reflection on outcomes and strategies.	- Stronger self-evaluation and judgment skills. - Increased transfer of learning to new tasks.
	Meta-AI Literacy Facilitator	- Prompting critical examination of AI outputs. - Calibration of trust and awareness of AI limitations.	- Development of meta-AI skills. - Sustained self-regulation without AI overdependence.
Cross-Phase Integration	Metacognitive Co-Regulator	- Orchestration of planning, monitoring, and evaluation cycles.	- Integrated self-regulated learning competence. - Enhanced adaptability and reflective judgment.

Metacognitive Phase	Role of Generative AI	Key AI-Supported Mechanisms	Learning Outcomes in T&D Contexts
Global Talent Development Context	Intercultural Reflection Scaffold	- Alignment of AI support with learner agency. - Support for sense-making in cross-cultural situations. - Perspective-taking through dialogic reasoning	- Improved global competence. - Adaptive performance in international and multicultural work settings.

The GenAI–Metacognitive Workforce Development (GMWD) Model

Figure 11 illustrates the proposed GenAI–Metacognitive Workforce Development (GMWD) model, which synthesises bibliometric patterns and systematic evidence into a coherent conceptual framework. The model conceptualises Generative AI as a metacognitive co-regulator that dynamically supports learners' planning, monitoring, and evaluation processes within Training and Development (T&D) contexts, while explicitly preserving learner agency.

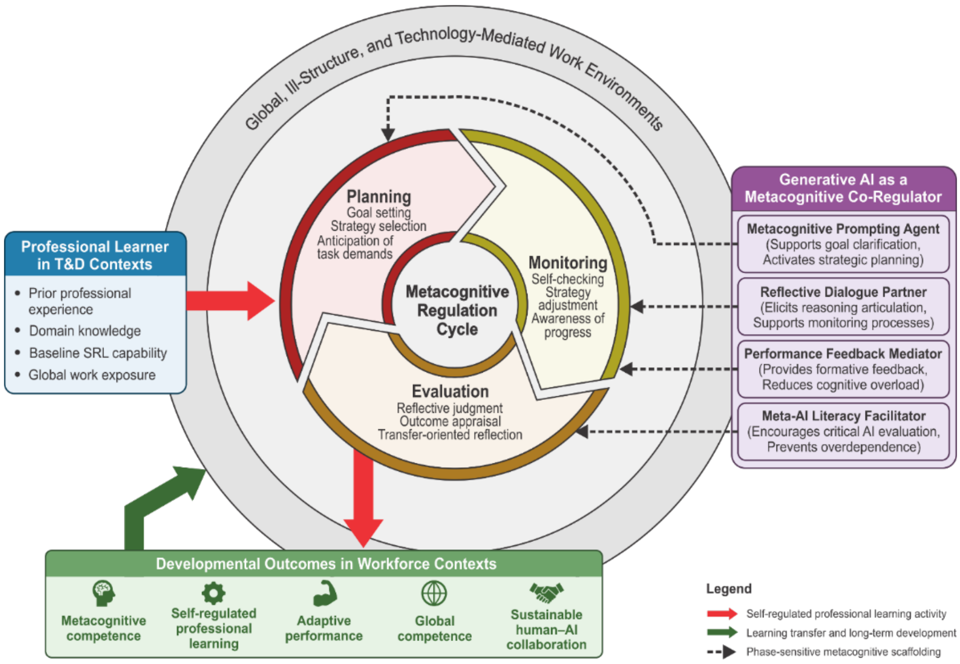

Figure 11. The GMWD Model

At the centre of the model lies the Metacognitive Regulation Cycle, which consists of three interrelated and recursive phases: planning, monitoring, and evaluation. As depicted in the inner circular structure, the planning phase involves setting goals, selecting strategies, and anticipating task demands. This phase reflects foundational metacognitive processes that enable learners to engage strategically with complex and ill-structured professional tasks (Flavell, 1979; Panadero, 2017). The monitoring phase encompasses self-checking, strategy adjustment, and awareness of progress, highlighting learners' ongoing regulation of cognition during task execution. The evaluation phase focuses on reflective judgment, outcome appraisal, and transfer-oriented reflection, which are essential for long-term professional development and learning transfer (Zimmerman, 2000; Salas et al., 2012).

On the left side of the model, the Professional Learner in T&D Contexts is positioned as the primary agent of learning. This component highlights learners' prior professional experience, domain knowledge, baseline self-regulated learning capability, and global work exposure. The directional arrow from the learner toward the metacognitive regulation cycle underscores that learning activity is initiated and controlled by the learner, reinforcing the principle that GenAI supports rather than replaces human regulation and decision-making.

On the right side, the model specifies Generative AI as a Metacognitive Co-Regulator, operationalised through four functional roles derived from the systematic synthesis. First, the Metacognitive Prompting Agent supports goal clarification and activates strategic planning through reflective questioning. Second, the Reflective Dialogue Partner elicits learners' reasoning articulation and supports monitoring processes during task execution. Third, the Performance Feedback Mediator provides formative feedback and reduces cognitive overload by aligning feedback with learners' current regulatory needs. Fourth, the Meta-AI Literacy Facilitator encourages critical evaluation of AI outputs and calibrates learners' trust in AI, thereby preventing overdependence and fostering sustainable human–AI collaboration (Fan et al., 2024). The dashed arrows connecting GenAI roles to each metacognitive phase visually represent phase-sensitive metacognitive scaffolding, indicating that AI support adapts dynamically to learners' regulatory needs rather than operating as a static instructional tool.

Surrounding the core components, the outer ring of the model represents global, ill-structured, and technology-mediated work environments. This contextual layer situates the GMWD model within contemporary professional settings characterised by uncertainty, cultural diversity, and rapid technological change. By embedding the metacognitive cycle within this broader context, the model explicitly links individual learning regulation to global talent development demands (Caligiuri & Bonache, 2016; OECD, 2018).

At the bottom of the figure, the Developmental Outcomes in Workforce Contexts illustrate the expected learning and performance outcomes emerging from sustained engagement with the GMWD process. These outcomes include metacognitive competence, self-regulated professional learning, adaptive performance, global competence, and sustainable human–AI collaboration. The bidirectional arrows between the evaluation phase and developmental outcomes indicate that learning transfer and long-term development feed back into subsequent planning cycles, reinforcing continuous professional growth.

CONCLUSION

The findings of this study highlight several important conclusions and implications for future research and practice. Metacognition and self-regulated learning emerge as the theoretical core of effective Training and Development, as reflected in their central position across co-citation, keyword co-occurrence, and factorial analyses. These findings indicate that planning, monitoring, and evaluation are essential regulatory processes in professional and adult learning contexts. In this regard, Training and Development should not be viewed merely as a process of knowledge transfer, but as a structured learning environment that supports learners in regulating their goals, strategies, progress, and performance outcomes.

The study also shows that the role of Generative AI in professional learning has shifted from automation-oriented tutoring toward metacognitive support. Rather than functioning only as a content delivery system, Generative AI is increasingly positioned as a reflective dialogue partner and adaptive feedback mediator. Within the reviewed literature, GenAI-supported metacognitive scaffolding is associated with improvements in learners' planning accuracy, monitoring awareness, and evaluative judgment, particularly in complex and ill-structured learning tasks. This suggests that the pedagogical value of Generative AI lies not only in its ability to provide information, but also in its potential to guide learners in thinking about their own learning processes.

Despite these developments, global talent development and intercultural competence remain weakly integrated with AI-supported metacognitive learning. Their peripheral position in thematic and overlay network analyses indicates that these domains have not yet been sufficiently connected within the broader discourse on Training and Development. This gap is important because contemporary workforce development increasingly requires adaptive performance, intercultural sensitivity, and the ability to learn across diverse professional and organisational contexts.

To address this gap, the proposed GenAI–Metacognitive Workforce Development (GMWD) model offers an integrative theoretical framework that positions Generative AI as a phase-sensitive metacognitive co-regulator. The model links metacognitive regulation with adaptive performance and global workforce competence, thereby extending the conceptual foundation of Training and Development in the context of emerging AI-supported learning environments. By integrating Generative AI, metacognitive scaffolding, and workforce development, the model provides a basis for designing more reflective, adaptive, and competence-oriented professional learning systems.

However, several limitations should be acknowledged. This review is limited to journal articles indexed in Scopus and Web of Science, which may exclude practitioner-oriented insights, industry reports, and emerging evidence from organisational settings. Bibliometric techniques are useful for identifying structural patterns and intellectual trends, but they cannot fully capture contextual factors such as organisational culture, learner characteristics, task complexity, and workplace-specific learning demands. In addition, the proposed GMWD model remains conceptual and requires empirical validation through future studies. Further research should test the model across different professional sectors, learning environments, and cultural contexts to examine its effectiveness in supporting metacognitive development, adaptive performance, and global workforce competence.

RECOMMENDATION

Future research should empirically test the GMWD model across diverse professional and cultural contexts using experimental, longitudinal, or design-based approaches. Particular attention should be paid to meta-AI literacy and sustainable human–AI collaboration. Practically, Training and Development practitioners are encouraged to design AI-enhanced learning environments that prioritise metacognitive prompting, reflective dialogue, and evaluative scaffolding rather than relying solely on automated feedback or content generation. Such approaches are essential for fostering adaptive, self-regulated, and globally competent employees.

ACKNOWLEDGMENTS

The authors would like to express their sincere gratitude to Universitas Negeri Surabaya for its academic support and institutional facilities that contributed to the completion of this study. The support provided by the Master's Program in Science Education, Postgraduate School, Universitas Negeri Surabaya, played an important role in facilitating this research. The authors also acknowledge the Graduate Institute of Digital Learning and Education, National Taiwan University of Science and Technology, Taiwan, for the collaborative academic environment that enabled the successful conduct and dissemination of this study.

FUNDING INFORMATION

This research received no external funding.

AUTHOR CONTRIBUTIONS STATEMENT

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Fida Rachmadiarti				✓						✓		✓		
Mita Anggaryani				✓						✓		✓		✓
Alif Syaiful Adam				✓	✓					✓				

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

ETHICAL APPROVAL

This study did not involve human participants, animal subjects, clinical procedures, experimental interventions, surveys, interviews, or the collection of personally identifiable information. The research was conducted as an integrated bibliometric analysis and systematic review using publicly available scholarly literature obtained from Scopus, Web of Science, and Google Scholar. Therefore, formal ethical approval from an institutional ethics committee was not required. All procedures in the review process were conducted in accordance with principles of academic integrity, transparency, and responsible research practice. The authors ensured that the identification, screening, eligibility assessment, coding, synthesis, and reporting of the reviewed literature were carried out systematically and without manipulation of the original sources. Proper attribution was given to all cited works, and the study did not use confidential, sensitive, or private data.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request. The data are not publicly available due to privacy considerations of research participants.

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