

Review

Training Wheels or Real Balance? AI Self-Efficacy and Performance in Knowledge-Intensive Work: A Systematic Review

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Abstract: Evidence on how artificial intelligence (AI) affects knowledge workers appears contradictory: some studies report that AI raises confidence and performance, while others find that it heightens anxiety and erodes expertise. This systematic review clarifies that picture. Following PRISMA 2020, we searched Scopus and Web of Science for peer-reviewed studies of employees in knowledge-intensive roles available online by 31 December 2025. After screening 244 unique records, 91 studies were included (84 empirical, 7 reviews). The corpus was characterized bibliometrically in R (bibliometrix and its Biblioshiny interface), and findings were integrated through thematic synthesis, because the heterogeneity of the primary studies' designs and measures precluded a meta-analysis. Three results emerge from the synthesis. First, AI-specific self-efficacy (AISE) performs three evidenced functions: it is built by AI adoption and use; it buffers threat, reducing the job insecurity and anxiety that AI awareness otherwise produces; and it moderates other relationships, conditioning whether AI exposure helps or harms outcomes such as performance. Second, the efficacy–performance link weakens under high task complexity and unreliable tool output. Third, and this is the review's central finding, none of the 91 included studies tests whether AI-enhanced performance persists when the tool is withdrawn: every available measure captures comfort with the technology rather than tool-independent competence. To explain this pattern and guide future testing, we propose that confidence formed through AI use can be durable (grounded in the worker's own mastery) or tool-contingent (grounded in the tool's output); we name this proposal the efficacy-durability framework and specify the designs required to test it. The review closes with a research agenda and implications for training, performance evaluation, and AI deployment.

Keywords: generative AI; AI self-efficacy; job performance; knowledge workers; human–computer interaction; social cognitive theory; systematic literature review; PRISMA

1. Introduction

A person using a large language model (LLM) to complete a task at their knowledge-intensive workplace produces a stronger outcome in less time (Brynjolfsson et al., 2025; Noy & Zhang, 2023) and reports a stronger feeling of capability (Wang & Chuang, 2024). Whether this is good news depends on a question the literature has not yet answered thoroughly: did the tool make the worker more competent, or did it do the thinking while leaving the worker only *feeling* more competent (Koch, 2026; Lee et al., 2025)? This question is pertinent because adoption has been unusually fast. ChatGPT reached an estimated 100 million monthly users within two months of its November 2022 release (as cited in Kobiella et al., 2024), and early estimates suggest LLMs could affect roughly 80% of the U.S. workforce (Eloundou et al., 2023). The debate

over whether technology displaces or complements labor long precedes this era (Autor, 2015; Frey & Osborne, 2017). Economists have long documented how automation substitutes for human labor in routine tasks, driving job polarization (Autor et al., 2003; Autor & Dorn, 2013; Goos & Manning, 2007; Goos et al., 2014). More recent frameworks, however, argue that automation and new tasks proceed together rather than as simple substitution (Acemoglu & Autor, 2011; Acemoglu & Restrepo, 2018, 2019, 2020). Management scholars have framed this tension as an automation–augmentation paradox, in which AI simultaneously replaces and enhances human capability (Raisch & Krakowski, 2021; Tschang & Almirall, 2021). Macroeconomic evidence suggests the declining labor share of income (the fraction of national income paid to workers rather than to capital) is partly attributable to the falling cost of ICT capital, which substitutes for labor (Eden & Gaggl, 2026; Karabarbounis & Neiman, 2014; Krusell et al., 2000). Generative AI compressed this dynamic into months: workplace adoption reached a quarter to a third of employees within a year of release (faster than the personal computer or the internet), though productivity returns often lag until complementary skills catch up (Brynjolfsson et al., 2021, 2025; Budhwar et al., 2023). The operational case for AI is therefore increasingly settled, while the employee-level consequences are not, and it is that consequence this review takes as its object.

Knowledge-intensive roles, where complex, non-routine tasks and specialized expertise are the main source of value (Alvesson, 2004; Starbuck, 1992; defined formally in Section 2.1), are revealing of these changes because expertise is not just helpful; it is the work itself. Tools such as LLMs and, by extension, generative AI tools (e.g., ChatGPT, Claude, DeepSeek) that can draft, summarize, analyze, and reason touch the core of professional identity and competence, as well as these workers' belief in their most valuable input: their knowledge. That belief in one's own capability, self-efficacy in Bandura's work (Bandura, 1977, 1997), is one of the most robust and longest-studied psychological predictors of work-related performance, with a meta-analytic correlation of approximately .38 across 114 studies (Stajkovic & Luthans, 1998). If AI systematically alters self-efficacy in expert workers, it therefore alters one of the most consequential antecedents of how well that work is done. This is not new in kind: technology-specific self-efficacy and job performance were studied directly as early as the 1990s, in workers whose jobs were subject to major technological change (McDonald & Siegall, 1996). What is new is whether the same logic holds when the tool can fully and (almost) flawlessly complete a highly cognitive and expert task rather than merely support it.

Two bodies of evidence sit uneasily together: the first documents AI raising output, quality, and confidence (Brynjolfsson et al., 2025; Dell'Acqua et al., 2026); the second documents anxiety, identity threat, and erosion of the confidence these knowledge workers' performance relies on (Bankins et al., 2024; Golgeci et al., 2025; Jarrahi, 2018). The evidence synthesized in this paper shows these are not competing findings about one relationship: AI-specific self-efficacy is repeatedly and independently found to be built by generative AI use, to buffer AI-related threat (that is, to reduce the job insecurity and anxiety that AI awareness otherwise produces), and to moderate other relationships (conditioning whether AI exposure helps or harms outcomes such as engagement and performance): three distinct, well-evidenced functions of one construct, not a contradiction. A second, equally important pattern is what the evidence does not contain. Across all 91 studies synthesized in this review, none uses a design measuring a worker's performance with a generative AI tool withdrawn against performance with the tool present. Every available measure of AI self-efficacy, including the field's own validated instrument (Wang &

Chuang, 2024), captures comfort and perceived skill, not whether that confidence corresponds to competence retained independently of the tool. This measurement gap is therefore a result this review establishes through its synthesis, not an assumption it starts from; identifying it, and proposing how to close it, is the review's contribution. We therefore ask: **How do AI-related perceptions influence employee self-efficacy and job performance in knowledge-intensive roles?** Three research questions specify this overarching question:

RQ1. What is the relationship between AI-related perceptions and employee self-efficacy in knowledge-intensive roles, and which antecedent family (adoption-related perceptions or threat-related appraisals) is associated with higher versus lower AI-specific self-efficacy?

RQ2. Through which mechanisms and under which conditions does self-efficacy translate into performance?

RQ3. What are the principal evidentiary gaps, particularly in measurement design, and which designs would address them?

2. Conceptual background

2.1 Core definitions

Generative AI is understood here, following Jarrahi (2018), as the capacity of computational systems to perform functions ordinarily associated with human intelligence and, in its generative form, to produce novel text, code, and analysis (Feuerriegel et al., 2024). A note on scope is needed at the outset: although generative AI is this review's motivating case, the eligibility criteria and the synthesized evidence cover AI-related workplace perceptions more broadly, including smart technology, robotics, and algorithms (STARA), because the self-efficacy constructs of interest were developed and measured across this broader family. "AI" is used accordingly throughout, and "generative AI" is reserved for studies of generative tools specifically.

Self-efficacy refers to beliefs "in one's capabilities to organize and execute the courses of action required to produce given attainments" (Bandura, 1997, p. 3). It is task- and domain-specific rather than global (Bandura, 1977, 1982; Gist & Mitchell, 1992), and it is distinct from outcome expectancy, a difference that matters once AI can supply the outcome directly.

AI self-efficacy, the variant this review centers on, descends from computer self-efficacy (Compeau & Higgins, 1995; McDonald & Siegall, 1996), though the term originates in consumer adoption research (Hong, 2022). Its only validated instrument resolves into four factors (assistance, anthropomorphic interaction, comfort, and technological skill; Wang & Chuang, 2024), none of which assesses whether confidence corresponds to competence retained independently of the tool: a measurement limitation that motivates this review's central proposal.

Knowledge-intensive work delimits this review's population and eligibility criteria, yet is contested rather than settled. Starbuck (1992) coined the term by analogy to capital- and labor-intensive firms, identifying esoteric expertise as the defining resource; Alvesson (2004) cautions against treating it as an objectively verifiable job property. Taking that caution seriously, this review operationalizes the category through three jointly applied criteria: analytical, advisory, or creative output; specialized expertise not readily substitutable; and non-routine judgement under incompletely specified conditions: a working definition for reproducible screening rather than a claim to have settled the debate.

Job performance denotes the effectiveness and efficiency of role execution, measured across at least four related but non-interchangeable forms in the included studies: task, contextual, innovative-behavior, and creativity. **Table 1** summarizes the five core constructs and their anchoring sources.

Table 1. Core constructs and their anchoring definitions.

Construct	Working definition adopted in this review	Anchoring source
Generative AI	Computational systems performing tasks ordinarily requiring human intelligence; in generative form, producing novel content and analysis.	Jarrahi (2018); Feuerriegel et al. (2024)
Self-efficacy	Task-specific belief in one's capability to organize and execute the actions required to attain a given level of performance.	Bandura (1997)
AI self-efficacy	Domain-specific variant of self-efficacy: belief in one's capability to use AI technologies to accomplish work tasks. The field's only validated instrument resolves it into four factors (assistance, anthropomorphic interaction, comfort with AI, technological skill).	Hong (2022); Wang & Chuang (2024)
Knowledge-intensive work	Work whose principal output is analytical, advisory, or creative; requiring specialized, non-readily substitutable expertise; and involving non-routine judgement under incompletely specified conditions.	Starbuck (1992); Alvesson (2004)
Job performance	Effectiveness and efficiency of role execution; measured across task, contextual, innovative-behavior, and creativity forms in the included studies.	Stajkovic & Luthans (1998)

2.2 Social Cognitive Theory as primary framework

Social Cognitive Theory (SCT) is adopted as the sole primary framework for the following reason. The Technology Acceptance Model and its successors (Davis, 1989; Venkatesh & Bala, 2008) explain whether a technology is adopted (TAM3 even includes computer self-efficacy among the antecedents of perceived ease of use), but they treat efficacy as an input to adoption, not as a consequence of sustained use for the worker's own sense of competence (Scherer et al., 2019). TAM is therefore retained as the adoption-stage literature this review moves beyond, not as a co-equal pillar.

Bandura (1986, 1997), by contrast, positions self-efficacy as a self-regulatory mechanism shaping the goals people set, the effort they invest, and their persistence under difficulty (Gist & Mitchell, 1992). Meta-analytic evidence confirms that self-efficacy predicts work performance (Stajkovic & Luthans, 1998), moderated by task complexity: the correlation weakens for highly complex tasks, which depend on knowledge and resources confidence alone cannot supply. Because knowledge-intensive roles are high-complexity by construction, self-efficacy's translation into performance is more conditional there than in routine work.

Efficacy beliefs form through mastery experience, vicarious learning, social persuasion, and affective states, each plausibly shaped by AI and confirmed empirically rather than only theoretically in the included studies examined below: a tool that reliably helps supplies mastery and raises efficacy, while one experienced as opaque or threatening supplies the anxiety Bandura identifies as efficacy-eroding. Which of these a given worker experiences with a given tool is an empirical question about antecedents, addressed next.

2.3 Two antecedent families

The included studies converge on two distinguishable antecedent families, not a single undifferentiated "AI perceptions" construct. The first is **adoption-related perceptions** (usefulness, ease of use, perceived intelligence), which relate positively to AI self-efficacy (Bankins et al., 2024; Ma et al., 2025), confirmed directly where perceived intelligence and personalization both predicted self-efficacy in a workplace generative-AI sample (Sivathanu et al., 2026). The second is **threat-related appraisals** (perceptions that AI is opaque, surveilling, or capable of replacing one's role), instrumented as awareness of smart technology and algorithms (Brougham & Haar, 2018) and grounded in conservation of resources theory (Hobfoll, 1989), the job demands-resources model (Bakker & Demerouti, 2007), and technostress research (Ayyagari et al., 2011); these relate

to anxiety, insecurity, and at times reduced self-efficacy.

The two families are not opposite ends of one scale: a system can be simultaneously useful and threatening, which is why collapsing them into a single “AI perceptions” construct, as much of the primary literature does, hides rather than reveals which antecedent is doing the explanatory work.

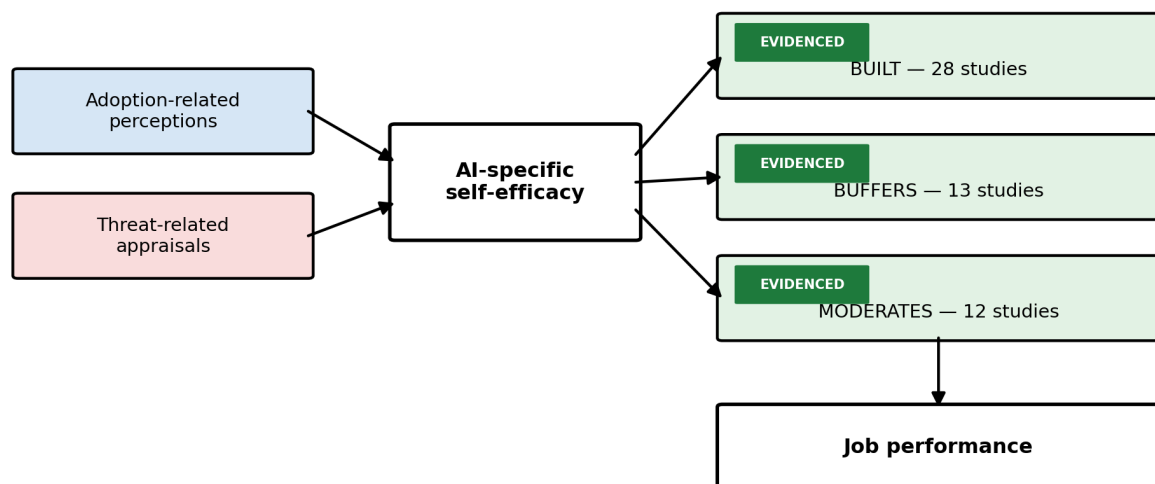
2.4 Three functions of AI-specific self-efficacy

Read across the included studies, AI-specific self-efficacy performs three distinguishable functions rather than sitting in one causal chain, and this is what the systematic evidence directly supports. It is **built** by adoption-related perceptions and direct AI use; it **buffers**, reducing the insecurity that threat appraisals otherwise produce; and it **moderates**, conditioning whether AI exposure helps or harms other outcomes, such as engagement, performance, and well-being (**Figure 1**).

One closely related finding sharpens the third function. In a 405-employee generative-AI sample, self-efficacy positively predicted job performance ($\beta = .265$, $p = .001$), significantly weakened where the system’s tendency to produce confident but incorrect output was high ($\beta = -.209$, $p = .001$) (Sivathanu et al., 2026), the most direct evidence available that the efficacy–performance link is conditional on the reliability of the tool the efficacy formed around.

The three functions of AI-specific self-efficacy supported by the evidence

All elements drawn directly from the 91 included studies (Section 2.4)



Note: this figure shows the evidenced pattern only. It does not distinguish whether the underlying self-efficacy is durable or tool-contingent — no included study measures this (see Figure 2).

Figure 1. The evidence-supported three functions of AI-specific self-efficacy.

2.5 A proposed distinction for future testing: the efficacy-durability framework

Everything to this point is evidence. What follows is this review’s own proposal, motivated by, but not established by, that evidence. The starting point is a result of the synthesis reported in Section 4, not a premise: none of the 91 included studies, including Sivathanu et al.’s (2026) reliability moderation, measures task performance with the AI tool withdrawn against performance with it present, and every available measure of AI self-efficacy captures comfort with the technology, not whether confidence tracks competence retained independently of it. Establishing this gap through systematic synthesis, and formalizing what would be required to close it, is the review’s primary contribution.

Self-efficacy formed through AI use may be **durable** (grounded in developing mastery, where AI scaffolds genuine skill such that performance would hold up if the tool were withdrawn), or **tool-contingent** (grounded in the tool's output, where skill does not develop and performance would decline sharply if the tool were withdrawn). Both are hypothesized to raise felt self-efficacy identically and to be indistinguishable using current measures, which is why the seven studies closest to observing this distinction approached it through six unrelated lenses (STARA awareness, self-regulation, cognitive appraisal, feedback systems, leadership ethics, and personality–technology fit) rather than through a shared instrument. That six independent traditions converged on the same bidirectional pattern motivates this proposal; it does not, on its own, test it.

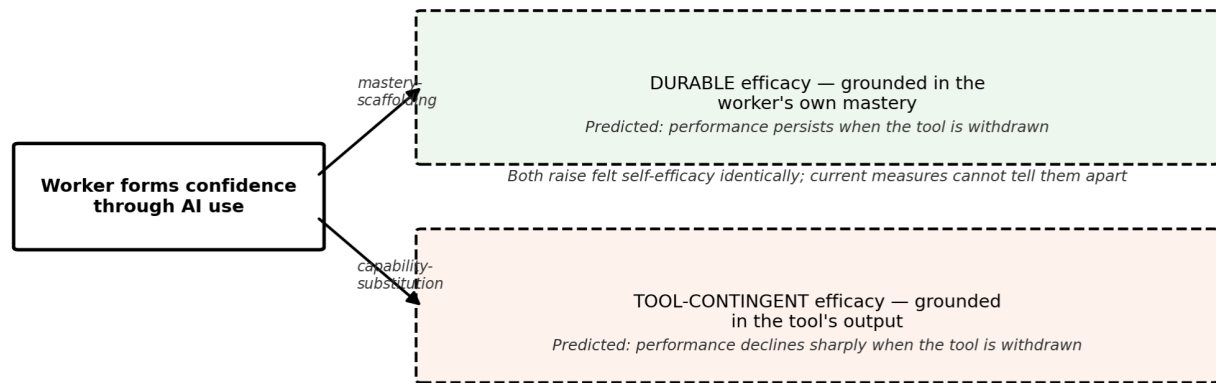
Two further terms are used below and defined here. **Routing** denotes the set of conditions (task type, tool design, prior expertise, and evaluation regime) proposed to determine which form of efficacy a given episode of AI use produces. The framework additionally proposes that self-efficacy operates as a **calibration gate**: it does not prevent threat appraisals from arising, but it conditions how much damage an appraisal does once it arises.

The underlying logic, withdrawing a support to check whether the confidence it produced is real, is not new. Bandura's own 1977 studies withdrew aids from phobic patients to confirm unassisted function; the same concern recurs in aviation (Bainbridge, 1983) and in memory research (Sparrow et al., 2011). In education, the design has recently been run: a randomized experiment with nearly a thousand mathematics students found that unrestricted LLM access sharply raised assisted performance but lowered subsequent unassisted exam performance, while a tutor-style interface avoided the decline (Bastani et al., 2025), proof of concept that assisted and tool-withdrawn performance can diverge, and that the divergence is measurable. What has not been done is applying this logic to employees in AI-assisted knowledge work, this review's precise contribution.

The distinction is defined by an outcome, not a belief: **a child whose training wheels have just been removed either rides steadily, because the balance was theirs, or falls, because the wheels were doing it, though both looked equally confident beforehand**. Durable efficacy is the first case, tool-contingent the second, distinguishable only at the moment the support is withdrawn. The framework's central prediction is that the two diverge once the tool is withdrawn or wrong: durable efficacy persists, tool-contingent efficacy declines sharply (**Figure 2**). Testing this requires a design pairing AI-specific self-efficacy with tool-withdrawn performance assessment, a design that does not yet exist in the employee literature. Until it is run, the distinction is a motivated hypothesis, not a finding. It is nonetheless stated with the precision of a theory (named constructs, a mechanism, boundary conditions, and falsification tests). For this reason, we name this proposal the efficacy-durability framework, and we call its core prediction, that the two forms of efficacy diverge when the tool is withdrawn, the efficacy-durability hypothesis.

The efficacy-durability framework — a proposed distinction

A testable hypothesis motivated by Theme 4 (Section 4.3.4), not an established finding



No published study of employees has run this comparison. It is the review's primary identified gap (Sections 2.5 and 6.1), not a reported result. Dashed borders mark proposed, untested constructs.

Figure 2. The efficacy-durability framework: a proposed distinction for future testing.

3. Method

3.1 Protocol, reporting standard, and choice of synthesis method

This review was designed and reported as a systematic review with thematic synthesis: search and selection were systematic and reproducible, while synthesis was thematic rather than meta-analytic.

A meta-analysis was considered and deliberately not pursued, for three reasons. First, the constructs are not commensurable across studies: self-efficacy appears as AI self-efficacy, technology self-efficacy, creative self-efficacy, AI-learning self-efficacy, and digital self-efficacy, and performance appears as task, contextual, innovative-behavior, and creativity forms, so a pooled effect would average across constructs that are related but not equivalent. Second, the designs are heterogeneous, spanning cross-sectional and time-lagged surveys, experience-sampling studies, field and laboratory experiments, and mixed-methods designs, which do not yield comparable effect-size metrics for the same perceptions–self-efficacy–performance pathway. Third, the review's purpose is to map an emergent and fast-moving field, reconcile apparently contradictory findings, and identify its principal evidentiary gap, aims for which thematic synthesis is the appropriate method (Thomas & Harden, 2008; Snyder, 2019), whereas meta-analysis presupposes a mature literature testing one well-specified relationship with shared measures. Proceeding directly to a systematic review with thematic synthesis was therefore a methodological decision matched to the state of the literature, not a fallback.

The review followed the PRISMA 2020 statement (Page, McKenzie, et al., 2021; Page, Moher, et al., 2021), informed by guidance for evidence-informed management reviews (Snyder, 2019; Tranfield et al., 2003). Combining PRISMA-guided synthesis with bibliometric characterization follows recent methodological guidance (Mishra & Pandey Mishra, 2024) and published hybrid designs (Wicaksono et al., 2023). A protocol specifying the question, eligibility criteria, search strategy, and synthesis plan was prepared in advance. The protocol was not prospectively registered; that is, it was not deposited in a public systematic-review registry (such as PROSPERO or the Open Science Framework) before screening began, a transparency practice PRISMA 2020 asks authors to report either way. The protocol, the completed PRISMA 2020 and PRISMA-A

checklists, and the full audit trail will be deposited as supplementary material on the journal's repository upon acceptance.

3.2 Eligibility criteria

Eligibility was specified using a PICO-style logic (Stern et al., 2014): *Population* (employees in knowledge-intensive roles), *Phenomenon of interest* (AI perceptions in relation to self-efficacy and/or job performance), and *Context* (organizational settings). The population criterion applied the three-part operational definition of knowledge-intensive work from Section 2.1, not occupational labels alone: several frontline service or hospitality studies were excluded despite using AI-related constructs, because the roles did not satisfy the expertise and judgement criteria, while nurses, radiologists, and academics were retained because they did. The inclusion window was set to January 2015–December 2025; records available online by 31 December 2025 were eligible regardless of their assigned issue year, which is why several included studies carry 2026 issue dates. Criteria are summarized in **Table 2**.

Table 2. Eligibility criteria.

Inclusion criteria	Exclusion criteria
Peer-reviewed empirical or theoretical articles in reputable journals (Scimago indexed). Available online January 2015–December 2025. Addressing AI perceptions and their relation to self-efficacy and/or job performance. Samples in knowledge-intensive sectors (e.g., technology, finance, healthcare, professional services, academia). Published in English or French.	Non-peer-reviewed material used only as contextual signposts. Consulting-firm, student, and journalistic reports. Studies outside knowledge-intensive roles. Studies with no measured or theorized link between AI and an employee psychological or performance outcome. Publications predating 2015 (except foundational theoretical sources). Duplicate reports of the same dataset.

3.3 Search strategy

Scopus and Web of Science were searched via full institutional access, combining two core concept blocks (AI-related terms; self-efficacy and performance terms) using consistent Boolean logic across both databases (**Table 3**), refined per database with document-type, language, and subject-area filters and, for Scopus, an additional employee-context block; records were processed in R using the bibliometrix package and its Biblioshiny interface (Aria & Cuccurullo, 2017). The search was last run in July 2026; the full executed search strings for each database, including field codes and filters, are reproduced verbatim in **Appendix B**. Terms for knowledge-intensive work were deliberately excluded from the Boolean string because of their heterogeneity; the population criterion was instead applied manually during screening, to avoid missing relevant material.

Table 3. Core concept blocks common to both databases.

Concept block	Search terms
AI	(“artificial intelligence” OR “generative AI” OR “AI” OR “ChatGPT” OR “large language model”*)
Self-efficacy / performance outcome	(“self-efficacy” OR “self efficacy” OR “job performance” OR “task performance” OR “work performance”)
Combination	Block 1 AND Block 2, further refined per database by publication year, document type (article/review), language (English/French), and subject area (Business, Psychology, Sociology); see Appendix B for the exact per-database strings.

The search yielded 84 Scopus and 200 Web of Science records (284 combined); after deduplication, 244 unique records remained (**Figure 3**). The 40 duplicates across 284 records (14.1%) indicate the two databases capture

complementary rather than redundant literature. No registers, grey-literature sources, or supplementary citation searches were used beyond the two databases.

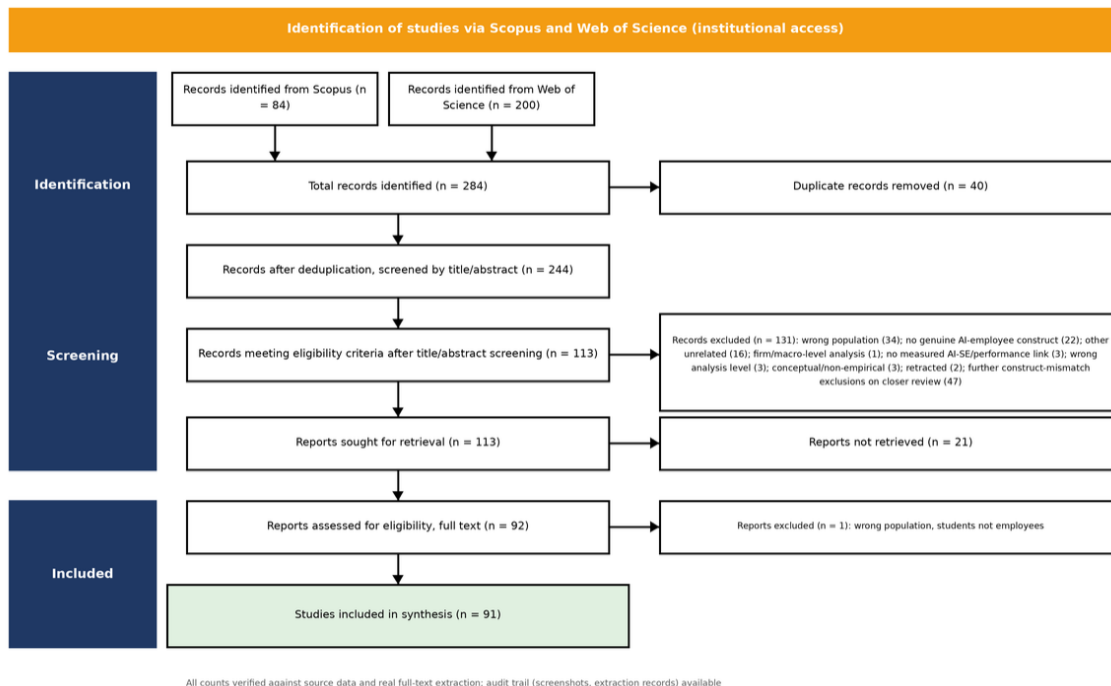


Figure 3. PRISMA 2020 flow diagram, Scopus and Web of Science institutional-access search (Page, McKenzie, et al., 2021).

3.4 Selection process

Title-and-abstract screening proceeded in stages of increasing strictness: an initial pass excluded records with no genuine AI–employee construct, wrong population, or wrong analytical level; a second re-verification pass checked every provisionally included record against the exact eligibility wording, catching records let through on topical relevance alone. Both authors independently screened all records at both the title-and-abstract and full-text stages; disagreements were resolved by discussion until consensus was reached, and no automation tools were used to screen or exclude records. In total, 131 of 244 records were excluded, leaving 113 eligible records on title and abstract (Figure 3).

Full-text retrieval was attempted for all 113; 21 could not be retrieved (paywalled, not recoverable within the review timeline) and are reported rather than omitted. The remaining 92 were read in full text; one further exclusion, a custom AI-tutoring-chatbot study with engineering students that did not meet the employee-population criterion, is documented with its full citation and exclusion reason in the supplementary screening log, alongside the reason for every other full-text exclusion. This yields **91 studies included in the final synthesis**: 84 empirical, 7 reviews.

The complete audit trail, database export screenshots, the full screening log with a reason for every exclusion, and the retrieved source for each included study, is provided as supplementary material rather than on request. Following APA convention for systematic reviews, included studies are marked with an asterisk in the reference list.

3.5 Data extraction and quality appraisal

A standardized extraction form captured bibliographic details, country, sector, design, sample, AI technology, constructs and measures (including how each study operationalized self-efficacy and performance), and principal

findings. One author extracted data from all included studies; the second author independently applied the Mixed Methods Appraisal Tool (MMAT, described below) to each empirical study, and discrepancies between extraction and appraisal were resolved by discussion until consensus. The MMAT permits consistent quality appraisal across quantitative, qualitative, and mixed-methods designs. Appraisal informed evidential weight rather than serving as an exclusion threshold, considered alongside study design, sample size and reported power, and journal indexing, the last used only as a coarse screen of peer-review stringency, not as a proxy for the quality of individual studies. MMAT categorization for a representative subset of the 84 empirical studies is reported in Section 4.1; the full MMAT appraisal for all 84 empirical studies is provided in the supplementary extraction record. The 7 reviews are not MMAT-scored, as they inform theoretical scaffolding rather than empirical evidence.

3.6 Synthesis approach

Findings were integrated through thematic synthesis of studies following Thomas and Harden (2008), with coding conducted in the six-phase sequence familiar from thematic analysis (Braun & Clarke, 2006); coding was performed and audited in NVivo 15 (Lumivivo), drawing on mixed-methods research principles (Creswell & Plano Clark, 2017), given that the corpus combined quantitative, qualitative, and mixed-methods studies. The five analytical themes correspond to the framework's components: perceptions and acceptance; the perception–efficacy link; the efficacy–performance link; moderators and mediators; and contextual variation.

For the reasons detailed in Section 3.1, no effect measures were pooled and no meta-analysis was conducted; quantitative results are reported narratively in the studies' own metrics. No formal reporting-bias assessment (e.g., funnel-based methods) was conducted, as such methods presuppose pooled effects; the likely direction of publication bias is addressed in the Limitations. No formal certainty-of-evidence assessment (e.g., GRADE-CERQual) was applied to the synthesized themes; instead, the confidence warranted by each theme is signalled narratively alongside the number, design strength, and consistency of the contributing studies.

4. Results

4.1 Characteristics of the included evidence

In total, 91 studies met full eligibility criteria (**Figure 3**): 84 empirical studies and 7 reviews. The evidence is concentrated in 2023–2025 (79 of 91 studies) and spans 23 countries, with pronounced concentration in China (41) and South Korea (14), across manufacturing, hospitality, healthcare, education, IT, financial services, and the public sector. Cross-sectional and time-lagged survey designs analyzed via structural equation modelling (SEM) dominate (68 of the 84 empirical studies); a smaller but methodologically important set of field experiments, longitudinal panels, and mixed-methods designs permits stronger causal or temporal inference. **Table 4** summarizes the five analytical themes. Theme assignments were not mutually exclusive: several studies contributed evidence to more than one theme (e.g., Song et al., 2025, to Themes 1 and 3; Q. Zhang et al., 2025, to Themes 1 and 2), while a small number informed the synthesis without a primary thematic assignment; the study counts in **Table 4** report primary assignments and do not sum to the empirical total. Full characteristics for every included study, together with the search, screening, and extraction audit trail, are provided as supplementary material.

Table 4. Summary of the five analytical themes across the 84 empirical studies (primary assignments).

Theme	Studies	Principal pattern	Representative evidence
1. AI perceptions build self-efficacy directly	28	Direct, positive path from AI adoption/usage/perception to AI-specific self-efficacy, grounded in Social Cognitive Theory.	Jeong (2025); J. Wen et al. (2026); Han et al. (2025)
2. Self-efficacy carries through to performance/behavior	23	Self-efficacy mediates AI perceptions to task performance, job performance, innovation, or creativity.	Lu & Currie (2026); Low et al. (2025); Q. Zhang et al. (2025)
3. A parallel threat-based pathway	13	AI awareness/dependence operates via job insecurity or anxiety, with negative downstream consequences; self-efficacy often buffers rather than blocks this.	Chung et al. (2025); Kim & Kim (2024); Suseno et al. (2022)
4. Both pathways within a single sample	7	Building and threat-adjacent pathways co-occur in the same population, documented from unconnected theoretical starting points.	Tang et al. (2023); Zang et al. (2024); Tong et al. (2021)
5. Boundary conditions	12	Task complexity (curvilinear), leadership, organizational support, and self-efficacy-as-moderator determine which pathway dominates.	Akben & Dong (2025); Di Stefano et al. (2025); Kong et al. (2026)

MMAT categorization of illustrative studies spans the corpus's design range: three-wave longitudinal (J. Wen et al., 2026, N = 1,108), curvilinear cross-sectional SEM (Akben & Dong, 2025), cross-sectional moderation analysis using the PROCESS macro (Hayes, 2018) (Di Stefano et al., 2025, N = 71), experience-sampling field designs (Lu & Currie, 2026, 13 hotels), and mixed experience-sampling-plus-simulation, the subset's strongest causal design (Tang et al., 2023, two studies). The distribution of MMAT ratings across all 84 empirical studies, and the full appraisal table, are provided in the supplementary extraction record.

4.2 The broader corpus: bibliometric characterization

Beyond the included studies, the 244-record corpus characterizes the broader research landscape. It spans 149 sources (distinct journals and other publication outlets) with a 23.83% annual growth rate and a mean document age of 1.99 years. **Figure 4** shows annual production: negligible before 2020, rising to 24 articles in 2023, then sharply to 99 in 2025 (roughly 40% of the entire corpus), substantiating the field's characterization as emergent and consistent with the concentration of the included studies themselves in 2023–2025.

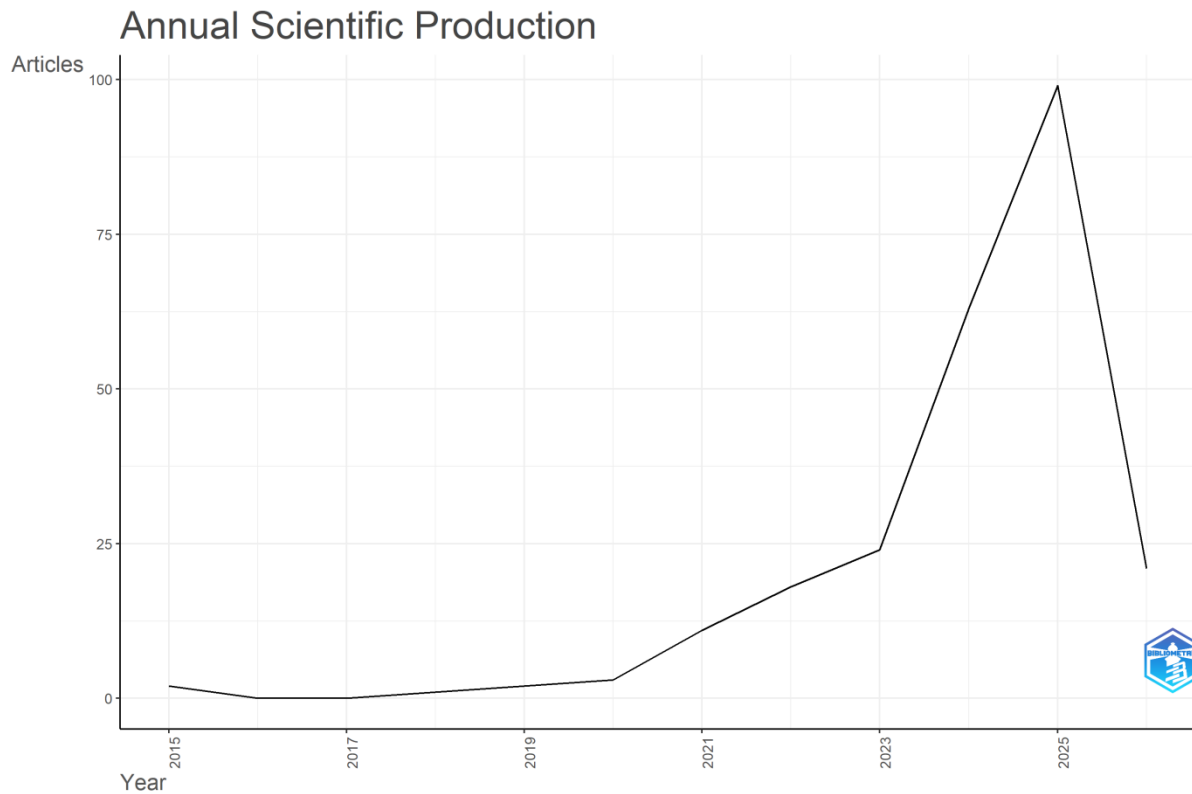


Figure 4. Annual scientific production, Scopus and Web of Science corpus (n = 244), 2015–2025 (Biblioshiny-generated).

Author-affiliation analysis shows pronounced geographic concentration (**Table 5**): China and the United States account for most of the production. **Table 5** reports author-affiliation counts, not document counts: each record contributes one count for every country represented among its authors, so counts can exceed, and sum to more than, the 244 records. This concentration is an evidence-generalizability constraint developed in Sections 4.4, 5.2, and 6.2.

Table 5. Country scientific production by author affiliation, Scopus and Web of Science corpus (n = 244 records; affiliation counts; top 6 of 47 countries represented; Biblioshiny-generated).

Rank	Country	Frequency (affiliation counts)
1	China	241
2	United States	108
3	Australia	42
4	South Korea	41
5	Germany	26
6	Malaysia	24

A keyword co-occurrence analysis resolves the corpus into six thematic clusters (**Figure 5**): self-efficacy, performance, artificial intelligence, management, model, and motivation, corroborating, at corpus scale, the construct landscape developed qualitatively in the thematic synthesis below and informing the research-gap mapping in **Appendix A**.

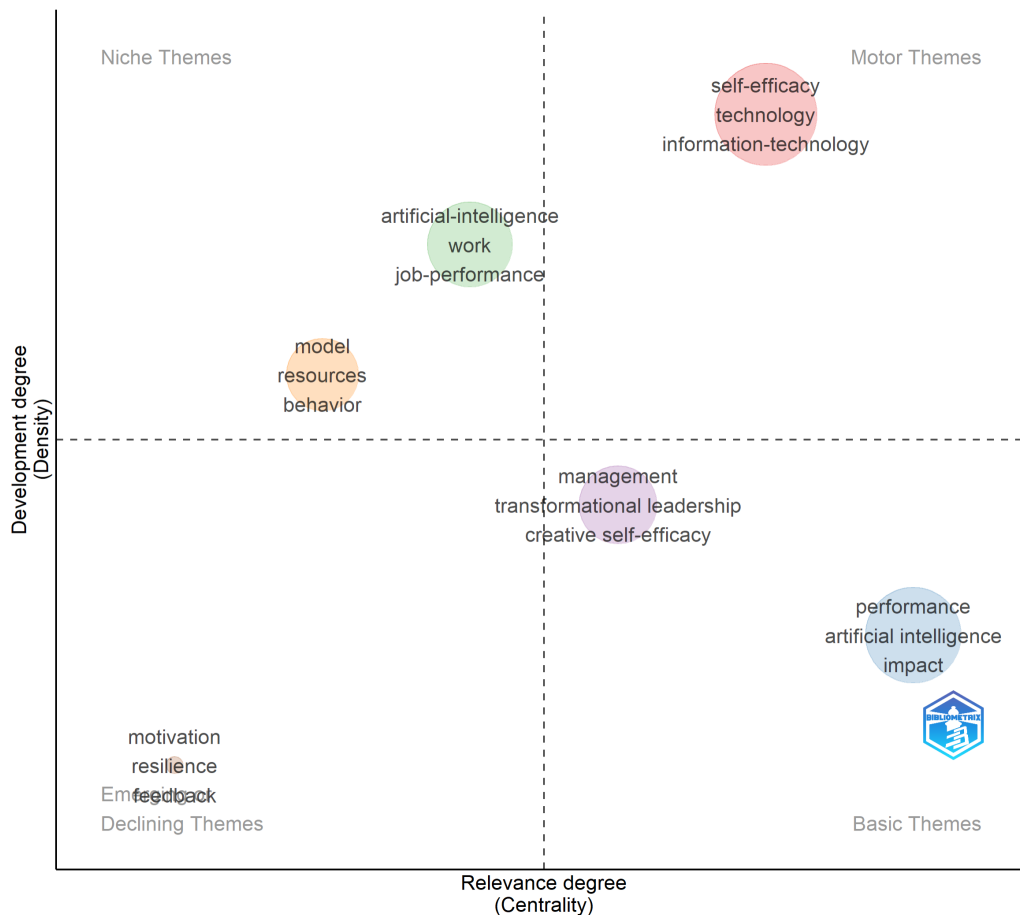


Figure 5. Thematic map, Scopus and Web of Science corpus (n = 244). Quadrant position indicates each theme's centrality (x-axis) and internal development (y-axis) (Biblioshiny-generated).

4.3 Thematic synthesis

The evidence across these 91 studies does not describe a single, uniform relationship between AI and employee self-efficacy or performance. It describes at least five distinguishable patterns, each recurring across multiple independent samples and national contexts. In terms of the research questions, Themes 1 and 3 bear primarily on RQ1 (the perception–efficacy relationship and its two antecedent families), Themes 2 and 5 on RQ2 (mechanisms and boundary conditions of the efficacy–performance link), and Theme 4, together with the measurement observations running through all five themes, on RQ3 (evidentiary gaps). The themes are reported here in the primary studies' own terms; what they may jointly motivate is taken up in the Discussion (Section 5.2).

4.3.1 Theme 1: AI perceptions build self-efficacy

The largest pattern is a direct, positive path from AI-related perceptions, adoption, or usage to employee self-efficacy, replicated across 28 samples spanning manufacturing (Jeong, 2025; Q. Zhang et al., 2025), education (Ding et al., 2025; Berkovich & Eyal, 2025), healthcare (Song et al., 2025), IT (Jia et al., 2025), financial services (Basri & Almutairi, 2023; Basri, 2024), and general knowledge work (J. Wen et al., 2026; Han et al., 2025; X. Liu et al., 2025). The grounding is consistently Social Cognitive Theory (Bandura, 1997): AI is treated as a mastery-experience source, with AI-specific self-efficacy or its variants (technology, AI-learning, creative, and digital self-efficacy) as the proximal outcome. Several studies confirm self-efficacy as a mediator rather than a mere correlate of the downstream outcome (J. Wen et al., 2026; Han et al., 2025; Q. Zhang et al., 2025; Kim & Lee, 2025).

4.3.2 Theme 2: From self-efficacy to performance

Twenty-three studies extend this pattern, showing self-efficacy mediating through to a genuine performance or behavioral outcome: task performance (Lu & Currie, 2026; J. Wen et al., 2026), job performance (Low et al., 2025; Chen et al., 2024), innovative work behavior (Q. Zhang et al., 2025; X. Li et al., 2022), creativity (Jeong & Jeong, 2025; Y. Yang et al., 2025), and organizational performance metrics (M. Li et al., 2022; Lin et al., 2022). Across these studies, AI-linked confidence does not merely co-occur with use; it carries through measurably to task-level outcomes, in contexts too varied to attribute to a single industry or culture. Whether that confidence reflects durable or tool-contingent capability cannot be determined from these designs, a question taken up in the Discussion.

4.3.3 Theme 3: A parallel threat-based pathway

Thirteen studies document AI awareness, dependence, or adoption operating through job insecurity, anxiety, or overqualification rather than through self-efficacy, with negative consequences for engagement, performance, or well-being (Chung et al., 2025; Song et al., 2025; Zhao et al., 2025; Kim & Kim, 2024; Kim, Oh, et al., 2024; Suseno et al., 2022; Kim & Lee, 2024). In several, self-efficacy re-enters not as the mechanism generating harm but as a moderator that buffers it: higher-self-efficacy employees show measurably less job stress or attrition risk from the same objective exposure (Kim & Lee, 2025; Hassan et al., 2024; Kim, Kim, & Lee, 2024b). In these studies, self-efficacy does not prevent the threat appraisal from arising; it conditions how much damage the appraisal does once it occurs.

4.3.4 Theme 4: Both pathways within a single sample

Seven studies document both a building and a threat-adjacent pathway within the same sample, found by researchers working from unconnected theoretical starting points: STARA awareness (L. Zhang et al., 2025); self-regulation, naming dependence a “mixed blessing” (Tang et al., 2023); cognitive appraisal, with a U-shaped effect via challenge appraisals and an inverted-U via hindrance appraisals (Zang et al., 2024); feedback systems, with co-occurring quality-improving and perception-damaging effects of the same feedback (Tong et al., 2021); leadership ethics, with change behavior raising both performance and unethical behavior (He et al., 2024); and personality–technology fit and individual differences (Tang et al., 2022; Hafeez et al., 2025).

The convergence carries a different kind of weight than any single study: six unrelated traditions, none designed to test durability, each produced a result that is difficult to explain with a single source of efficacy, a recurring anomaly rather than a preference for parsimony. Tang et al.’s (2023) two-study design warrants the most weight, since within-person and experimental designs rule out between-person confounds; the remaining studies, mostly cross-sectional, show the pattern is not confined to one design. None was built to measure durability directly: the gap this review addresses, and the empirical starting point for the proposal examined in Section 5.2.

4.3.5 Theme 5: Boundary conditions

Twelve studies identify conditions under which the building pathway dominates, converging on one claim: which pathway dominates depends on how tool, task, and organization interact, not on a fixed tool property. The effect of task complexity is curvilinear: self-efficacy peaks at moderate complexity (Akben & Dong, 2025; Guan et al., 2025), so neither novices nor experts are most likely to build it. Leadership helps but is insufficient alone, strengthening adoption-to-efficacy links (Jeong & Jeong, 2025; Jia et al., 2025) yet depending on the leader’s own digital literacy (Matsunaga, 2022). Organizational support brakes the threat pathway rather than accelerating the building one (Berkovich

& Eyal, 2025; Suseno et al., 2022). Self-efficacy's own level moderates other relationships directly (Di Stefano et al., 2025; Kong et al., 2026), the latter identifying a threshold below which AI awareness harms engagement and above which it helps: quantitative evidence that this moderating role is measurable, not metaphorical.

This subset also contains a genuine disconfirming result: one study finds AI-driven training adaptability has no significant effect on effectiveness or performance, with motivation and conventional training remaining the stronger predictors (Nirmala et al., 2025). This null result constrains rather than contradicts the synthesis, indicating that boundary conditions determine not only which pathway dominates but whether AI meaningfully alters the relationship at all in some settings, a qualification this paper carries forward explicitly.

4.4 Sectoral and geographic variation

As reported in Section 4.1, coverage concentrates in East Asia, with China and South Korea accounting for 60% of included studies, and secondarily in hospitality and healthcare, where AI is highly visible to expert workers (hotel employees: Lu & Currie, 2026; Song et al., 2025; Hassan et al., 2024; nurses: X. Li et al., 2024; radiologists: Di Stefano et al., 2025). This concentration holds across both the original and the larger verified corpus, so the evidence base is strong on cross-theoretical convergence but narrow on cultural and institutional variation, a distinction developed into a specific research priority in Section 6.2.

5. Discussion

The three research questions posed in the Introduction structure this section. RQ1 (the perception–efficacy relationship and its antecedent families) and RQ2 (mechanisms and conditions of the efficacy–performance link) are answered by the directly supported evidence in Section 5.1; RQ3 (evidentiary gaps and the designs that would address them) is answered in Sections 5.2 and 6.

5.1 What the evidence directly supports

RQ1 asked what the relationship is between AI-related perceptions and employee self-efficacy, and which antecedent family drives it. The answer the evidence supports is that the relationship is real, sizeable, and bidirectional in valence depending on the antecedent family involved. Adoption-related perceptions (usefulness, ease of use, perceived intelligence) relate positively to AI-specific self-efficacy across 28 independent samples (Theme 1), while threat-related appraisals (opacity, surveillance, replacement) relate to anxiety and insecurity rather than to efficacy directly, with self-efficacy buffering rather than blocking that pathway (Theme 3). The two families are empirically separable, and collapsing them into a single “AI perceptions” construct obscures which one is doing the explanatory work.

RQ2 asked through which mechanisms, and under which conditions, self-efficacy translates into performance. Social Cognitive Theory holds that self-efficacy predicts performance, and the meta-analytic record supports this robustly (Stajkovic & Luthans, 1998); Theme 2 confirms the mediating mechanism in AI contexts across 23 studies. Two directly evidenced findings show the link is conditional rather than universal. First, the original meta-analysis found the correlation weaker under high task complexity, which describes knowledge-intensive work by definition. Second, a 405-employee generative-AI study finds the link significantly weakened when the tool's tendency to produce confident but incorrect output is high (Sivathanu et al., 2026). Confidence formed around an AI tool does not translate into performance unconditionally; it depends on task complexity and tool reliability. This is the review's most defensible conclusion, and it does not require the durability

distinction to be true. It also refines the widely cited claim that automation and augmentation are interdependent rather than cleanly separable (Raisch & Krakowski, 2021), by identifying tool reliability as a measurable condition determining which of the two a deployment produces.

5.2 What the evidence motivates but does not establish

RQ3 asked what the principal evidentiary gaps are and which designs would address them. The first part of the answer is the finding already established in Sections 2.5 and 4: none of the 91 included studies measures performance with the tool withdrawn, so the field cannot currently distinguish confidence that tracks retained competence from confidence that tracks the tool. This subsection addresses what that gap motivates; the designs that would close it are specified in Section 6.

The proposed explanation for *why* the link weakens, that efficacy can be durable through genuine mastery or tool-contingent through reliance on the tool's output, is a theoretical interpretation, not a tested mechanism. It is motivated by a real pattern: seven studies, across six unrelated traditions, each find AI exposure producing both a performance-building and a performance-undermining effect within the same sample (Theme 4). That convergence is suggestive; it is not evidence that the durability distinction is correct rather than, say, unmeasured heterogeneity in task type or experience.

Read through the framework, the Results acquire a consistent, but strictly interpretive, shape, and this is where the mapping belongs. Theme 2's mediation pattern is what a durable-efficacy pathway would produce, though none of its designs can rule out tool-contingency. Theme 3's buffering pattern is the structural signature the framework predicts for the calibration gate defined in Section 2.5: self-efficacy conditioning the damage a threat appraisal does rather than preventing the appraisal. And the threshold identified under Theme 5 (Kong et al., 2026) suggests that, if the gate exists, it is measurable rather than metaphorical. Each of these readings is an interpretation laid over designs that cannot distinguish durable from tool-contingent efficacy; they should be read as this review's proposed answer to a well-evidenced question, not as findings.

A further caution concerns where the evidence comes from. Because the corpus concentrates in China, South Korea, and the United States, some evidenced patterns may not travel. Threat-appraisal findings plausibly interact with labor-market protections and the pace of state-led AI deployment, both distinctive in the most-studied economies; buffering effects may differ under different job-security regimes, since the resource self-efficacy protects is partly institutional; and leadership moderators are likely sensitive to power distance. These are theoretical reasons, not merely ritual ones, to treat cross-cultural measurement invariance as a precondition for generalizing this synthesis (Section 6.2).

5.3 Managerial relevance of the evidenced pattern

This implication follows without requiring the durability hypothesis to hold. No instrument distinguishes an employee whose AI-linked confidence would survive the tool's removal from one whose confidence would not, because none measures tool-withdrawn performance. Dashboards record output, not the durability of the capability behind it. Since the efficacy–performance link is demonstrably weaker under complexity and unreliable output, this invisibility matters most where stakes are highest: in the most complex roles, when the tool is least reliable.

6. Research Agenda

This agenda completes the answer to RQ3. The contribution of this review is not a list of gaps but a proposal that can be wrong in specified ways. It states

what would have to hold if the efficacy-durability hypothesis is correct, what new constructs the field needs to measure, and which adjacent disciplines hold the tools to test it.

6.1 Testable propositions

The single highest-priority proposition is the review's primary contribution: a precise, unaddressed measurement gap, not the durability mechanism proposed to explain it. The remaining propositions are conditional extensions that only become testable once P1 has been run.

P1 (the decisive test). A worker's task performance measured with an AI tool present will diverge from the same worker's performance measured with the tool withdrawn, in proportion to how tool-contingent rather than durable their AI-linked self-efficacy is. No published study of employees has measured both conditions in the same design, and none of the 91 studies reviewed here does; this comparison is the precondition for testing everything that follows.

P2 (mechanism). What separates durable from tool-contingent efficacy is whether AI use functioned as mastery-scaffolding or capability-substitution, distinguishable by whether independently measured tool-free skill also improved over the same period.

P3 (routing conditions). Durable efficacy is more likely under non-routine tasks, greater prior expertise, and explanatory interface design; tool-contingent efficacy under codified tasks, novicehood, opaque interfaces, and performance regimes rewarding short-run output alone. Interface design and evaluation criteria are therefore manipulable routing levers (Section 2.5), not fixed costs.

P4 (reliability moderation, partially evidenced). The efficacy–performance link weakens as tool error rate increases, already directly supported for perceived hallucination potential, i.e., the perceived likelihood that a generative system produces fluent but factually incorrect output (Sivathanu et al., 2026). P1 asks whether this is explained by the durability distinction specifically or operates independently of it.

6.2 Matching gaps to designs

Table 6 (Appendix A) pairs each of the seven principal gaps identified across this agenda with a priority research design, the key mediators and moderators it should measure, and the context in which a test would be most informative. The seven gaps are: durability being inferred rather than observed; the divergence of short- and long-run effects; calibration's potential to invert the efficacy–performance link; the under-theorized social origin of routing; differential routing by expertise and task type; AI design as a manipulable lever; and geographic concentration.

The decisive tests are temporal and comparative: the durability distinction can be established only by designs following the same workers over time and across the tool's competence boundary. The most consequential gap is methodological and follows directly: no included study was designed to measure the durability distinction, each approaching a similar bifurcation through a different pre-existing lens without a shared instrument. Closing it requires purpose-built measurement separating tool-free skill (tool withdrawn) from AI-assisted output, since every included study conflates the two; the education experiment cited in Section 2.5 (Bastani et al., 2025) shows the design is tractable. This calls for designs the employee literature currently lacks: panel and latent growth-curve studies tracking cohorts across an AI rollout, diary studies during onboarding, and measurement of skill with the tool withdrawn, not only performance with it present. Several designs, notably manipulating AI transparency, are experimentally tractable now.

The evidence base is also narrow in a second sense: concentrated in

few national and institutional contexts, which constrains how confidently the boundary conditions reported above generalize elsewhere. Testing whether these moderators hold, or interact with power distance, regulatory context, or labor-market structure across under-represented regions, is both a methodological priority and a genuine theoretical question (Section 5.2). Cross-cultural measurement-invariance testing of AI self-efficacy, anxiety, and usefulness (Benhmama et al., 2026; Soulami et al., 2024) is a precondition for any claim that this synthesis generalizes beyond the contexts studied.

6.3 Conceptual extensions

Three questions follow that the field could not previously pose: whether tool-contingent efficacy can be converted into durable efficacy by design, for instance through AI that withholds answers rather than supplies them; whether an optimal reliance threshold exists beyond which augmentation tips into dependency; and whether algorithmic feedback should be theorized as a fifth source of efficacy information alongside Bandura's four.

The efficacy-durability framework extends Social Cognitive Theory with a competence-durability parameter: whether confidence tracks skill that persists without the tool. Cognitive science's work on cognitive offloading supplies the substitutive mechanism; labor economics' account of skill-biased technical change (Acemoglu & Restrepo, 2019; Autor, 2015) supplies its macro-level shadow; judgment and decision-making research on algorithm aversion (Dietvorst et al., 2015) addresses trust calibration; and occupational sociology's account of professional identity supplies the appraisal-switch mechanism.

Five of the gaps above share a common signature: each is experiential, temporally extended, and socially situated: the lived experience of developing durable versus tool-contingent efficacy; the social origin of routing, particularly managers' and peers' everyday modelling; how confidence becomes fastened to, or detached from, tool-free competence; the temporal divergence cross-sectional evidence cannot address; and boundary conditions in under-represented settings. An empirical program addressing these gaps is underway and reported separately; it is sequential and mixed-methods by design, an interpretive qualitative phase, appropriate because the object is a mechanism rather than an effect size, followed by a quantitative phase carrying the resulting constructs into measurable form, including the tool-withdrawn comparison specified in P1. Neither phase alone suffices: the qualitative phase cannot establish magnitude; the quantitative phase cannot generate the constructs it would test.

7. Practical Implications

The framework reclassifies as capability decisions several choices organizations treat as efficiency questions. AI procurement and job design are routing levers in the sense defined in Section 2.5: explanatory tools and protected practice support durable capability, while opaque tools optimized for throughput buy short-run output at the cost of long-run expertise (Budhwar et al., 2023; Tambe et al., 2019). Paradoxical leadership and individual technophilia jointly condition whether adoption translates into productive knowledge exchange (Hu et al., 2025), and organizations rarely pair adoption with the skill development the durable pathway requires (Bodea et al., 2024).

Six practice areas follow. **Training** should include deliberate tool-free repetition, not tool familiarization alone. **Competency frameworks** should center judgement (knowing when output is wrong) rather than fluency, consistent with the evidenced weakening of the efficacy–performance link under unreliable output (Sivathanu et al., 2026). **Performance evaluation** should supplement AI-assisted metrics with periodic tool-free assessment. **Leadership practice** matters because managers' own visible AI use is a legitimacy signal

formal policy cannot replicate (Li et al., 2026). **Organizational learning** should capture cases in which AI use converted into durable skill. **Talent management** criteria rewarding output volume alone risk selecting for confidence that would not survive the tool's absence.

8. Limitations

Several limitations qualify these conclusions beyond those already reported above. Restricting eligibility to English- and French-language, peer-reviewed sources may under-represent work in other languages or grey literature. Heterogeneity of designs and measures precluded meta-analysis, so the synthesis is interpretive and cannot quantify a pooled effect. Twenty-one records passing title/abstract screening could not be retrieved in full text and are reported directly rather than treated as complete.

The evidence base is very young: 79 of 91 included studies date from 2023–2025, with a mean corpus document age of 1.99 years. This matters for one claim specifically: the proposal that durable and tool-contingent efficacy diverge over time cannot itself be tested by literature this recent, since insufficient time has passed for such divergence to be observed in any available design. This limits what current evidence can show; it is not a weakness this review claims to have already overcome.

Four further limitations concern the primary studies' methods, each affecting confidence in the widely cited self-efficacy–performance link. Most included studies measure self-efficacy and performance through the same respondent on the same survey, so part of the reported relationship may reflect common method bias rather than a real effect. Few measure the same people more than once (for exceptions, see J. Wen et al., 2026; Xavier & Korunka, 2025), making it difficult to establish whether self-efficacy precedes performance or follows an early success, a question unresolved in the wider literature for two decades (Vancouver & Kendall, 2006). Generative AI tools change quickly, so findings tied to an early version may not generalize and can date faster than in most management research. Finally, studies reporting dramatic results are easier to publish than null findings, and no formal reporting-bias assessment was conducted (Section 3.6), so the included studies may overstate how consistently AI use affects self-efficacy and performance.

None of these four points is specific to this review; they apply to the primary studies it synthesizes, and they are stated because a synthesis is only as reliable as the evidence it draws on.

9. Conclusion

This review set out to explain why the evidence on AI, self-efficacy, and job performance in knowledge-intensive work seems to contradict itself. Following PRISMA 2020, it synthesized 91 studies (84 empirical, 7 reviews) identified through Scopus and Web of Science, characterized the broader 244-record corpus bibliometrically in R, and integrated the findings thematically around three research questions.

The answers can be stated compactly. On RQ1, AI-related perceptions do shape employee self-efficacy, but through two separable antecedent families working in opposite directions: adoption-related perceptions build AI-specific self-efficacy, while threat-related appraisals feed insecurity and anxiety, a pathway that self-efficacy buffers rather than blocks. On RQ2, self-efficacy carries through to performance as Social Cognitive Theory predicts, but conditionally: the link weakens under high task complexity and unreliable tool output, precisely the conditions of knowledge-intensive work at the frontier of what AI can reliably do. On RQ3, the central finding is a measurement gap the synthesis itself establishes: none of the 91 included studies measures

performance with the tool withdrawn, so every existing measure of AI-linked confidence captures comfort with the technology rather than tool-independent competence.

The answer we propose to the field's apparent contradiction follows from these results and is simpler than the disagreement suggests: self-efficacy under AI may be two things, not one. When AI supports a worker's own mastery, it may build efficacy that is real and lasting; when it stands in for the worker's thinking, it may lend an efficacy that feels identical but rests on the tool. If the distinction holds, the two should be hard to tell apart in the short run, which would explain why cross-sectional studies disagree, and should separate over time and at the edge of what the tool can reliably do, where the field's warnings and anomalies sit.

What this review offers is therefore a reframing rather than another extension of an existing model. Treating self-efficacy under AI as potentially durable or tool-contingent turns a contradictory literature into a structured one, and converts a general worry about dependence into a specific, falsifiable prediction with a specified test, one no study of employees in knowledge-intensive roles has yet run. For research, the agenda in Section 6 details the propositions, designs, and measures that test can use; for practice, the implication is immediate even before the test is run, since organizations currently reward and measure a confidence whose durability they cannot see. Whether the prediction survives contact with data is now an empirical question, and this review's purpose is to make it a tractable one.

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Use of generative AI: In accordance with the journal's AIGC policy, the authors used a large language model to assist with language editing and the formatting and verification of references. The research design, the analysis, the interpretation, and all substantive conclusions are the authors' own.

Conflict of interest: The authors declare no conflict of interest.

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Note. References marked with an asterisk () denote studies included in the systematic synthesis reported within the PRISMA 2020 flow diagram.*

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Appendix A. Research gaps matched to priority designs

Table 6. Seven principal research gaps, priority designs, key variables, and priority contexts.

Gap	Priority design	Key mediators / moderators	Priority context
Durability is inferred, not observed: no study measures performance with the tool withdrawn	Experience-sampling and diary studies pairing AI-assisted and tool-withdrawn task assessment (P1)	Durable vs. tool-contingent efficacy; tool-free skill measured independently	Expert knowledge workers with an established pre-AI skill baseline
Short- and long-run effects may diverge; all evidence is short-run	Panel and latent growth-curve designs tracking cohorts across an AI rollout; rollout quasi-experiments	Trajectories of self-efficacy and tool-free skill over time	Organizations undergoing staged generative-AI deployment

Continued table:

Gap	Priority design	Key mediators / moderators	Priority context
Calibration may invert the efficacy–performance link at the tool’s competence boundary	Experiments assigning tasks at and beyond the AI’s reliable frontier	Confidence calibration; perceived vs. actual tool reliability	High-stakes analytical roles (finance, medicine, law)
The social origin of routing is under-theorized	Multilevel designs; leader-modelling field experiments	Leader and peer AI use; psychological safety; team norms	Intact work teams with observable leader behavior
Expertise and task type may route efficacy differently	Comparative experiments across skill levels and task codifiability	Prior expertise; task routineness; novicehood	Mixed-seniority professional samples
AI design is a manipulable routing lever, not a fixed property	A/B experiments contrasting explanatory vs. opaque interfaces	Interface transparency; answer-withholding (tutor-style) designs	Tools amenable to interface manipulation
Evidence is geographically concentrated (China, South Korea, U.S.)	Cross-cultural, measurement-invariance-tested replications	Power distance; labor-market protections; regulatory context	Under-represented regions (Africa, Latin America, South Asia, Europe)

Appendix B. Executed search strings

The conceptual blocks in **Table 3** were executed in each database as follows, reproduced verbatim including field codes and filters.

Table B1. Verbatim executed search strings by database.

Database	Executed string (verbatim, including field codes and filters)
Web of Science	TITLE-ABS-KEY((“artificial intelligence” OR “generative AI” OR “AI” OR “ChatGPT” OR “large language model*”) AND (“self-efficacy” OR “self efficacy” OR “job performance” OR “task performance” OR “work performance”)) AND PUBYEAR > 2015 AND PUBYEAR < 2025 AND (LIMIT-TO (DOCTYPE , “ar”) OR LIMIT-TO (DOCTYPE , “re”)) AND (LIMIT-TO (LANGUAGE , “English”) OR LIMIT-TO (LANGUAGE , “French”)) AND (LIMIT-TO (SUBJAREA , “BUSI”) OR LIMIT-TO (SUBJAREA , “PSYC”) OR LIMIT-TO (SUBJAREA , “SOCI”))
Scopus	TITLE-ABS-KEY ((“artificial intelligence” OR “generative AI” OR “AI” OR “ChatGPT” OR “large language model*”) AND (“self-efficacy” OR “self efficacy” OR “job performance” OR “task performance” OR “work performance”) AND (“employee*” OR “workplace” OR “organi?ation*” OR “workforce”)) AND PUBYEAR > 2015 AND PUBYEAR < 2025 AND (LIMIT-TO (SUBJAREA , “BUSI”) OR LIMIT-TO (SUBJAREA , “PSYC”) OR LIMIT-TO (SUBJAREA , “SOCI”)) AND (LIMIT-TO (DOCTYPE , “ar”) OR LIMIT-TO (DOCTYPE , “re”)) AND (LIMIT-TO (LANGUAGE , “English”) OR LIMIT-TO (LANGUAGE , “French”))

Note. Both strings share the same core AI and self-efficacy/performance concept blocks (Table 3) and apply identical document-type, language, and subject-area filters. The Scopus string adds a third concept block restricting records to an employee/workplace/organizational context. The publication-year field bound (2016–2024) is narrower at the upper end than the January 2015–December 2025 eligibility window in Section 3.2; 2025- and 2026-dated records were assessed and included under the “available online by 31 December 2025” rule described there rather than via this field.